Predicting the effectiveness of early senior decision-making in urgent internal medical care:

Application of a hybrid agent-based and discrete event systems simulation model to evaluate UK healthcare policy recommendations

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This thesis is dedicated to my nieces – Hailey and Hollie. You light up my life and inspire me with your kindness, and confidence. Never let other people determine what is possible for you to achieve.

Abstract

Background

Hospital systems face year-upon-year rises in demand for in-patient services. Moments when urgent care departments are overwhelmed with more patients than they are resourced to provide care for (overcrowding) frequently emerge due to poor availability of hospital beds. Policymakers and healthcare leaders in the UK recommend an early senior decision-making (ESDM) strategy to divert suitable patients away from in-patient services at the time of referral into urgent care. Policies also advise expert clinicians – the highest grade of clinical staff - should perform this task. This research specifically explored the effectiveness of the ESDM strategy when applied to urgent internal medical populations – the largest consumers of in-patient services – with the intention of informing a cost-effectiveness analysis of ESDM.

Methodology

A systems simulation model (SSM) combining agent-based and discrete event systems simulation model was created to reproduce ESDM in a representative acute medical unit in the UK. Data to inform model conceptualisation, programming, and parameter inputs was gathered via observational ethnography, analytic autoethnography of expert early decision-making in urgent care, and prospective data collection of patient-reported outcomes. Outputs aligned with the goals of patients, staff, and provider goals were defined. Upon validation, the model was used to predict how outputs could change with different configurations of expert and non-expert staffing in the decision-maker role. Staffing strategies were analysed at increasing levels of tolerated overcrowding in the department

to mimic high hospital occupancies that limited transfer from the unit. Modelled outputs were analysed for meaningful differences and trends.

Results

Early senior decision-making realised meaningfully fewer moments of overcrowding and delays, but only when departmental overcrowding was enforced. This occurred via of intuitive decision-making by clinical experts - a phenomenon not previously reported in literature available at the time of writing. System-wide inefficiencies begin to emerge when experts perform decision-making for all patients referred. Impact upon patient health is unclear.

Conclusion

The ESDM strategy has the potential to realise safer in-patient care and generate local efficiencies in hospitals that face frequent moments of overcrowding, but not in systems that maintain urgent care bed occupancy levels below 100%. Improving currently available decision-support tools to harness the decision-making of experts may deliver efficiency gains at lesser cost. Further research into the health impact of admission avoidance and overcrowding in urgent care areas outside of the ED is warranted before cost-effectiveness may be explored.

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List of abbreviations

Main and frequently used initialisms are listed below. Further initialisms are section specific and identified during the document.

AEC	Ambulatory Emergency Care	Facility for provision of urgent assessment and care without in-patient observation
AIM	Acute Internal Medicine	Clinical practice specialising in the care of acute (adult) health decline in fields typically described as medical (e.g., cardiology, gastroenterology, neurology, respiratory medicine)
AMU	Acute Medical Unit	Urgent care area specialising in the provision of care for acute health decline for internal/general medical conditions
SSM	Systems simulation model	Simulation model of events/phenomena created in computer software
ED	Emergency Department	Area of urgent care for immediate threat to health or minor injury
ESDM	Early senior decision-maker	Clinician who determines investigation and/or care needs at the start of the patient journey to tailor care according to need a resource availability
HI	Health Index	Measure of health calculated via the EuroQol health survey
HRQoL	Health-related quality of life	Quantitative value representing health and well-being
NHS	National Health Service	Central government authorities in the UK overseeing healthcare delivery – devolved to each UK nation
NHSE	National Health Service England	As above for England
NHSS	National Health Service Scotland	As above for Scotland
PROM	Patient-reported Outcomes	Measures of the outcomes of healthcare self-reported by patients
QALY	Quality adjusted life years	Measure of HRQoL used in economic evaluation

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1. Introduction

1.1 Research overview

Western healthcare systems are under increasing pressure to meet the urgent care demands of an aging population that is growing in size and clinical complexity (The Academy of Medical Sciences, 2015). This has created shift to investigate and treat an increasing number of urgent conditions via out-patient services, thus focus in-patient resources on only those who require direct observation and care (Yang; Tian et al., 2012). Hospitals in the UK achieve this via co-located facilities within urgent care areas termed ambulatory (or same day) emergency care (NHS England, 2019; NHSE, 2019; NHSS Director General, 2020).

United Kingdom policymakers advocate early recognition of patients whose needs may be met via urgent out-patient pathways, preferably at the point of referral into hospital (NHS England, 2019; NHSE, 2019; NHSS, 2015; NHSS Director General, 2020; Society for Acute Medicine & RCEM, 2019). Published health policies are explicit in their recommendations that these decisions are by made by senior clinicians. Although the documents are vague in their definition of which staff they mean, local healthcare leaders have interpreted this to mean a consultant or trainee nearing completion of training.

This research sought to explore the value of using consultant physicians (senior medical staff) to make early remote decisions in urgent internal medical populations referred with acute health decline. Informed by an ethnographic study of the ESDM strategy in action in a university teaching hospital, a systems simulation model combining agent based and discrete event modelling was created to reproduce ESDM for acute internal medical patients – the largest consumers of in-patient resources (Steventon et al., 2018). The model was used to predict how outcomes with meaning to patients, staff, and providers may vary when different types of staff are charged with remote admission avoidance decisions. The findings provided modelled outputs of different staffing configurations for use in economic evaluation of ESDM. These could be used to evaluate the policy recommendations and inform healthcare leaders of the value of introducing ESDM into their organisation.

1.2 Research motivations

High-stakes health decisions about admission avoidance performed with limited information and without a clinical evaluation present risks that should be understood before the recommended intervention is implemented. An early senior decision-maker (ESDM) strategy assumes that care without direct in-patient observation is as effective as in-patient care, is less costly, is preferred by patients, and is less harmful (NHS England, 2019). These assumptions are not supported by current evidence because little research has been done. Some risk in acute internal medicine (AIM) populations is mitigated by the process of patient referral into acute medical units (AMUs) – these facilities invariably take referrals only from clinicians who have first evaluated the patient in the community or the emergency department (ED).

Of greater concern, is a philosophy of out-patient care for acute health decline amongst policymakers and healthcare leaders across the UK that has gained traction as hospital bed numbers diminished. The emergence of AEC coincides with a decreasing number of in-patient resources across the UK in the last 20years. This downward trend in in-patient resource availability does not reflect predicted needs over the coming years and contradicts professional body recommendations (RCEM, 2022; SAM, 2019). This observation raises concerns that remote decision-making functions to ration in-patient resources as much as meet assumed patient preferences to avoid admission. A model for early decisions on admission avoidance is not a poorly conceived one for ensuring effective use of resources, but it does rely on the assumption that ambulatory emergency care (AEC) is as effective as in-patient care and non-harmful.

Finally, the costs of staffing an ESDM model with senior clinicians should not be underestimated. Consultant staff represent the smallest cohort of medical staff in an acute hospital setting whilst junior trainees make up the largest. All are employed to deliver an increasing amount of clinical, managerial, administrative, and training services. Consultant staff in acute medicine already face significant challenges to deliver existing services (Society for Acute Medicine, 2017). Introducing an ESDM model delivered by consultants and/or higher specialist trainees will require substantial reconfiguration of work and/or additional staff (Irvine et al., 2022). Other interventions may deliver better outcomes for the same or less costs.

1.3 The research question and objectives

How effective is the proposed early senior decision-making model compared with other remote decision-maker staff strategies?

It is not hard to identify the theoretical merits of an ESDM strategy, but this is insufficient to recommend its widespread introduction without further evidence of its value. Early identification of patient need enables proactive management of patient flow, proactive management of patient care via early identification of need, and allows tailoring of standardised practices to meet patient-centred goals (e.g., manipulation of resources to meet patient needs via established organisational networks). That said, amongst AIM specialist, it is known to be a very time-consuming activity. This makes it difficult to perform alongside other clinical activities. Evidence of it being an effective use of time is required.

Effectiveness in urgent care delivery is not easy to define. The finite nature of healthcare resources, the costs of new technologies, and dwindling availability of in-patient resources mean that performance metrics and costs of care will continue to inform national leaders on the state of services for the foreseeable future, but improvement in population health is arguably the key goal. Measuring health in urgent care is easier said than done; many patients will pass through an urgent care setting before transfer to another department – determining the contribution of one department to improvement in health may be impossible. Patients' conditions and the treatments required vary widely; in some situations, the goal may be solely to prevent deterioration whilst in others it may be to cure. Answering the research question required defining the nature of effectiveness.

Consistent with the NHS Constitution and the new policy goals (The NHS Constitution for England, 2021; NHS England, 2019; NHSS Director General, 2020), effectiveness was defined as timely access to resources, fewer in-patient admissions, no overcrowding, improvement in health, and a positive experience of care. The main research question was broken down into focused queries used to explore the available literature and define the objectives for planning the research methodology as shown in Table 1:1.

By collecting data of ESDM in a real-world setting and reproducing the model of service delivery in a systems simulation model, I predicted how the outcomes of effectiveness may differ according to the type of staff performing the task. This facilitate a safe and efficient evaluation of the difference between experts and non-experts in the early decision-maker role without the logistical, ethical, and resource exhaustive challenges that a controlled field study would present.

Table 1:1 The research objectives and methodology

Queries	Objectives	Methodology overview
What does remote allocation decision-making by consultants look like and how may it differ from remote decisions by other staff?	Gain knowledge of the processes of expert and non-expert decision-making that are required for remote urgent care decisions. Understand how expert systems currently function	Create a conceptual model for reproducing remote allocation decision-making in a real-world setting
How is the urgent care system affected by consultant ESDM decisions compared with early decisions by other staff?	Gain knowledge of the effects of early allocation decisions on the performance of urgent care – demand on services, delays to care, departmental occupancy levels, resources used	
What impact does consultant ESDM have on the hospital system compared with early decisions by other staff?	Gain knowledge of the effects of early allocation decisions on the hospital systems – transfers, occupancy levels, other services	
How does the dynamic and stochastic nature of the urgent care environment influence decision-making and decision outcomes?	Understand how the urgent care environment works and interacts with the other parts of the healthcare system Gain knowledge of how staff decision-making may alter in the face of external influences Gain knowledge of the types of patients accessing care and using non-admission pathways	
What are the health outcomes for patient allocated to non-admission pathways compared with urgent in-patient pathways?	Gain knowledge of the health outcomes of patients managed in urgent care via in-patient and out-patient services	Create model inputs representing patient health and experience that can be applied to predict the value of ESDM for patients
What are the experiences of patients allocated to non-admission pathways compared with urgent in-patient pathways?	Gain knowledge of the lived experience of patients undergoing urgent care treatment via in-patient and out-patient services	
How might these the processes of early decision-making and their outcomes be usefully reproduced in a systems simulation model to predict the effects of consultant ESDM on a hospital system?	Apply the knowledge and techniques of operational research to create a series of virtual experiments that can reproduce the decision environment and demand and predict outcomes of ESDM when performed by experts and non-experts	Create a systems simulation model based on the conceptual model may predict the patient, department, and system outcomes of different categories of staff making early remote decisions

1.4 Thesis structure

Researching ESDM in acute internal medicine (AIM) required understanding of how consultant and non-consultant staff make remote allocation decisions for AIM populations, the influences upon them, how they may be reproduced via programming, and how the outcomes of decisions may be captured and analysed. This required appreciation of the epistemological challenges involved in understanding how complex systems may be explored, captured, and understood. It required the application of both established and novel methodology in the observation and analysis of institutional behaviours and the decision processes of staff. It also required understanding of the power and limitations of systems simulation modelling.

The thesis is structured to reflect this complicated journey in a narrative that explains how the assimilated knowledge came together to answer the main research question. It begins in **Chapter Two** by providing the reader with context of the ESDM strategy via a description of how urgent care delivery in the UK came to be in its current state. This includes the emergence of admission avoidance and Ambulatory Emergency Care for acute internal medical populations. A literature review in **Chapter Three** exposes the gaps in the knowledge of the effectiveness of ESDM in urgent care and explores the usefulness of systems simulation modelling in addressing these gaps. The available knowledge that may be of use to inform the programming and parameter inputs of a predictive systems simulation model of ESDM in different staff is also presented. The chapter concludes with a discussion of the gaps identified and how the research proposed could address these.

Chapter Four explains the methodology applied to answer the research question. It begins with a discussion of the ontological nature of a social system and how this relates to the chosen research technique of systems simulation modelling. This leads onto a discussion of the use of case study research, ethnography, and analytic autoethnography to inform a systems simulation model (SSM). Thereafter, the chapter describes the techniques applied for data collection and analysis in each component of the research strategy: the ethnographic study of decision-making and the decision environment, the quantitative study of activity on the case site, the creation and validation of an explanatory SSM, and the strategy for predicting the outcomes of alternative staffing models for early decision-making.

To reflect the components of the research and the SSM building process described in Chapter Four, the results are presented over four chapters. **Chapter Five** delivers the findings from the first arm of the research - the analytic autoethnography, and ethnographic study of the case study site. **Chapter Six** then explains how these findings were used to conceptualise and create the SSM. Validation and sensitivity analysis of the SSM is presented in **Chapter Seven**. This demonstrates the explanatory power of the SSM and discusses it usefulness for predicting the outcomes of alternative staffing models. **Chapter Eight** presents the model outputs when alternative staffing strategies are considered. Discussion of the alternative staffing SSM outputs relating to the extant literature is presented in **Chapter Nine**. The implications of the research findings for the case study site, other sites delivering acute internal medical care are included here. Chapter Nine concludes with a discussion of recommended next steps to build upon the knowledge created and the limitations of the research. Conclusion and contributions are presented in **Chapter Ten**.

1.5 Terminology

Definitions of and terminologies for the processes of urgent care delivery used in this research are presented here. Individual healthcare systems and organisations vary in the terminologies used to refer to identical or broadly similar processes of care. Urgent care delivered without hospital admission is variably referred to in the UK as ambulatory emergency care (AEC), same day emergency care (SDEC), or rapid assessment and care (RAC). Such services are almost always situated in or near to urgent in-patient facilities on hospital premises and share resources with in-patient areas. In this research, the term ambulatory emergency care (AEC) refers to all such services. International organisation may use this term to describe different services (e.g., the United States). A further important point concerns the terms urgent care and emergency care. Non-healthcare persons may use interchangeably but they have slightly different meanings to clinicians. In this thesis, ‘urgent care' is an umbrella term to cover all areas and processes within a secondary care system responsible for managing unplanned threats to health that require assessment within 48hrs. Where discussion concerns a specific department in an urgent care system, e.g., the Emergency Department, the nature of illness and the department are explicitly described. All services out with of acute and emergency medicine are described as elective services unless explicitly stated.

Acute Medical Unit (AMU) refers to all areas of care into which acute internal medical (AIM) populations are directed when attending for evaluation and care via the community and the ED. The terminology preferred by the Society for Acute Medicine is AMU (R. Dowdle, 2021). Hospitals in the UK and internationally use different terminology used to describe departments designed to house AIM populations (e.g., combined assessment unit). I will use AMU to describe all departments outside of ED settings that care for AIM populations.

This research uses the word ‘system’ to refer to the acute hospital in which an AMU functions. The World Health Organisation defines a healthcare system the collection of “organizations, institutions, resources and people whose primary purpose is to improve health” (World Health Organisation, 2010). Providing knowledge of how expert ESDM could affect a system using this definition would be labour intensive and, arguably, impossible. Thus, in exploring the effects of the expert ESDM beyond urgent care, the definition of system was narrowed to mean the acute hospital in which urgent care is delivered.

Terminology of staffing roles requires clarification as the term clinician may be used to describe many categories of healthcare professionals. In this work, the word ‘consultant’ refers to a fully trained hospital doctor. This is someone who has completed undergraduate and post-graduate training on a program recognised by the Royal Colleges as sufficient to be awarded a certificate of completion of training. ‘Medical staff’ refers to anyone who has undergone a medical and/or surgical training programme after achieving an undergraduate medical degree. ‘Trainees’ in this body of work are doctors in post-graduate training but it also includes healthcare professionals who are trained to deliver clinical care below the level of a senior doctor such as advanced nurse practitioners and physician associates. The competencies in these latter professions may be assumed to be commensurate with those of trainee medical staff excepting those nearing completion of consultant training.

Finally, in this study, a hospital admission was defined as a transfer to an in-patient setting from the AMU or AEC area. The definition of a hospital admission lacks clarity in the relevant, available literature (for example, the definitions for 'admission' and 'in-patient in the ISD Data dictionary (2023) used by NHS Scotland). The NHS has previously defined an in-patient episode as any time spent in an available staffed bed under the care of specialist consultant (National Services Scotland, 2023). This could easily include attendances of less than one hour. As will be explained in Chapter Two, the urgent care landscape has changed dramatically over the last 20years. Where urgent care is delivered via ED, the difference between an in-patient bed and a temporary assessment space (such as a trolley) is clear. With newly developed areas like AMUs, the difference is blurred. These areas receive patients directly from the community like EDs, however, they place many of their patients into staffed in-patient bed (Society for Acute Medicine, 2022). The devolved UK healthcare services are in the process of adapting how hospital attendances are defined and recorded to reflect this. The definition chosen for this research is designed to reflect that fact that urgent care beds are not available for elective use in the same way that other hospital beds may be.

2 Background

"Our Vision for Healthcare in Scotland is that, by 2020, everyone is able to live longer, healthier lives at home, or in a homely setting... When hospital treatment is required, and cannot be provided in a community setting, day case treatment will be the norm. Whatever the setting, care will be provided to the highest standards of quality and safety, with the person at the centre of all decisions. There will be a focus on ensuring that people get back into their home or community environment as soon as appropriate, with minimal risk of readmission"

2020 Vision for Healthcare in Scotland (2013)

2.1 Introduction

Before considering the evidence behind the ESDM strategy, it is necessary to understand its origins and context. To do this requires knowledge of the changing landscape across urgent care over the last 20 years, how admission avoidance via Ambulatory Emergency Care (AEC) emerged, and where policymakers' desires for a consultant-delivered (rather than consultant-led) services arose. The provision of urgent care without admission is a relatively new phenomenon in healthcare that has only been possible with advances in health technology and innovations in clinical practice over the last 15years (Ham & Brown, 2015; NHS England, 2019). It is still in a relatively infant period. Not all healthcare systems globally practice it - decisions to avoid admission in urgent health care require sound clinical knowledge because they are high risk. However, a reduction in the resources to provide in-patient care, an expanding, ageing, and multi-morbid population, and fears for iatrogenic harm have all made admission avoidance a priority for clinicians. The rising costs of in-patient care have made it a priority for those funding care. Rationing services in this way is high risk, hence a desire to make the most clinically qualified person in the service take responsibility for decisions.

Section 2.2 provides the backdrop to the changes in urgent care delivery in the UK with Section 2.3 revealing the emergence of AEC to manage spiralling inefficiencies thought to lead to high occupancy levels. Section 2.4 describes the influence of the evolving AEC on national health policy and identifies the challenges that an ESDM strategy faces. The value that research into the ESDM may bring is discussed in Section 2.5. A summary of the background, and how the research question formed concludes the chapter.

2.2 Urgent care landscape in the 21st century

The changes in population health, clinical care delivery, health policy, and technology towards the end of the 20th century contributed to a progressive increase in urgent care activity in the UK and worldwide (Mathers & Loncar, 2006; The Academy of Medical Sciences, 2015). Access standards were created to encourage rapid transit through urgent care and ensure available provision for all new arrivals (Guilfoyle, 2012; P. Jones & Schimanski, 2010; Tenbensel et al., 2020). This created incentives to admit patients into areas not subject to performance targets, bottlenecks in AMUs, and contributed to high hospital occupancy levels that affected non-urgent care (Bevan & Hood, 2006; Mason et al., 2012; Propper et al., 2008).

The causes of the increased demand for urgent care in the UK and the reduced supply of resources are presented in Table 2:1.

Table 2:1 Influencers of supply and demand of urgent care resources

Supply (direction of influence)	**Demand** (direction of influence)
Reduction in acute hospital beds (↓)	Increasing population over 60years (↑)
Reduction in community hospital beds (↓)	Increasing co-morbid burden (↑)
Technological advances in diagnostics and therapies[a] (↑/↓)	Technological advances in diagnostics and therapies[a] (↑)
Reduced availability of primary care doctors (↓)	Performance targets for care delivery (↑)
	Recognition of iatrogenic harms (↓)

[a]increases supply as we can treat more efficiently & increases demand as we become more aware of what can be treated

(J. F. Coughlin et al., 2006; Mason et al., 2012; Paddison & Rosen, 2022; RCEM, 2022; The Academy of Medical Sciences, 2015)

2.2.1 Clinically driven changes in supply and demand

A higher burden of poor health and a larger population in the UK has increasingly overwhelmed NHS services' capabilities over the last few decades. The aging population is worldwide phenomenon that has seen an increase in the size and the proportion of the UK population aged ≥60yrs (Storey, 2018). This has made multimorbidity - the co-existence of two or more medical conditions in one individual - increasingly prevalent in the UK (Head et al., 2021). This increases demand for both the elective and urgent care as chronic disease follows a trajectory of gradual decline, punctuated by illness events that require urgent intervention (Lynn & Adamson, 2003). These acute episodes become more frequent as age and diseases progress, and/or preventative (elective) services are inaccessible. Utilization of urgent care services rises in the later stages of life (Steventon et al., 2018).

As the volume of chronic ill health (and its costs) has risen, so has the scope to provide care in non-traditional ways - for example, technical and clinical innovations in surgery have seen a reduction in operation and recovery times allowing a wider availability of surgical care without overnight hospital admission (Skues, 2013). Such innovations have significantly reduced hospital admissions for elective care of surgical patients, but the elective care of medical (non-surgical) populations is largely delivered in the community where the availability of GPs has been steadily outpaced by demand (Jefferson & Holmes, 2022; Public Health Scotland, 2022a). Reduced access to GP care in a timely manner, naturally, limits prevention of acute events and/or health decline at an earlier stage. This increases the risk of urgent care need and admission.

2.2.2 The introduction of the urgent care performance standard

Performance standards introduced at the beginning of the 21st century improved many aspects of care but the focus on time and not clinical need had a negative impact on care throughout the hospital system. In the early 2000s, the UK Labour government introduced the first, urgent care performance measure for the UK – the four-hour access standard (Department of Health, 2000). Similar performance metrics were subsequently adopted by other international health systems with mixed results (C. Sullivan et al., 2016; Tenbensel et al., 2020). The four-hour access standard[1] was a nationally mandated performance metric designed to reduce waiting times and overcrowding in EDs; It had a significant impact on urgent care flow following its introduction, but this was not consistently seen nor maintained across the UK (P. Jones & Schimanski, 2010). Crucially, although designed to be implemented in all urgent care

[1] assessment, treatment, and disposal from the ED within 4hrs of presentation in 95% of all patients (this was initially set at 98% but was reduced a few years following its introduction)

areas, it was widely interpreted as only applying to areas where care was delivered on trollies meaning it was seldom applied to other urgent care areas where patients were routinely cared for in traditional hospital beds.

The pressure to achieve the new access standard led to unintended, although arguably predictable, changes in staff behaviours that were not always in the best interests of patients (Guilfoyle, 2012; Tenbensel et al., 2020). Prioritization of patients according to time rather than clinical need was reported (Bevan & Hood, 2006). Although some disputed these claims (Kelman & Friedman, 2009), analyses revealed many patients hurriedly transferred to alternative areas as the target neared, creating bottlenecks and pressure upon other urgent care services (Mason et al., 2012). These areas were not subject to the access standard provided they did not house patients on trollies; some received >50% of all urgent care referrals for their specialty directly, bypassing the ED and the access standard altogether (Lasserson et al., 2019). Bottlenecks emerged but harm, overcrowding, and quality of care outside of EDs was poorly captured (Morris et al., 2012, Boyle et al., 2012)

2.2.3 Acute hospital flow in the 21st century

Despite initially successful efforts to reduce long waits in EDs, the increasing demands upon all four UK healthcare systems outstripped the adequacy of resources to meet needs. Urgent care performance in EDs has been gradually declining for the last 10years, more rapidly so since the COVID-19 pandemic abatement. Post-2010, A combination of the factors listed in Table 2:1 has smoothed out previously observed seasonal variations in urgent care demand leading to year-round ‘winter pressures’ (Fisher & Dorning, 2016). Prior to the COVID-19 pandemic, NHS hospitals across the UK saw occupancy rates of approximately 85% (ISD, 2021; NHS England, 2018). This was enough to slow patients' transfer from urgent care areas creating overcrowding, and saw failures in meeting the access standard for many organisations (Fisher & Dorning, 2016). Although lessened during the initial stages of the COVID-19, hospital occupancy data has shown a rapid rise to levels that exceed all previous recordings – the Winter 2022-23 mean occupancy levels were consistently >90% (NHS England, 2022b). This has resulted in persistent overcrowding in urgent care with consequences that impact community paramedic services and access for all patients in emergency circumstances (Iacobucci, 2021).

2.3 Urgent care and hospital occupancy

The relationship between urgent care and whole hospital system occupancy is complex. When few beds are available, urgent care areas are obviously more likely to experience overcrowding (>100% clinical capacity). When overcrowding occurs, quality of and safety in care declines (Morley et al., 2018). The four-hour standard was introduced to mitigate this by encouraging other parts of the system to minimise waste and reduce patients' lengths of stay. The short-lived success of the standard highlights the myopia inherent in applying linear thinking to urgent care processes, but the same linear frameworks are being applied to Ambulatory Emergency Care (AEC). AEC was never a feature of healthcare policy prior to 2010; it emerged from the ground-up in the early 2000s via collaborative clinician networks responding to the pressures introduced by the access standard. Its delivery is more akin to a complex than a linear system.

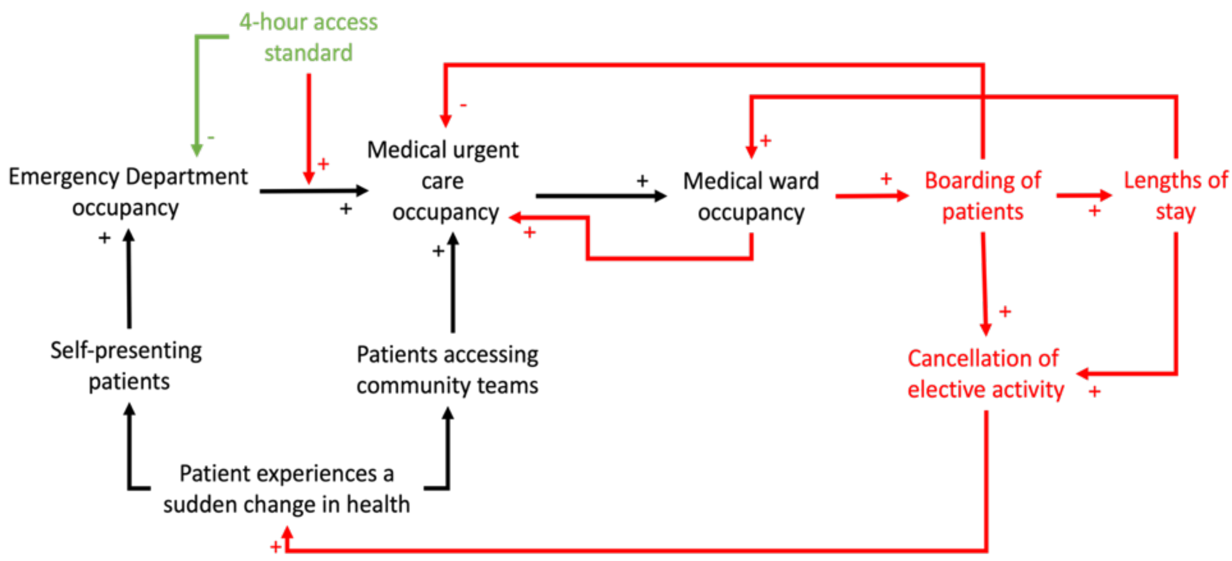
2.3.1 The spiraling inefficiencies of high hospital occupancy

High hospital occupancy levels create inefficiencies in urgent care. Poor bed availability delays the timely transfer of patients from urgent care. This is shown to lead to overcrowding – unsafe departmental occupancy levels (Forster et al., 2003; Rathlev et al., 2007). Overcrowding has been shown to increase the number of high-risk discharges from ED settings (Blom et al., 2014). In many settings, it is correlated with increased hospital admissions with clinicians shown to increase transfers in the presence of overcrowding to reduce risks to safe care (Blom et al., 2014; Gorski et al., 2017; Jung et al., 2021; Ouyang et al., 2022). The presence of a performance standard creates an additional incentive to transfer patients out of the ED (home or transferred) as clinical and non-clinical leaders seek to avoid the punitive consequences of poor performance (Bevan & Hood, 2006; Guilfoyle, 2012; Propper et al., 2008; Tenbensel et al., 2020). If ED discharge is not achieved within four-hours, then movement to a downstream ward is compulsory in NHS Scotland, Wales, and Northern Ireland provided no compelling clinical reason exists not to (ISD, 2020; NHSS, 2015). As of 2019, the four-hour standard is no longer a key performance indicator in England.

Rapid movement of patients from the ED has the potential to introduce system-wide inefficiencies that are compounded by high hospital occupancy levels. As Figure 2.1 describes, urgent medical departments (hence forth referred to as acute medical units or AMUs) receive patients from ED in addition to direct community referrals. Capacity to accommodate new patients is created by transferring assessed patients requiring ongoing care and admission to an appropriate medical ward (e.g., to a cardiology ward for unstable angina). If no beds are available on the appropriate ward, delays to transfer emerge, and patients remain in urgent care pending less efficient ways of creating capacity (identified via the red arrows in Figure 2.1). Alternative ways to create capacity largely amount to a phenomenon called 'boarding'.

Boarding is a reactive measure to deal with demand that creates whole system inefficiency and risks patient health. When boarding, urgent care patients transferring, or established patients on the preferred ward are moved to a non-preferred department (e.g., an orthopaedic ward) to create AMU capacity. Alternatively, patients may be forced to remain in the urgent care area for protracted periods or their entire stay (front-door boarding). Further system inefficiencies emerge with boarding. Staff competencies are often ill-suited for boarded patients' needs and ward resources are deviated from other patients to deal with non-usual care (Åhlin et al., 2022; McMurdo & Witham, 2013). In some cases, planned admissions are cancelled. Acute health decline in the populations whose care is delayed has been observed and increases urgent care demands (Sobolev et al., 2013). Unobstructed transfers to AMUs from ED to meet performance targets are often encouraged by policymakers (highlighted in green in Figure 2.1) (NHSS, 2015). This exacerbates AMU overcrowding as similar rules to mitigate overcrowding and performance measures are not routinely applied to these areas. [2]

[2] The access standard is explicitly applicable to only urgent care areas that provide care for patients on trollies. AMUs are largely furnished with stationary in-patient beds.



LoS: Length of stay

Figure 2:1 Cycle of whole system inefficiency in urgent care overcrowding

The diagram shows how activities and behaviours in response to demand affect occupancy levels in urgent care. Planned pathways and activity are shown in black, innovation introduced to influence activities are green, and emergent activities/outcomes are red. The plus/minus symbols indicate whether a behaviour or activity increases/decreases a behaviour or activity elsewhere in the system. The 4-hour access standard is an introduced behaviour to intentionally reduce ED occupancy. However, it increases demand on medical urgent care areas because patients with incomplete information about suitability for discharge must be transferred to the medical unit once 4-hours has passed. Note that boarding patient, whilst beneficial for urgent care occupancy, is inefficient as it increases urgent care occupancy in other ways (e.g., increased lengths of stay for in-patient areas).

2.3.2 Maintaining pressure in urgent care area to encourage efficiency

Policymakers and national leaders in health have tended towards a belief that the problems facing urgent care largely stem from inefficiencies in the processes of urgent care delivery rather than a lack of in-patient resources. As Figure 2.1 showed, high hospital occupancy levels have the potential to exacerbate inefficiencies in urgent care. This is also observed in non-UK settings (Claret et al., 2015; Derlet & Richards, 2000).

Evidence correlating increased ED discharge rates with high in-patient occupancy level in some settings has encouraged policymakers to argue that departmental inefficiency is at the heart of urgent care's problems (Blom et al., 2014; NHS England, 2017). This is evident in national policies published over the last decade that seek to change how urgent care is delivered and who may access it without support via increased resources (e.g., redirection rules upon ED arrival to prevent 'inappropriate' attendances) (Ham, 2017; NHS England, 2017; NHSS, 2015). A belief held by national NHS leadership that current UK population to hospital bed ratios are sufficient is not shared by clinicians who argue that a lack of in-patient beds is the leading cause of poor urgent care performance (NHS England, 2017; RCEM, 2022; P. Smith et al., 2014).

The competition for in-patient resources between urgent and elective care is an important consideration. Elective waiting lists are heavily scrutinized by politicians and the public, and affect a greater number of people than urgent care delays (Propper et al., 2008; RCEM, 2023; Torjesen, 2023). The consequences of cancelling elective activity may present a greater cultural and political risk for hospital leaders than overcrowding. Referral to treatment times in the UK have been declining for the last decade and have sharply declined since COVID-19 (NHS England, 2023; Public Health Scotland, 2023). Addressing perceived inefficiencies (waste) in urgent care processes is an attractive solution to overcrowding that limits disruption to elective care.

The concept of waste in healthcare delivery is inspired by the manufacturing industry but, the frameworks used to recognize and minimize it have little relevance to urgent care settings (Plsek & Greenhalgh, 2001). Industry-inspired techniques such as Lean Thinking and Six Sigma have led healthcare leaders to consider how overcrowding and admissions could be mitigated by reducing inputs and minimising variation in service delivery via linear models of thinking (Asplin et al., 2003; Linderman et al., 2003; Womack & Jones, 1997). Despite a poor record of success with these methodologies in healthcare settings (Åhlin et al., 2022; Deblois & Lepanto, 2016; Ham et al., 2017; Mazzocato et al., 2010), their influence in urgent care persists (Rosa et al., 2023). Experiences of the failings of linear thinking during the COVID-19 pandemic may change this line of thinking in future (Kuiper et al., 2022).

2.3.3 Reducing inputs and minimising variation: the role of ambulatory emergency care in the UK

Despite the non-linear nature of urgent care services, linear thinking is evident in the new healthcare policies. Asking senior doctors to broadly categorize patients as suitable for out-patient care (AEC) or not via telephone triage is presented by policymakers as a way to minimise variation in urgent care, schedule attendances, and contain costs (NHS England, 2019; Urgent and Unscheduled Care Directorate, 2022). However, measuring efficiency in AEC utilization is far from straightforward. Ambulatory emergency care has all the features of a complex adaptive system (Plsek & Greenhalgh, 2001). Firstly, the unpredictable nature of acute health decline creates a large amount of stochasticity on a daily basis than requires flexibility in processes. Secondly, it emerged via clinical networks in response to unforeseen challenges and continues to rapidly evolve via these networks despite its limited evidence base (Acute Medicine Task Force, 2007; R. Dowdle, 2021; Lasserson et al., 2018). Finally, it absorbs energy and resources from elsewhere in the system to achieve its goals of non-admission which, again, will vary daily - e.g., same day access to diagnostic services used by other patients in the system.

While policymakers promote AEC as a cost-containing strategy for urgent care, its rapid growth in the face of limited evidence suggests it emerged as a pressure valve for urgent care crowding and poor hospital capacity (Hamad & Connolly, 2018; Lasserson et al., 2018). This is appreciated in Figure 2.2 which shows where diverting patients to AEC services from the pool of attending and referred patients reduces pressure. The introduction of dedicated acute internal medical (AIM) specialists and AMUs in the early 2000s, saw discharge decisions occurring more rapidly than had been the case with historical models of care (Bell et al., 2013). Faced with increasing demand from the access standard and high hospital occupancies, AIM clinicians sought to create capacity by identifying patients with a high potential for discharge upon initial evaluation (Acute Medicine Task Force, 2007; Bell et al., 2013; McNeill et al., 2009). This supported care focused on excluding immediate risk to health and arranging out-patient investigation and treatment (Hamad & Connolly, 2018). As Figure 2.2 shows, AEC created the capacity to support the ED access standard without increasing hospital transfers. The pressure to provide timely care, however, remains in the AMU.

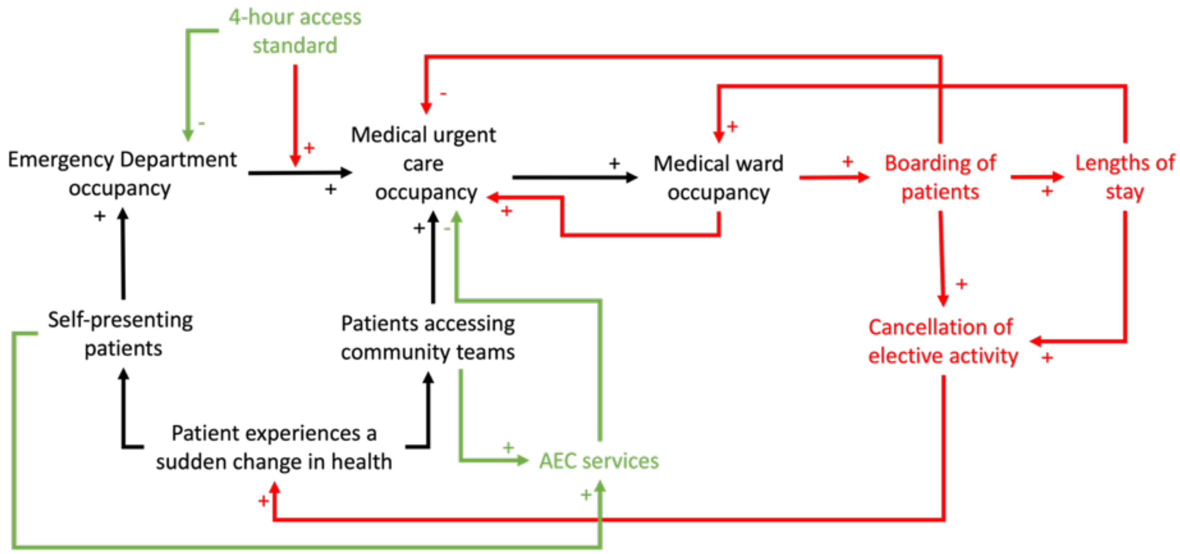


Figure 2:2 The role of ambulatory emergency care to mitigate system inefficiencies

The diagram shows how activities and behaviours in response to demand affect occupancy levels in urgent care. Planned pathways and activity are shown in black, innovation introduced to influence activities are green, and emergent activities/outcomes are red. The plus/minus symbols indicate whether a behaviour or activity increases/decreases a behaviour or activity elsewhere in the system. By removing some categories of patients from medical urgent care reduces the number of patients requiring hospital admission, reduces the likelihood of overcrowding, thus reducing the pressure to board into non-medical areas.

2.4 How health policy informed the research question

As a move to reduce waste in urgent care, UK healthcare policies advocate the early identification of AEC suitability by clinical experts (NHS England, 2019; NHSS Director General, 2020; Welsh Government, 2021). Policies are explicit in recommending that decisions should occur at the point of patient referral into an urgent care system via telephone triage. This strategy is assumed to maximise the number of patients managed without admission and reduce hospital attendances. The next section briefly describes the emergence of policy recommendations and the challenges face when determining their effectiveness. Policymakers and healthcare leaders now laud it as the great hope to minimise variation in care, reduce hospital admissions, and reduce costs. With senior staff directing services via ESDM, they assume that a greater number of patients will be managed without admission and at a lesser cost.

2.4.1 AEC in health policy

The success AEC in avoiding hospital admission in some patients and in some locations led to assumptions of significant gains in waste reduction and admission avoidance if the practice was rapidly extended to a greater number of patients and settings (McCallum et al., 2010; S Purdy et al., 2009; Sarah Purdy & Griffin, 2008). These assumptions informed the recommendations made by policymakers in the NHS England Long Term Plan in 2010 followed by the Scottish and Welsh government policies (NHSS Director General, 2020; Welsh Government, 2021). Recommendations in the NHSE policy cited evidence of a reduction in urgent care hospitalisations over the previous five years despite limited additional funding – this was attributed to greater efficiency in resource use via urgent out-patient services. However, evidence of clinical outcomes, and resource use were absent from the document and it related to Emergency Department attendances only not AMUs (Wyatt et al., 2017). Trends in NHSE data pre- and post-COVID lockdowns reveal an increase in the number of admissions for urgent conditions that allegedly have the greatest potential for out-patient care despite the increasing ubiquity of AEC (Nuffield Trust, 2022). This contradicts policy claims of the impact of AEC on admission avoidance at the macroscopic level.

In line with the policy assumptions that more patients assessed via AEC will lead to fewer admissions, NHS England introduced a new performance standard - utilisation of same day emergency care (i.e., AEC) in 30% of urgent care attendances – as an incentive to increase the use of non-admission care pathways. No objective measure of patient outcomes was recommended, but a fundamental shift towards patient-centred care via consideration of the values and preferences of the individual, and shared decision-making was encouraged. At the time of writing, NHSS and NHSW had not adopted a target for AEC utilisation. The NHS body for Northern Ireland had yet to specify either the role of AEC or any performance metrics beyond the four-hour access standard.

Realising that placing patients with acute health decline may be high risk, NHSE and NHSS made explicit recommendations that senior clinicians should determine patient suitability thus enhancing the use of AEC to its maximum potential. NHS Scotland recommends that decisions are made remotely via dialogue between clinicians at the point a potentially urgent health concern is identified. NHS England is less explicit about remote decision-making but recommends clinical hubs where phone triage and dialogues between clinicians is facilitated to schedule patient attendances implying remote triage is preferred here also. Neither policy is explicit on what is meant by a senior decision-maker. Many healthcare leaders have interpreted this to mean a consultant specialising in acute medical care or a trainee nearing consultant qualification. Anecdotally, some organisations assumed it to include non-medical clinicians such as advanced nurse practitioners or physician associates.

2.4.2 Expert senior decision-making

Based on the presented knowledge of the UK's urgent care systems - we may deduce several challenges to introducing an early decision-making strategy that have, arguably, influenced the recommendation for expert involvement. These are summarised in Box 2:1.

Box 2:1

Challenges to introducing an early decision-making strategy

- Complexities of acute health decline in patients with multiple co-morbidities
- Psychosocial lives of patients
- Variation in patient needs across medical disciplines (e.g., surgical versus medical)
- Variation in resource access for AEC delivery (e.g., remote versus urban locations)
- Evaluation of effectiveness beyond departmental efficiency

The challenges described in Box 2:1 involve clinical knowledge, knowledge of the local system's capabilities, patients' needs, and the uncertainty inherent in acute health decline. This requires consideration of the safety, effectiveness, feasibility of out-patient care, and patient preferences as shown in Figure 2:3.

Figure 2:3 The inter-relational challenges of an early decision-making model

The patient's acute health concern is at the core of and urgent health decision with all the elements that inform the decision to manage via in-patient or out-patient services surrounding it. Knowledge of clinical medicine and appreciation of the systems' capabilities in delivering AEC, based on what is known about the patient at the time of referral, are the primary considerations. Patient-specific, contextual elements are also influential as these will inform the feasibility of AEC and facilitate the desired patient-centred approach. Consideration of feasibility and safety create a holistic approach to effective admission avoidance. Feasibility also relates to resource capabilities to administer care traditionally provided as an in-patient (e.g., intravenous therapy). Effectiveness encompasses the elements that an admission avoidance strategy in urgent care seeks to address according to policy.

2.4.3 The value of expertise

Navigating the inter-relational challenges within the time-frame available to make an urgent decision requires expertise that is likely to be task specific (Shanteau, 1992). As Figure 2:3 demonstrates, the skill in early decision-making is multi-faceted and covers several domains of scientific and social knowledge. These will differ for each domain of clinical practice – AIM consultants have a different skill set and domain of practice to ED consultants. There is also an individual element of professional accountability and attitude toward risk-taking to be considered (Pikkel et al., 2016). Variation in performance of early, remote decision-making is likely to exist between differently trained staff.

Disagreement exists between urgent care clinicians about the value that consultant staff bring over other staff when making decisions in the earliest stages of health decline (Abdulwahid et al., 2018). Staffing costs, inadequate resources to respond to decision outcomes, and uncertainty in the remit of the role are concerns that clinicians report but that policies fail to address. Some healthcare leaders may feel consultant time generates greater value once the patient has arrived in the system an undergone further evaluation. This is the style of decision-making that they have been trained to perform and employed to deliver.

2.4.4 Measuring effectiveness of the recommended strategy

Performance metrics that evaluate urgent care are few. Time to access care continues to be measured and utilisation of AEC services is a new addition, but neither provide a measure of value or of quality (P. Jones & Schimanski, 2010). Introduction of an ESDM strategy may improve both but there are no measures of value. Cost-benefits of the strategy and cost-effectiveness over other models will be impossible to determine with current metrics.

The value-based health movement that emerged in the United States in 2006 focuses determination of value solely in the measurement of health outcomes and costs (Teisberg et al., 2020). But UK health policies are explicit in their belief that quality, safety, and waste reduction must also play a part. This is also the approach suggested by the Institute for Healthcare Improvement who describe value management as "changing point-of-care models to better manage costs and efficiency"[3]. Cost-effectiveness analysis remains the preferred methodology for evaluating healthcare interventions in the UK, but as this form of economic evaluation compares health outcomes in the form of quality adjusted life years (QALYs) it does not incorporate all of the stated policy goals (NICE, 2013). Furthermore, although improved patient health may be the goal of a healthcare system, measurement of health alone will not capture the appropriate outcomes for all patients. For example, patients with a terminal illness or patients whose frailty and social circumstances pose an immediate risk to health but no actual health loss. Such patients may still appropriately access urgent care services.

The devolved UK nations clearly prioritize efficiency in their urgent care delivery alongside better patient outcomes, and high-quality care, but policymaker definitions often blur. For example, NHSS describes quality as "safe, effective, equitable, person-centred, timely, and efficient" (Scottish Government, 2011). The second term excepting,

[3] https://www.ihi.org/Topics/QualityCostValue/Pages/Overview.aspx

these are factors that describe effectiveness (Poskart, 2014). It is also unclear whether the desired effectiveness is goal or system based. Based on the frameworks produced by the health policies, this research assumes effectiveness in urgent care is goal based (Poskart, 2014). Measures of effectiveness reflecting the goals of all stakeholders are poorly described in the policy documents.

2.5 Researching the Early Senior Decision-Maker strategy

As the recommended ESDM strategy is based on expert opinion, research into the effectiveness over other methods of directing care is warranted. The poor description of how it should be measured by policymakers creates a challenge in this regard. The opportunity to evaluate outcomes with different types of decision-making staff and under real-world conditions would require a lengthy period of prospective data collection and reconfiguration of services that could realistically take several years. Systems simulation modelling holds promise as an alternative method to study the effectiveness of ESDM but the challenge measuring effectiveness that reflects all stakeholder goals remains.

A series of controlled field studies could create knowledge of the outcomes of ESDM, but there are significant obstacles to this. Firstly, variations in the delivery of care, resources, and population needs across regions means that between-site comparisons would be challenging and potentially misleading (Reid et al., 2016). Secondly, differences in practice across clinical specialities limit comparability across urgent care domains on a single site. Finally, the logistical and ethical challenges of performing a field study of this phenomenon are considerable: the data collection period would need to capture stochasticity; established cultures of practice would have to be navigated;

each staff would have to be observed in the same controlled conditions; patient harm through poor decision-making introduced by the research design could occur.

Systems simulation modelling (SSM) could overcome the obstacles of a field study by reproducing controlled experimental conditions whilst allowing for the natural stochasticity of urgent care and social systems to be represented. Creating a SSM of the ESDM strategy would require knowledge of the factors that influence early allocation decisions, the human behaviours involved, and the effectiveness of AEC services over in-patient care.

2.6 Summary

This chapter explained how advances in technology, desires to control costs, reduced in-patient resources, performance metrics, and recognition of the harms of the hospital environment contributed to the emergence of out-patient management for some urgent care conditions. It explained how enhancing the use of AEC facilities via telephone triage became recommended practice in the UK and why senior clinicians in urgent care – consultants – are the recommended category of staff to perform early decision-making.

A preference for expertise in remote decision is understandable. Healthcare decision-making in Western populations of the 21st century is clinically challenging as longer life-expectancies come with increasing co-morbidities. Expert knowledge of the capabilities of local system are required to ensure patients and resources are effectively aligned. However, staff with the requisite expertise are already engaged in large volumes of high intensity clinical work. Adoption of an ESDM strategy will require an increase in the number of clinicians with expertise. This brings high costs. There may be equivalent or less costly methods of admission avoidance. On the other hand, ESDM could be the key to realising whole system efficiencies and better patient outcomes making the investment in staffing worthwhile.

The value of additional information about the costs and consequences of an ESDM strategy is arguably high for healthcare organisations in the UK and international settings who follow UK service models. Research that improves knowledge of the outcomes of ESDM and decision-making by other staff could be efficiently performed via systems simulation modelling, but knowledge of how decisions are made in different staff, the outcomes of decisions, and the influence of the decision-environment will be necessary to inform the programming and parameter inputs. Search for this knowledge, and knowledge of systems simulation modelling in healthcare, formed the basis of the literature review presented in the next Chapter.

3 Literature review

This research sought to measure the effectiveness of the early senior decision-maker (ESDM) strategy in acute internal medical (AIM) populations via systems simulation modelling (SSM). To inform the conceptual model and parameter inputs of an SSM that may reproduce ESDM and its outcomes, a literature search was performed. This included evidence of the effectiveness of ESDM phenomenon in urgent care populations, current knowledge of the process and outcomes of remote clinical decision-making, expert clinical decision-making, and how the outcomes of admission avoidance via AEC may be measured. Evidence of the usefulness of SSMs in healthcare research and the available techniques that may be applied to this research question were also explored.

The Chapter begins with an overview of findings (Section 3.1), followed by a description of the literature search strategy (Section 3.2). After this point, my review is divided into three stages reflective of the progress toward knowledge of ESDM, how it may be reproduced, and how outcomes may be usefully explored. In Section 3.3 I critique the currently available evidence of the effectiveness of an ESDM strategy in urgent care, adjacent domains of remote decision-making, and decision support tools for urgent care. In Section 3.4 the evidence for the usefulness of systems simulation modelling in urgent care is discussed with reference to my research aims. The final part of the literature review concerns currently available knowledge that may be used to inform a systems simulation model of ESDM and where vital knowledge is absent (Section 3.5). I divided this section into two parts: how expert clinical decision-making systems function and may be represented in an SSM, and a critique of the metrics available to determine effectiveness and value in urgent care.

3.1 Literature search strategy

Due to inconsistent use of terminology in extant literature on early senior decision-making in urgent care, an iterative process that included snowballing was adopted (Wohlin, 2014). Snowballing has been shown to have equivalency in the comprehensive identification of literature as systematic review via key word database searching (Badampudi et al., 2015; Jalali & Wohlin, 2012; Wohlin, 2014).

Forward and backwards snowballing was performed over multiple iterations until no new papers were found. Available literature was sparse. Much practice in early senior decision-making (ESDM) and identification of out-patient suitability was based upon expert recommendation. To perform a comprehensive critique of ESDM, published work available on the websites of clinical professional bodies, national, and international governments was included. Independent, self-published research commissioned by charities (such as The Health Foundation), and non-government organisations was included where relevant to provide a perspective beyond healthcare leaders, avoid selective bias, and alleviate the absence of peer-reviewing in professional body publications.

Papers not in English or without an accompanying English translation by the authors were excluded. Articles not accessible via University of Strathclyde service (e.g., paywall access limitations) were excluded if the available abstract identified poor relevancy to the research question. Studies involving non-UK healthcare systems were explored for relevancy and comparability before inclusion. Literature that was deemed important to include but was not peer-reviewed (e.g., government reports, professional body meetings) is clearly identified with the online hosting source referenced alongside the date the site was last accessed.

3.2 Early remote decision-making in urgent care

This section critiques available evidence of ESDM in hospital-based teams delivering urgent care, the process that the SSM seeks to reproduce. Specifically, it explores the effectiveness of ESDM – outcomes relating to health production, efficiency, and safety – and factors that influence decision to inform conceptual modelling. As studies were few, the search was extended to primary care clinicians involved in remote decisions for patients with acute health decline. Review included the decision-support tools used by clinicians in identifying out-patient suitability primarily to explore their usefulness in the systems simulation model (SSM).

3.2.1 Early senior decision-making in hospital urgent care teams

Early consultant involvement in identifying patients in whom admission may be avoided appears to have its origins in an opportunistic and retrospective observational study of ED services in New Zealand following a junior doctor strike in the late 1990s (Harvey et al., 2008). Although decisions were made after patient arrival on site, an appreciable reduction in hospital admissions was noted. This led to enthusiasm for early consultant involvement in both ED care and the newly emerging specialty of AIM (Bell et al., 2013; McNeill et al., 2009). Early ED senior decisions to allocate patients to 'fast-track' services for minor injuries has since shown to improve ED performance - reducing length of stay (LoS), meeting national access standards, and mitigating ED overcrowding (Asha & Ajami, 2013; Christmas et al., 2013; Davis et al., 2014; Harvey et al., 2008; White et al., 2010). Redirection of patients for whom community services may be more appropriate (e.g., GP or pharmacy services) was found by some (White et al., 2010), but evidence suggesting a slight increase in hospital admissions when senior clinicians make early decisions in the ED also emerged (Davis et al., 2014).

Findings from studies in ED settings should not be assumed to represent outcomes of early decision-making via AMUs as the patient populations vary (J. R. Dowdle, 2004). In most UK settings, patients falling under the remit of AIM are evaluated by community clinicians and referred directly to AMUs, bypassing EDs altogether (SAM, 2019). This initial community assessment may redirect patients towards alternative community services where appropriate and available, mimicking the success of ED senior redirection (White et al., 2010). It is likely that the decision events leading to the successful use of non-admission pathways and AEC services for AIM patients differ from those used in self-presenting ED populations.

Although differences in the populations limits the transferability of evidence from ED studies to AMUs, it is reasonable to draw comparisons between the trends seen in the early identification of 'fast-track' patients and opportunities to identify patients suitable for AEC – i.e., experts cherry-picking patients for admission avoidance within their own field of practice. This is supported by a small number of observational studies in populations referred to AMUs and AIM specialists directly. Reschen et al. (2020) looked into urgent care performance following the introduction of a dedicated AEC service with consultant or higher-level trainees fielding all referrals. In their model, AEC was the default allocation unless the referral dialogue suggested otherwise. The findings reveal more AEC allocations with a consultant decision-maker compared to a trainee nearing completion of training. This suggests a higher risk threshold in admission avoidance in consultant staff on that site although there is no comparative data of to suggest this is superior to strategies without involvement of expertise (e.g., nurses, administration staff, or junior trainees).

The study by Reschen et al. (2020) found reduced admissions over a 3-year period, but attributing outcomes to call-handling alone would be naive, and the authors make no such claims. The reduction is likely to result, in large part, to the creation and expansion of a dedicated AEC service. This introduces the possibility that, beyond initial gains, the marginal returns of expert decision processes over the longer term could diminish as referring community teams and local non-consultant staff improve their knowledge of local resources, emerging technologies, and clinical evidence as they gain familiarity with new ways of working. The clinical outcomes reported - mortality and readmission - were too insensitive to inform on meaningful health improvement.

Westall et al. (2015) found greater admission avoidance when consultants performed referral call handling compared with senior nurses in AIM populations. This was a small observational study but a clear trend towards fewer in-patient episodes was seen. The study is methodologically weak with little description of staff decision processes, no context of decision events, or the environment, and naively exaggerated claims of performance and cost outcomes. For example, the authors use mean length of stay (LoS) to estimate the gains of avoiding admission despite wide-spread knowledge of acute in-patient LoS having a rightward-skewed distribution. In spite of its flaws, the study does corroborate trends in decision outcomes when comparing clinician experts with non-experts.

There are significant limitations that prevent concluding effectiveness in consultant delivered ESDM over other staff in AIM populations based on the extant literature. The only available cost-effectiveness analysis of ESDM in urgent care has predicted costs in excess of £98,000 per QALY when compared with usual practice (NICE, 2018a). It would be unwise to draw conclusions from this analysis alone particularly as it was ED focused with few studies included. Studies in AIM populations are too few and processes too poorly described to appreciate whether the initial allocation decision contributed to admission avoidance or if the processes of care upon arrival influenced outcomes. The measures of effectiveness were insufficient as none of the studies described health and well-being outcomes and did little to explore harm beyond mortality.

3.2.2 Decision support tools to aid remote decisions

This section explores decision support tools for identifying patients suitable for ambulatory emergency care (AEC). Decision support tools are an increasingly common features of acute medical care (Atkin, Riley, et al., 2022). They may be separated into two distinct categories as shown in Box 3:1 – condition-based and (generic) AEC allocation.

Box 3:1

Condition-based decision-support tools
(Atkin et al 2022)
- Deep Vein thrombosis
- Pulmonary thromboembolism
- SSTI
- TIA
- Acute coronary syndrome
- Pneumonia
- Anaemia

AEC allocation decision-support tools
- Amb Score (Ala et al. 2012)
- Glasgow Admission Prediction Score (GAPS) (Cameron et al. 2017)

The Royal College of Physicians, the main professional body representing acute internal medical specialists, recommend staff apply them to identify AEC-suitable populations (RCP, 2014). The following two sections discusses decision-support tools in both the condition-based and AEC allocation categories.

3.2.2.1 Condition-based tools

Professional clinical bodies in the UK advocate the use of evidence-based guidelines as an adjunct to identification of admission avoidance suitability (RCP, 2014). Condition-specific tools (see Box 3:1) can be incorporated in local guidelines to create standardised pathways of care. This facilitates healthcare policy desires to 'schedule unscheduled care' by safely deterring attendance until the following day or supporting investigation at a later data. Provided an existing governance structure for responsibility of care and follow-up is in place, pathways for conditions like venous thromboembolism, acute coronary syndrome, and skin/soft tissue infection (SSTI) are shown to successfully reduce LoS for those conditions and support safe admission avoidance (Kline et al., 2004; Musey Jr et al., 2021; Olivot et al., 2011; Seaton et al., 1999; Zondag et al., 2013).

It is unclear how often these tools are applied and in what contexts. The incidence of UK patients managed via non-admission pathways using decision-support tools is not clear from available NHS datasets (NHSE, 2020). The number of tools available are few compared with the scope of conditions cared for in AIM populations which contain all internal medical emergencies. Many clinical settings do not use all that are available, preferring to use their clinical judgement on a case by case basis (Irvine et al., 2022; Reschen et al., 2020). They are also risk averse. The multi-morbidity of aging UK populations and desires to include patients' needs beyond the clinical suggested that knowledge of when decision tools are applicable required expertise (Atkin, Riley, et al., 2022; Castro et al., 2016; Manski, 2019). Senior clinicians are shown to ignore decision-support tools and successfully apply higher risk thresholds than tools allow for in some settings which may reflect a desire to accommodate patients' preferences and clinical judgement given the context (Reschen et al., 2019).

In terms of the costs and consequences (use in out-patient versus in-patient care), there are few examples of cost-effectiveness evaluation. Only research into SSTI and deep vein thrombosis services have progressed towards this (Minton et al., 2017; Othieno et al., 2018). This has not included the costs of employing clinical experts for suitability decisions at the points of referral.

3.2.2.2 AEC allocation tools

Two scoring systems to aid staff in the identification of AEC suitability in AIM populations exist – the Amb and the GAP score (Ala et al., 2012; Cameron et al., 2017). Both are designed to replace the decision-making of a senior clinician in the identification of AEC suitability so serve to mimic the ESDM process that this research seeks to reproduce and study. As with the condition-specific tools, the outcomes tend towards risk aversion, and none have been validated for use outside of their study setting.

Both the Amb and the GAP scores are based on appraisal of the physiological stability of a patient[4] and the assumed clinical need at time of assessment and/or referral. However, they differ in scope and usefulness in reproducing senior decision-making via systems simulation modelling. The Amb score was specifically developed for AIM populations referred by community teams whilst GAPS was created for ED populations referred by ED triage nurses. Deriving as they do from different clinical populations, direct comparisons are futile (Lasserson et al., 2018). The GAPS was derived from multiple sites but the Amb from one. Both have been internally validated but neither had been externally validated at the time of writing nor undergone cost-benefit analysis. Both tools demonstrated safe identification of when AEC is not suitable, rather than high levels of accuracy in the positive detection of AEC suitability (Thompson & Wennike, 2015). Much like condition-specific tools, they present a risk averse approach to early decision-making when compared with expert clinicians (Cameron et al., 2018).

[4] The National Early Warning Score developed by NHS England and used across the UK in adult populations https://www.england.nhs.uk/ourwork/clinical-policy/sepsis/nationalearlywarningscore/

Their usefulness in admission avoidance outside of their original settings is difficult to judge as neither have been externally validated at the time of writing (Keane et al., 2022; Salvato et al., 2021; Thompson & Wennike, 2015). Thus, their usefulness for informing a SSM is poor. They face limitations in settings where the physiology scoring system they apply is not validated (e.g., non-UK settings) or if the physiology scoring system undergoes recalibration as has previously happened (Hodgson et al., 2018). Changing practice in the face of new evidence - e.g., safety of IV therapy at home (Minton et al., 2017) - also renders the Amb score somewhat obsolete in mimicking senior decision-making as need for IV therapy adds weight towards in-patient admission (Ala et al., 2012).

3.2.3 Early decision-making in other domains

As evidence of the ESDM phenomenon and its outcomes in hospital settings was limited by a paucity of research, studies of remote decision-making in clinical domains that provide support for hospital urgent care were explored. Such studies are also few in number, but they support findings of variable compliance with the outcomes of decision support tools. They also identify external influences upon admission avoidance decisions not observed in studies of urgent care teams in hospital. The findings enhance understanding of how ESDM processes may occur and be successfully reproduced in an SSM.

Studies outside of hospital settings involve on primary care teams – general practitioners (GPs) and district or specialist nurse practitioners. The events seen are remote decisions made following direct dialogue with patients rather than decision following clinician-to-clinician dialogue (Lake et al., 2017), but there are similarities in the types of patients and the stakes of decisions to be made. Remote primary care systems may employ nurses, administrators, and/or medical staff to perform telephone triage and make use of computerised algorithms to support decisions (Lake et al., 2017). Non-compliance with the outcomes of decision support tools, in favour of clinical judgement, has been frequently observed in clinical staff (Leprohon & Patel, 1995; Wouters et al., 2020).

Risk taking in remote primary care decisions is found to be inconsistent with individual attitudes towards personal risk. Decisions tend towards risk aversion in less experienced staff or where information is limited by language barrier (Wouters et al., 2020). Senior nurses and GPs comfortably overrule algorithm decisions of urgency to non-urgency much like their consultant counterparts in AIM but the accuracy of decisions varies (Lake et al., 2017; Wouters et al., 2020). Perceived responsibility for managing scarce resources effectively are reported to have influence on the decisions of both senior nursing and medical staff (Jørgensen et al., 2021; Wahlberg et al., 2003).

3.2.4 Conclusion

This review found no evidence to support policymaker assumptions that ESDM is an effective strategy AIM populations referred to urgent care. This is largely because studies of ESMD are few. However, those available consistently revealed fewer hospital admissions when consultants performed allocation decision-making in their specialist domain. This effect lessened when consultants performed ESDM outside of their usual domains of practice, for example an ED specialist allocating AIM patients. These findings support policymaker assertions senior clinicians make more out-patient allocations in referred/attending populations than non-experts. Outcomes beyond this are lacking and data to inform SSM of ESDM are inadequate.

Decision-support tools are similarly inadequate to reproduce ESDM for SSM. Although the purpose of decision-support tools is to aid decision-making in the absence of expertise, evidence of non-adherence to recommendations is not infrequently encountered amongst non-expert clinicians (non-clinicians rarely ignore recommendations). This may be because they are a poor mimic of expert decision-making; the decisions generated are consistently risk averse compared with observed practice in AIM experts. Non-adherence may be appropriate if a tool fails to adequately represent the patient and context, but individual fears poor decision-making and perceived responsibility for managing scarce resources are reported influences. Knowledge of when and why non-adherence may occur to incomplete for the purposes of conceptual modelling.

This section sought to establish the evidence base for the healthcare policy recommendations of ESDM. As evidence of its effectiveness over other strategies was absent, information to inform a systems simulation model to reproduce ESDM for AIM population was sought. This too was incomplete. What was known suggested nuance in how allocation decisions emerge and their influencers. Influencers were found to be external, internal, specific to individual staff, and specific to groups of staff. As outcomes of effectiveness were poorly explored, it remained unknown if variations in allocation decision-making would realise meaningful consequences. Conceptual modelling to inform SSM required greater knowledge of early decision-making in real-world settings in different categories of staff. Conceptual modelling also required appreciation of suitable SSM techniques for reproducing urgent care systems and ESDM. This is the subject of the next section.

3.3 Systems simulation modelling in healthcare

The previous section confirmed that evidence of the effectiveness of the early senior decision-maker strategy advised by healthcare policy is poor. Furthermore, data to inform a systems simulation model to improve this knowledge state is lacking. Before considering how an SSM could be created and what data should inform it, appreciation of the usefulness of the methodology for this research purpose is warranted. This includes knowledge of the SSM methods available and their suitability for reproducing the ESDM phenomenon and its outcomes. This section introduces the evidence for the use of systems simulation modelling in healthcare and explores its value in researching ESDM in an urgent care setting.

3.3.1 Systems simulation modelling in urgent care

The application of SSM application to health services, including urgent care, has steadily risen, although few researchers seen their findings applied in real-world settings (S. C. Brailsford et al., 2009; Tako & Robinson, 2015; Zhang, 2018). As a methodology that facilitates insight into the workings of complex systems and predict the outcomes of strategy change, SSM is attractive to healthcare leaders (Fone et al., 2003). It has several appealing advantages over direct experimentation: it is less expensive than direct experimentation, results are more rapidly available than would be with a large-scale field study, it allows for replication of studies by other researchers, and it avoids introducing changes to care that may harm patients (Pidd, 2004). Despite enthusiasm amongst operational research academics and some clinical leaders, most research applying SSM to urgent care has remained theoretical rarely proceeding to implementation (S. C. Brailsford et al., 2009; Mohiuddin et al., 2017; Vázquez-Serrano et al., 2021; Zhang, 2018). Its application is overshadowed by a preference for direct experimentation upon local systems via the 'Plan-Do-Study-Act' approach of operations management (Proudlove et al., 2007). This "big gains through small changes" approach applies data-analytics and model-testing than SSM, and heavily engages healthcare staff in the research process allowing healthcare leaders to directly witness outcomes in their location (Proudlove et al., 2007; Spear, 2005). The appeal of PDSA over SSM is understandable when this is considered particularly when the body of evidence of successful implementation is small. In their review of SSM studies, Fone et al. (2003) argued that the value of SSM to healthcare systems was unknown (Fone et al., 2003). However, the use of SSM to guide national policy, community, and hospital care delivery during the COVID-19 pandemic that emerged in 2020 have arguable advanced this position to demonstrate value (Ferguson et al., 2020; Irvine et al., 2021; Nguyen et al., 2022).

Acute medical care's complexity and stochasticity may present substantial programming and computational burden when using SSM (S. C. Brailsford et al., 2004; Siebers et al., 2010). Within urgent care, SSM has almost exclusively focused on emergency departments (ED) (Cassidy et al., 2019; Vázquez-Serrano et al., 2021; Zhang, 2018); its application to acute medical units is rare by comparison (Bokhorst & van der Vaart, 2018; Chalk, 2020). This may be because AMUs represent an intersection between community care, emergency care, and hospital care (elective and urgent) as all services may refer patients here (Acute Medicine Task Force, 2007); performance targets to support its efficiency do not exist as they do for EDs. The numbers and natures of relationships within an AMU are quite different to those of an ED. This means greater complexity as urgent care environments are demonstrate clear features of complex adaptive systems (Plsek & Greenhalgh, 2001). Research methodology informed by modelling frameworks that do not accommodate complexity are likely to be inadequate to explore service delivery, long-term planning, and evaluation (Deblois & Lepanto, 2016). This may explain why implementation of some forms of SSM research has been rare (Mohiuddin et al., 2017).

Credibility in SSM findings presents a barrier to implementation in healthcare (Günal & Pidd, 2010). Previous work has emphasised the need for appropriate stakeholder involvement in conceptualisation, and model building, and adequate level of detail for relevant stakeholders (S. C. Brailsford et al., 2004; Günal & Pidd, 2010; Harper & Pitt, 2004). Lane et al. (2003) describe repeated meetings and model demonstrations to help staff understand the nature of the assumptions modelled and the power of their unique involvement before organisational engagement could be usefully established. By demonstrating credibility in the insights generated, the 'converted' staff provided access to other relevant stakeholders increasing acceptance of the modelling work and outputs. This deeply collaborative approach is evident in the SSM work that successfully guided healthcare delivery and policy development during the COVID-19 (Irvine et al., 2021; Nguyen et al., 2022). That said, credibility is not the only barrier to implementation. Desires for fast, inexpensive solutions to the problems of healthcare delivery are as influential today as they were four decades ago (Wilson, 1981).

3.3.2 SSM methods

Choice of SSM method should be determined by the nature of modelled relationships, outputs sought, and level of the system reproduced. Consideration of the role of entities with specific behaviours, learning, and autonomy in the system to be reproduced is important because not all techniques may be able to usefully reproduce them. As Table 3:1 describes, the three most commonly applied techniques vary in their scope to reproduce entities behaviours across all levels of a social system like the one explored in this research. The level at which the object of research lies and that of the outcomes to be measured need to be determined before the correct technique/s is established. As do the levels at which events, activities, and behaviours that are known/theorised to meaningfully contribute to outcomes occur. There are three levels to consider: the microscopic level of the individual entity, the mesoscopic level of the group entity/or local system, and the macroscopic level of the whole system (Serpa & Ferreira, 2019). These levels, as they relate to the ESDM strategy, are shown in Figure 3:1.

Table 3:1 Comparison of systems simulation modelling techniques for healthcare

DISCRETE EVENT SIMULATION	AGENT-BASED MODELLING	SYSTEM DYNAMICS
Events 'top-down' driven	Events 'bottom-up' driven	Events 'top-down' driven
Stochastic (multiple futures)	Stochastic (multiple futures)	Deterministic (one future)
Entities are passive (Actions determined by the system)	Entities are active (Autonomous decision-making in the system)	Entities not a feature
Central control - entities are assigned characteristics at random from a distribution of possible values	Decentralised control - entities are assigned characteristics that inform their if/then logic of decision-making from a distribution of possible values	Entities not a feature
Entity actions according to fixed characteristics. May respond to environmental change determined by the system not the entity. No learning	Entity actions respond to environmental changes via an independent entity's 'if/then' logic with the capacity to learn and adapt for future actions	Entities not a feature
Scheduling of events a feature	Scheduling of events possible but programming burden may be high. This is dependent upon the software used, time-steps chosen, and volume of events to be programmed[a]	Schedules not a feature
Outcomes follow a linear logic	Outcomes emerge in non-linear fashion	Outcomes emerge in non-linear fashion
Model focus on networks of queues	Model focus on entity (agent) behaviours. Does not incorporate networks of queues	Model focus on stocks, flows, and feedback loops
Good for mid-level (mesoscopic) view of system flows	Good for emergence of system behaviour from microscopic-level	Good for system-wide (macroscopic) view of system flows and structure
Limited explanatory power but good predictive power	Good explanatory and predictive power	Good predictive power
Model building time-consuming	Model building time-consuming (more so than DES)	Model conceptualising time- consuming

[a] some ABM software may not include coding short-cuts for event scheduling; additional coding may have to be created increasing model building time

(Table informed by Fang et al., 2018; Marshall et al., 2015; Pidd, 2004; Siebers et al., 2010)

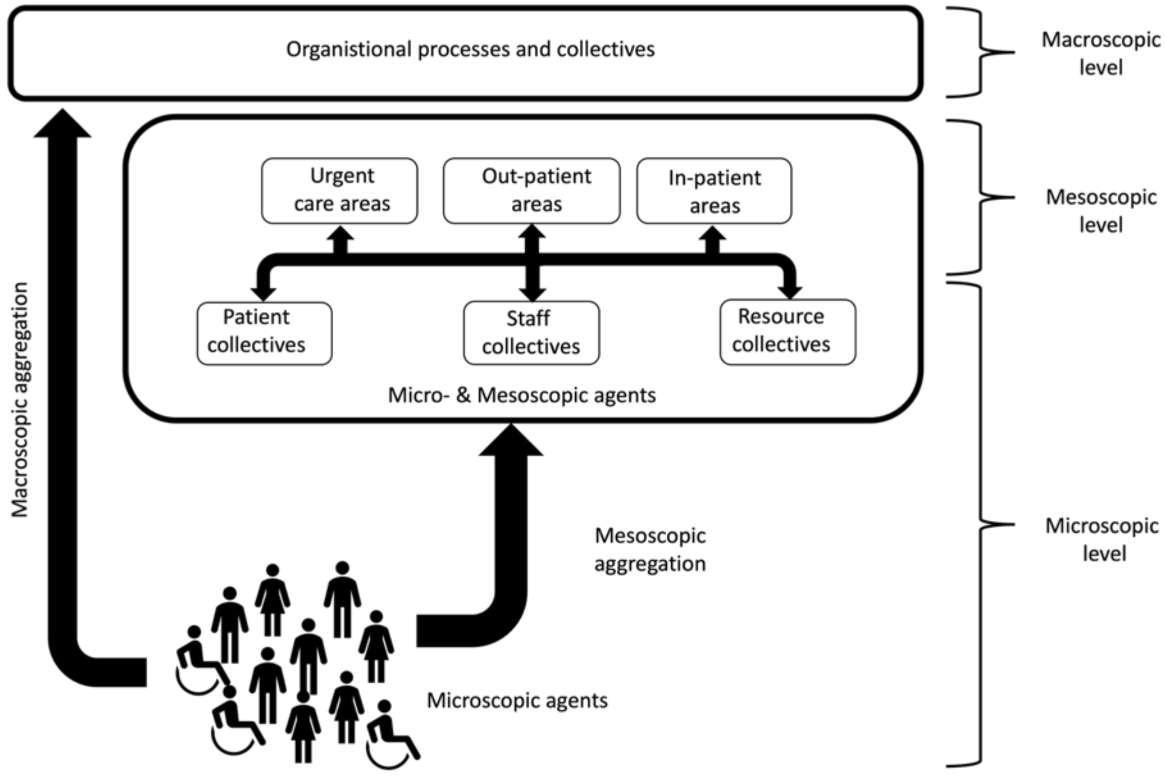


Figure 3:1 The levels of the hospital system in urgent care phenomena

The urgent care system may be viewed from the perspective of a social system level (Serpa & Ferreira, 2019). Systems simulation model incorporating a single technique will commit to one level of the social system. Combining modelling techniques (hybridization) allows for multiple levels and their relationships and/or networks to be explored. Notice that there is overlap between the meso- and the micro- at the level of collective entities/agents. This is because groups of entities may be capable of autonomous decision-making as a collective as well as system enforced behaviours (passive) at the group level.

3.3.2.1 Discrete event simulation

Of the three methods in Table 3:1, discrete event simulation (DES) has gained the most traction in the leap from theory to implementation in urgent care (S. C. Brailsford et al., 2009; Günal & Pidd, 2010). As a method with the capability to predict the outcomes of stochastic events over time, it has been shown to: usefully reproduce environments where activity may fluctuate minute-to-minute, to identify bottlenecks, and identify threats to efficiency. It is a method frequently applied to model ED settings (Günal &

Pidd, 2010). Successful examples of where application has led to a change in service or healthcare management includes its application in planning: in-patient hospital capacity management (Bagust et al., 1999; NICE, 2018b, Chapter 39), the provision of AEC services (Chalk, 2020), and critical care resource planning during the COVID-19 pandemic (Irvine et al., 2021).

Real world change in healthcare delivery or planning as a result of a DES modelled system is less frequently encountered than would be imagined given the volume of studies. A recent review by Vázquez-Serrano et al. (2021) found <10% of 170 DES applications published to have been implemented into practice. That said, 30% of the studies they cited were published in 2020/21; progress to implementation may have been delayed by the COVID-19 pandemic. This is consistent with the literature exploring all SSM applications in healthcare which see a small number of studies reach the implementation stage relative to the number performed in the last four decades (S. C. Brailsford et al., 2009; Mohiuddin et al., 2017; Wilson, 1981).

3.3.2.1.1 Advantages of DES

Discrete event simulation modelling is highly suited to reproducing how urgent care broadly functions as it sees patients passively undergo scheduled care events over time (S. C. Brailsford et al., 2004; Karnon et al., 2012; O'Cathain et al., 2008; Siebers et al., 2010). Because DES entities possess unique variables that are used by the pre-determined logic of the model to determine how they will experience events, it mimics how patients with heterogeneous health needs passively experience in-patient hospital care (O'Cathain et al., 2008; Shaffer & Sherrell, 1996). As a top down modelling method, it mimics the power of a hospital system (and its staff) in determining how patient care unfolds (Lim et al., 2013). For example, amongst populations presenting with chest pain, some patients will undergo 3 - 6hrly blood tests to exclude myocardial infarction, and some have immediate blood tests to exclude venous thromboembolism. The distinguisher is an additional variable describing the nature of the pain. Patients with the same chest pain and nature variables are placed on the same clinical pathway, but an additional variable (e.g., a an abnormal electrocardiograph) will indicates a different course of action (Bassand et al., 2007; Konstantinides et al., 2020).

The ability of DES to identify how, where, and when queues arise makes it an efficient method for identifying and addressing waste in an urgent care setting (Karnon et al., 2012). Because patients are moved through the system by the system, simulating their transitions through an AMU will reveal how the working model of a system may generate bottlenecks. Where these occur, familiarity with how the system processes and staff activity were programmed into the model allows us to analyse how they emerged and explore alternative activities that may mitigate them. The use of time steps aids identification of variations in activity and bottlenecks at different points in time (Pidd, 2004), a distinct advantage when activity is known to vary widely hour-to-hour.

The ability of DES to expose waste emergent in a system as entities are subject to stochastic events is also an advantage for this research (Pidd, 2004). Urgent care areas are subject to unpredictable events with consequences that have the potential to accumulate: departments experience rapid fluctuations in demand, necessary resources from elsewhere in the system can become suddenly unavailable (e.g., equipment failure), patient health can unexpectedly deteriorate. Processes of care that appear efficient on paper via aggregated activity data applied to a static model may be unstable in real life when multiple influential events occur in quick succession or simultaneously. Modelling activities as dynamic, interacting events over time in a DES model tests assumptions of averaged behaviours and delivers greater knowledge of how outcomes alter in the face of stochasticity when multiple linear logics are triggered (Pidd, 2004). Events with relevancy to the research question may be programmed to occur with plausible stochasticity. Equally plausible but extreme events may also be incorporated - e.g., a food poisoning outbreak at a large event. Agent based modelling also facilitates this (Railsback & Grimm, 2019), but the linear logic of DES coding makes it is better placed to generate knowledge of how and why established processes in a system contribute to inefficiencies and how they may be altered to address this. Agent-based modelling, in contrast, explores how the aggregation of individual behaviours leads to outcomes that have not been specifically modelled.

A DES approach may be perceived as more credible by healthcare than other SSM methods. Firstly, the linear nature of relationships modelled in DES makes the validation via tests of statistical significance possible (Banks, 1998). Clinical leaders may have more familiarity and comfort with this than a non-statistical approach to validation (Mays & Pope, 1995). Secondly, the representation of finite resources and queues of patients that DES provides also lends credibility to the practical application of findings where concerns about the artificiality of computer simulation models in healthcare planning exist (Caro & Möller, 2014). Finally, as Davies and Davies (1994) argue, the use of animation in the modelling process to facilitate direct visualisation of a system and outputs enhances engagement of clinical stakeholders (although DES is not the only method to provide this feature).

3.3.2.1.2 Disadvantages of DES

Discrete event simulation is less advantageous if autonomous behaviours of modelled entities are known or theorised to exert influence upon the system. Entity behaviour change in response to dynamic events, feedback loops, or learning are limited with DES (Siebers et al., 2010). To fit with modelling frameworks or software limitations, individual behaviours may need to be “overly simplified” or decision-making steps excluded altogether (Paul et al., 2010). Although many researchers have shown that it is possible to incorporate feedback into a DES (for example, Sally Brailsford & Schmidt, 2003; Greasley & Owen, 2018), identification of emergent activity from those behaviours remains limited. This obstacle has been shown to minimise a DES model's capacity to identify and explore problems associated with decision-making (Tako & Robinson, 2015), although not all influential modellers in the field agree that this is the case (S Brailsford, 2014).

The accessibility and usefulness of DES software has increased its application is case-based studies and local service design at the cost of generalisability and possibly quality (Günal & Pidd, 2010; Mohiuddin et al., 2017; Siebers et al., 2010). Recently available ‘off-the-shelf’ modelling software has made DES more accessible for short-term projects, researchers new to SSM, and healthcare leaders seeking to remodel their services. Modellers may now efficiently create DES models which are highly specific for their purpose. For example, Chalk (2020) demonstrated how expanding the opening hours of an AEC facility in the south of England would have a greater impact on admission avoidance that increasing the size of the unit, work by Irvine et al. (2021) was able to reassure critical care resource sufficiency for a regional population in Scotland during the COVID-19 pandemic. Such models are clearly advantageous for answering specific questions, but are limited in their knowledge applications beyond study settings (Günal & Pidd, 2010; Robinson, 2002; Siebers et al., 2010). Variations in care delivery across regions may make adopting changes proposed more challenging, costly, or logistically impossible than in the case study site (Appleby et al., 2011). For example, non-availability of specialist services on-site in remote settings. Generic DES models for urgent care have been presented, but evidence of implementation in sites beyond case study settings is absent from extant literature (Ferrin et al., 2007; Sinreich & Marmor, 2004).

3.3.2.2 Agent-based modelling

Agent based modelling (ABM) is methodologically suited to reproducing complex interventions that happen in social spaces such as healthcare settings (Bankes, 2002; Railsback & Grimm, 2019). By considering the behaviours of individual entities (agents) and/or collectives (also agents) in a system, ABM may be coded to create agents that respond to and interact with their environment, to other agents, and that may adapt their behaviours via learning (Railsback & Grimm, 2019). This gives ABM the capacity to reproduce and explore the non-linear emergence of outcomes in a variety of phenomena; not least those that would challenging to achieve via studies of real life participants, e.g., in human decision-making (Holland & Miller, 1991). Non-familiarity with ABM technique, the perceived difficulties of coding, and the dominance of DES software in healthcare modelling are likely to have contributed to its under underutilisation relative to other methods (Escudero-Marin & Pidd, 2011; Siebers et al., 2010).

Within healthcare, ABM has achieved its greatest traction in studies of infectious disease dynamics (Friesen & McLeod, 2014). Although increasing in its popularity, it application to urgent care is rare when compared with other methods like DES or regression modelling (Adleberg et al., 2017; Wiler et al., 2011). In urgent care, ABM has been applied to phenomena where the co-ordination of multiple agents and agent-sets are crucial to timely care delivery. For example, Lujak et al. (2016) employed ABM to represent patient, paramedic, cardiology, and hospital behaviours in an impressive but complicated model to predict optimal resource and communication strategies for emergency interventional cardiology. Tian et al (2014) used ABM to create a portable decision-support tool to assist with highly contextual, time-crucial disaster evacuation decision-making that incorporated an ABM with individual and agent-sets of patients and resources.

Studies explicitly modelling the hospital urgent care environment are exclusively set in EDs and rarely incorporate the cultural dynamics of the hospital system that an ED works within. In ED settings, ABM has been employed to: model an unspecified global decision-making entity (a prototype early decision-maker) for scheduling the attendance of non-critical patients to match demand with fixed resource capacity (Bruballa et al., 2019), predict optimal staffing strategies to cope with variations in patient arrivals (S. S. Jones & Evans, 2008), and explore the impact of redirecting non-urgent patients upon arrival to the department (Taboada et al., 2013). Of note, several studies are from the same team employing the same model in the same location in various iterations (Bruballa et al., 2019; Shojaei et al., 2020; Stainsby et al., 2009; Taboada et al., 2013). Moustaid et al. (2018) took an alternative approach to the single-site modelling of the previously cited studies and used ABM to reproduce patient decision-making when accessing a network of ED centres across a region. Their model demonstrated how information about current waiting times and time to travel could influence patient choice of centre, reducing variability in the waiting times experienced across multiple centres.

The literature cited above reveals the capabilities of ABM in successfully reproducing the dynamic urgent care environment and the decision-making processes, but none of these studies incorporated the influence of agents and/or resources elsewhere in the system. This would be necessary for the research proposed in this thesis. Only Jones & Evans (2008) incorporated a variable to reflect intra-physician variability in task management. No study described the incorporation of non-staff resource variability throughout the day or at weekends. That said, the successful reproduction of patient arrivals and application in modelling redirection of patients suggests an ABM is commensurate with some components of the research proposed in this thesis. Decisions made by the modellers not to incorporate influences from elsewhere in the system would appear to be missed opportunity of the benefits of ABM to explore how the socially-influenced realities of clinical care and hospital culture contribute to modelled outputs.

3.3.2.2.1 Advantages of ABM

As the previous section revealed, ABM offers clear methodological benefits to modelling the decision-making and behaviours of staff and patients in urgent care environments. It is shown to successfully facilitate decision-making based upon dynamic, and context-specific information via individual agent preferences/rules (Bruballa et al., 2019; Moustaid et al., 2018). This is a clear advantage as the SSM in this research seeks to reproduce decision-making that demonstrates adherence to the rules of evidence-based medicine in one context but chooses to ignores them in another (Manski, 2019; Reschen et al., 2019). It can incorporate individual, group, and system behaviours within the same model to reproduce activities in an organisation that has both standard processes and a shadow culture of deviation from standard processes (Escudero-Marin & Pidd, 2011). For example, for the research proposed in this thesis, it could reproduce an individual clinician's preference to allocate a patient to out-patient care within a system that varies in its agreement with the feasibility of out-patient care according to context. These are vital elements to consider in any SSM that seeks to understand how outcomes emerge in a system that has clearly defined operational procedures but incorporates autonomous humans in the execution of them (Baines et al., 2004). Although DES is capable of modelling unique psychological factors and decision-making in urgent care settings, it struggles to model how entities may fluidly respond to their working environment and each other (Escudero-Marin & Pidd, 2011; Gunal & Pidd, 2006)

The ease at which feedback to environmental influences and learning can be incorporated into individual agent decision-making is crucial for the research proposed (Railsback & Grimm, 2019). As Section 2.3.1 revealed, allocation decisions in ED settings are observed to be influenced by local resource availability and demand. The mixed findings of studies exploring the impact of the environment upon decision-making suggest that these behaviours are complex and may only be partially known; Insufficient evidence has been gathered to understand its impact. Whole scale adoption could lead to an unanticipated emergence of undesirable outcomes (e.g., poorer patient health in admission avoidance) or create unanticipated, costly inefficiencies elsewhere in the system. Expert guidance to inform conceptual modelling and rules of behaviour are fundamental to ABM and will help elicit which of the behaviours reported in the literature of ED settings are seen in AMUs and under which circumstances (Friesen & McLeod, 2014). Because ABM provides the closest representation of human decision-making in real world contexts, it is a powerful tool improve to safely explore how context and feedback may elicit unintentionally dangerous or unethical behaviours (An et al., 2021; Bankes, 2002; Bazghandi, 2012; Railsback & Grimm, 2019).

3.3.2.2.2 Disadvantages of ABM

One drawback to an ABM approach is the extent of programming that may be required. There is fewer commercially available software for non-academics to utilise compared with DES. This may increase the model building period and model run time as large or complicated models may be computationally exhaustive (Bazghandi, 2012; Railsback & Grimm, 2019). This will, naturally, dependent upon the system under scrutiny; relatively simple models may still yield powerful results[5]. Finally, ABM has an explicit focus on outcomes that emerge from behaviour variations amongst and across entities (Railsback & Grimm, 2019). If agents demonstrate homogeneous behaviours, there may be little merit in applying the method over DES or SD.

Assurances of model validity present a greater challenge with ABMs than for DES as their scope and design are highly varied and the resulting outcomes of emergence often pattern-orientated (Grimm et al., 2005; Railsback & Grimm, 2019). Model outputs are difficult to validate when exploration rather than explanation is the purpose (Frey & Šešelja, 2018). Explanatory models (programmed to realise outcomes of hypothesised

[5] The Netlogo™ sample model that mimics bird flocking behaviour with three simple rules is a perfect example of this (https://ccl.northwestern.edu/Netlogo™ /models/Flocking)

behaviours) must also be interpreted with caution as only partial knowledge of behaviours is likely to be exist (Frey & Šešelja, 2018; Gräbner, 2018; B. Heath et al., 2009). For this reason, scepticism of the usefulness of explanatory ABMs is expressed in some sectors of the simulation community (Frey & Šešelja, 2018)

A growing body of methods for validation and uncertainty analysis has helped to make ABM forecasts useful in complex systems (Fagiolo et al., 2007; Grimm et al., 2005; Hunter & Kelleher, 2020; Ormerod & Rosewell, 2006). Validation of the conceptual model as well as the SSM itself are useful ways to reassure representation of the real system (B. Heath et al., 2009). Consideration and analysis of alternative ways of representing behaviours may enhance validation and conclusions generated (Frey & Šešelja, 2018; Gräbner, 2018; Siebers et al., 2010). Thanks to improved rigor in model building and validation, accusations of limited usefulness in predictive power are increasingly unfounded (Bankes, 2002).

3.3.2.3 System dynamics

Systems dynamics (SD) modelling seeks to reproduce a complex system in terms of stocks, flows, feedback loops, time-delays, and influential sources of dynamic complexity (Pidd, 2004). Stocks being aggregates of any resource that accumulates or depletes over time; flows representing rate of change in the accumulation of stock considering in-flows and out-flows. Dynamics within an SD model arise from re-enforcing (positive), or correcting feedback loops known or theorised to exist in the system modelled (Sterman, 2001). For example, a large number of patients in an ED waiting area prompting a clinician to lower their threshold for admitting patients as

Gorksi et al (2017) found in one setting. As this example shows, variables included in an SD model may be quantitative (number of patients waiting) and qualitative (cultural fears of overcrowding).

System dynamics has been used to analyse the relationship been urgent care activity and other areas of healthcare system activity in a variety of international setting (S. C. Brailsford et al., 2004; Chong et al., 2015; Lane et al., 2000; Wong et al., 2010). As a method, it is more commonly applied when exploring the impact of new health policy proposals and/or innovation (Cassidy et al., 2019). Its representation of the interplay between urgent care and other parts of a healthcare system (hospital and community) is clearly advantageous for modelling patient flow in a holistic fashion (Davies & Davies, 1994). For example, Rashwan et al. (2015) used SD to reveal how a series of different policy proposals in community health provision in Ireland could only achieve sustained gains in overcrowding if applied in combination, Brailsford et al. (S. C. Brailsford et al., 2004) showed how a year upon year improvement in hospital bed occupancy could occur if admission avoidance strategies for a small number of elderly patients could be developed. Lane et al. (2000) used an SD model to demonstrate the inadequacy of ED waiting times as a performance metric due to the relative insensitivity of ED activity to total hospital bed occupancy.

3.3.2.3.1 Advantages of system dynamics

An SD approach is highly suited to explore how events in an urgent care environment contribute to flow throughout an entire hospital system (Davies & Davies, 1994; Lane et al., 2000). Urgent care resources may be realistically represented at the departmental level as aggregates of equipment, staff, patients, information that fluctuate continuously over time. Departmental elements may be modelled with other parts of a hospital or community health environment resulting in “both a systematic view of patient flows and information, and a more strategic perspective of the management of the system” (Lane et al., 2000). The granular detail of individual patients and staff is lost but departmental behaviours (e.g., desires to mitigate overcrowding), may be incorporated as feedback loops which influence flows into and out of the department. Whilst system behaviours (e.g., preservation of in-patient beds for elective activity) may be similarly modelled. Arguments supporting DES models approach to view patients as passive entities in urgent care (Section 3.3.2) are applicable to SD which models them in a similarly passive manner as stocks.

3.3.2.3.2 Disadvantages of system dynamics

The deterministic nature of SD limits its usefulness in this research proposal (Pidd, 2004). The early senior decision-making policy asks clinicians to determine a pathway of care best suited to a unique patient in a unique context. Representations of autonomous decision-making in staff and of individual patient attributes are not possible with the aggregated entity (stocks) approach of SD. As section 3.2.2. explained, expert decision-making in urgent care is poorly mimicked by currently available decision support tools – a form of aggregated decision-making. Too little is known early senior decision-making to know if the cumulative allocation decisions of multiple autonomous experts may be reasonably reproduced as aggregates. Section 3.2.2 also revealed the influence of the local environment, resource constraints, and the attributes of each patient referred in decisions made. Without evidence of the suitability of an aggregated approach to modelling these influences, variation in decisions made and the emergent outputs will require a stochastic modelling method.

A limited scope to reproduce discrete, repeated events time is another disadvantage of an SD approach for this research. Urgent care areas are known to undergo variations in patient demand and resource access at different moments of the day and on different days of the week. Fewer hospital resources are available at weekends and overnight (most organisations do not open AEC facilities overnight). This mean that the modelled system's resources states will have to change in regular but unequal time steps – something that an SD model will struggle to reproduce (Pidd, 2004). Any computer simulation model seeking to represent how staff decision-making influences and is influenced by urgent care activity would need the capacity to schedule realistic variations in demand and resources access, as well as staff mimic the staff shift patterns. These are not easy to include with a system dynamics approach.

Finally, although delays are a feature of SD models, networks of queues resulting from resource constraints, and stochasticity in demand, and patients' needs are not easily represented. In their SD model of emergency care in Nottingham, Brailsford et al. (2004) found a exploration of a narrowly-focused area of care for minor injuries within required a separate DES model to adequately represent patient demand and queues. This final point is a significant disadvantage to the research proposed in this model – the early senior decision-maker policy arguably seeks to create remove queues in one area of urgent care (in-patient facilities) by deliberately creating queues in another (ambulatory care). These are also stochastic – dependent upon demand at each point of the day and upon patients' presenting conditions.

3.3.2.4 Why a hybrid simulation model was necessary

The advantages and disadvantages listed above meant that no single method was entirely suited to answering the research question when applied in isolation. This is not uncommon in healthcare applications of SSM according to Brailsford et al. (2019). Because little knowledge of the nature and outcomes of early senior decision-making (ESDM) existed, but much was known about the system it operated within, the simulation created had to act as a mediator (a model that provides insight into the system) with the potential for predictive power (B. Heath et al., 2009). That is to say, this research sought to create a valid model hypothesising how outcomes emerged via ESDM and then use that model to predict how outcomes differed under alternative scenarios. A hypothesised model of autonomous staff behaviours and rules via ABM had to be part of the simulation. However, as departmental and system outcomes that emerged from the ESDM strategy were required to inform the model outputs, a paradigm would be crossed - as the simulation ran, the context of the model logic would need to move from that of the individual to include the logic of the processes, events, and influences working in the system. A hybrid model involving ABM was suitable.

3.3.2.5 Hybrid models

Researchers faced with addressing a problem for which no single SSM method could usefully represent have overcome this by combining methods. For example, Day et al. (2014) combined ABM with DES hybrid simulation to explore how diabetic eye disease, (manifesting over a number of years), progresses when the frequency of provider-scheduled screening and treatment (delivered in a matter of minutes and hours) is altered. Combining methods meant that the cohort of patients could exist in the same model but progress in two different time horizons; ABM reproducing individual disease progression and DES reproducing screening. Thus, a population of patients was created to develop over time and undergo hypothesis testing about the safety of reduced screening, a scheduled event. In another example, Nguyen et al. (2022) combined ABM with SD to create knowledge of how staff movement between care settings contributed to the emergence of COVID-19 outbreaks in nursing homes. Agent-based modelling was employed to reproduce the rostering of temporarily staff, their infection status, and the network of care homes; whilst the SD component modelled disease dynamics in each nursing home. This created an SSM capable of revealing how manifestations of contagion outbreaks could arise from the behaviours of individual staff as they moved between nursing homes for employment. Both serve as good examples demonstrating how the nature of the problem and context should inform the methods chosen and their arrangement (Morgan et al., 2017).

The hybrid studies referenced above represent only two possible ways to combine methods. Building upon previous work in multi-methodology (J. Mingers & Brocklesby, 1997; Schultz & Hatch, 1996), Morgan et al. (2017) describe five designs to apply when combining methods based upon how the techniques (tools) and theoretical perspectives (their paradigms) of each method may interact. These designs, presented in Box 3:2, are broad enough to be applied to combinations beyond SD/DES (S. C. Brailsford et al., 2019).

Box 3:2 Mixed method designs (Morgan et al., 2017)

Parallel	methods applied independently (possibly with separate paradigms) with comparisons drawn at fixed points
Sequential	methods operating in isolation (separate paradigms possible) with one method following another
Enrichment	a dominant (primary) method is enriched with elements from another method's paradigm/s
Interaction	connections made between methods with paradigm restriction relaxed
Integration	entirely new method created by combining methods in whole or in part

Hybridisation of models and methodology is increasingly in popularity amongst Operational Researchers (Mustafee & Powell, 2018). This is reflective of their discipline's reputation as "a toolbox of methods… from which the most appropriate method for solving any particular problem can be selected" (S. C. Brailsford et al., 2019). It is surprising then that few articles specifically covering the topic of hybrid models (HMs) exist to inform modellers in the Operational Research community seeking an appropriate toolkit although many exist in other domains such as engineering (S. C. Brailsford et al., 2019; Morgan et al., 2017; Mustafee & Powell, 2018). Software that is flexible enough to support the coding of HMs (such as *AnyLogic* and *NetLogo)* exists and is well maintained by community of programmers via open-source platforms (S. K. Heath et al., 2011; Payette, 2020). Software platforms like *AnyLogic* facilitate the automatic feeding of the outputs of one modelling method into another. This is the commonest method of integrating data in an HM although intermediary tools to dynamically exchange information are also present in software platforms for model creation (S. C. Brailsford et al., 2019).

Many combinations of methods are possible to represent levels of interest in healthcare studied (S. K. Heath et al., 2011). Hybrids of SD and DES are the most commonly seen and SD/DES/ABM the rarest (S. C. Brailsford et al., 2019). Combinations of SD and DES have a particular appeal in modelling healthcare systems where knowledge of how individual departmental activity contributes to the running of a whole system (such as an acute hospital) is required for integrated care. Of particular interest for this research is the feasibility of introducing individual, autonomous agents (via ABM) into an influential, event-orientated DES worldview (S. K. Heath et al., 2011).

There are many merits apparent in combining methods, but care should be taken when decided to employ HM. Several modelling methods may be equally suited for the same problem (S. C. Brailsford et al., 2019; Tsoi et al., 2015). Without building them all, it is not possible to know if results would be comparable (Morgan et al., 2017; Tsoi et al., 2015). Ultimately, the modeller's opinion determines which design of HM would be most useful, whether it is truly necessary to represent a system across multiple levels, or whether parsimony in approach will suffice (S. C. Brailsford et al., 2019). This translate as considerable time spent validating the conceptual model in an iterative process (S. C. Brailsford et al., 2019).

Validation of an HM is challenging and outputs observed may not be seen as credible (S. C. Brailsford et al., 2019; Eldabi et al., 2016; Siebers et al., 2010). When combining methods with different techniques and philosophical groundings, modellers need to be familiar with accepted standards of validation for each method, where in the model-building process these should be applied, and how the intended audience will perceive the results (S. C. Brailsford et al., 2019; Eldabi et al., 2016). Black-box validation is unlikely to be accepted as a credible approach (Pidd, 2004). Separate moments of validation applied to each method used is essential. For example (and by no means an exhaustive list), statistical analyses of numerical data in DES, face-validity of an SD conceptual model by stakeholders , and a pattern-orientated approach to ABM outputs (S. C. Brailsford et al., 2019; Grimm et al., 2005). This may not be enough to satisfy notions credibility in the intended audience. Whether the sum of validation parts equates to validation of the whole in HMs is not agreed upon in the OR community (Eldabi et al., 2016).

3.3.3 Summary of system simulation modelling methods

This section described the rich history of systems simulation in healthcare systems research. There is sufficient evidence to support the research proposal of using SSM to reproduce the early decision-making of different categories of staff and explore the effectiveness of early senior decision-making (ESDM). Each of the commonly applied methods delivers significant advantages in modelling ESDM and its outcomes, but their respective short-comings suggested that a hybrid model is more applicable. Hybrid models present challenges in conceptualisation and validation that will require considerable effort on the researcher's part to understand ESDM in real-world settings and generate credibility in model findings amongst healthcare leaders. Prospective collection of qualitative data concerning ESDM, and the decision environment may be required. The next section explores the current state of knowledge available to inform the SSM and the gaps that will need to be addressed via prospective data collection.

3.4 Informing a systems simulation model of the Early Senior Decision-Maker strategy

Having confirmed the suitability of SSM as a technique, evidence to inform the parameter and inputs was explored. This section of my literature is explicitly focused on sources of knowledge that may be used to reproduce the ESDM in an urgent care system. It begins by explaining current knowledge of how ESDM events may happen – clinical decision-making – and how current measures of effectiveness in urgent care may be employed as model outputs. The evidence base for the chosen method of data collection to address gaps in knowledge – case study research incorporating analytic autoethnography - is then presented.

3.4.1 Clinical decision-making

Many theories of clinical decision-making exist, but recent work has focused on the roles of systems thinking. Few studies exist that fully explore the use of systems thinking in expert clinicians to support this and many are methodologically flawed. The concept of clinical decision-making covers a variety of tasks beyond determining a diagnosis - the choice of diagnostic methods, the interpretation of results, and the treatment strategy employed. These tasks involve decisions informed by knowledge and skill in clinical care. Previous generations of clinicians believed that hypotheticodeductive reasoning was the model of decision-making in clinical practice (Elstein et al., 1978). This theory has since been replaced with newer ones that incorporate fast and slow cognitive processes influenced by systems thinking as researched in psychology, phenomenology, and behavioural economics described in Table 3:2.

Table 3:2 Processes involved in systems thinking

(Sadler-Smith & Shefy, 2004; Tversky & Kahneman, 1974; Wason & Evans, 1974; Yazdani & Abardeh, 2019).

MODE	ORIGIN	MANIFESTATIONS
Fast thinking (system one)	Non-conscious brain	**Guesswork -** random decision with no apparent influence **Instinct -** decision heavily influenced by hard-wired behaviours via the primitive brain of the individual (e.g., personal fear of events, personal desire for consequences) **Heuristics** – decision based on a ‘rule of thumb’ to achieve a mental short-cut **Intuition** – decision influenced by experiential learning and tacit knowledge
Slow thinking (system two)	Conscious brain	**Rational analysis -** comparison of known (or perceived) costs and consequences of alternative decision outcomes

Peer-reviewed field studies observing decision events in clinicians are few (Feufel & Flach, 2019; Risør, 2017). Closed, experimental research was more ubiquitous but less informative as studies frequently involved non-experts participants, explored single decision events, diagnostic accuracy alone, or were methodologically designed to seek error (Blumenthal-Barby & Krieger, 2015; Durning et al., 2015; Lesgold et al., 1988; Patel et al., 1990). Findings consistently included evidence of the involvement of fast and slow thinking, but there was little explanation of how these processes manifested or interacted during decision events to inform a conceptual model of ESDM (Helou et al., 2020; Yazdani & Abardeh, 2019).

Table 3:3 summarises the current theories that have been forwarded to explain clinical decision-making.

Table 3:3 Theories of clinical decision-making in medicine

THEORY	DESCRIPTION AS APPLICABLE TO CLINICIANS
Hypotheticodeductive reasoning (Elstein et al., 1978)	Explicit and extensive data gathering with suspension of analysis. Once sufficient information is available, rational analysis of the data (system two) is performed and differential of solutions is formed (exclusively forward reasoning). Differentials inform next stages of decision-making where costs and consequences of alternative solutions are considered, and the optimal solution chosen (system two). Multiple potential decisions compared before conclusion
Illness scripts (Schmidt & Boshuizen, 1993)	Scripts of illness presentations are stored in the long-term memory and moved into the conscious mind when a patient presentation triggers of a stored script (system one). Limited explanation of how scripts inform next stages of care - presumed an if/then logic that is retrieved form the long-term memory along with the diagnosis/clinical impression and/or conscious analysis informing decision-making (system two). Theory presented by research unclear on how many decisions are compared before decision taken
Systems thinking (Durning et al., 2015; Wason & Evans, 1974)	Movement between system one and system two thinking as information is gathered. Creation of potential diagnoses/clinical impressions via forwards and backwards reasoning (system two) and pattern recognition (system one). Conscious analysis in diagnosing and assumption of conscious analysis of next stages plan (system two). Theory presented by research unclear on how many decisions are compared before decision taken.
Heuristics and bias theory (Tversky & Kahneman, 1974)	Movement between system one and two thinking via flawed pattern-recognition (system one) caused by 'lazy' mental short-cuts. Leads to a high risk of bias feeding in to rational analysis (system two) processes when planning next stages of care. Decisions may be accepted without conscious consideration of alternatives, with high risk of error, but may also appear after conscious rational analysis (informed by bias)
Intuitive decision-making (Dörfler & Ackermann, 2012; Simon, 1987; Sinclair & Ashkanasy, 2005)	Holistic pattern recognition triggered by key data appearing the data streams as information is presented (system one). Accuracy of pattern recognition derived from experiential learning within the decision domain but included extends to learning beyond the self and creativity in abstract pattern-matching. Automatic awareness of decisions outside of domain of expertise leading to suppression of intuitive influence and enhancement of rational analysis (system two). Default to system two when decisions are not automatically generated or feel incomplete. Single decision solutions created and accepted (or rejected) without conscious comparison with alternatives. Includes novel solution creation pertinent to the context of the decision
Naturalistic decision making (Zsambok & Klein, 2014)	Combination of intuitive expertise and systems thinking where intuitive (system one) processes are used to formulate decisions which are then consistently enhanced by rational analysis (system two). Single or multiple decision outcomes may be generated simultaneously via intuition in the form of tried and tested solutions, pre-established rules, or novel solutions creation. Rational analysis may also feature if decisions are outside of expertise. Decisions considered in isolation with acceptance if sensed as being correct (no other alternatives considered) or rejection if sensed as incorrect with a single alternative solution immediately available to determine suitability (again without comparison of alternatives)

Although there have been studies that compare expert and non-expert performance in diagnostic tasks (Durning et al., 2015; Patel et al., 1990), much recent research has explored decision-making through a framework of heuristics and biases (e.g., Bornstein & Emler (2001), Cahan et al. (2003) - see Blumenthal-Barby & Krieger (2015) for a comprehensive systematic review). This has led to exploration of single decision events and a methodological focus on seeking error (Blumenthal-Barby & Krieger, 2015). Although the findings of this work would seem to support the limitations of heuristics in clinical settings, most participants were not experts – some were not even clinicians (Blumenthal-Barby & Krieger, 2015). Research from other domains reveal expert decision-makers use heuristics in a different and more effective ways than non-experts casting doubt on the validity of some previously reported findings on clinical heuristics (Feufel & Flach, 2019; Kahneman & Klein, 2009).

3.4.1.1 Expert decision-making in non-medical domains

Studies of experts in other domains have comparable features with urgent care decision-making and may be useful for understanding how ESDM events occur, may be observed, and understood. Field studies of expertise in military and fire-firefighting demonstrate the successful application of system one thinking in combination with rational analysis (system two) in a manner quite different to that of non-experts (G. A. Klein et al., 1986; Pascual & Henderson, 1997; Zsambok & Klein, 2014). Studies show that, in time-dependent, high stakes circumstances with large uncertainty, experts are consistently shown to combine tacit knowing with conscious, focused analysis to make effective decisions that display features of 'tried and tested', prototype solutions and spontaneous creativity in novel solution formation reflective of the immediate context of the dilemma and the environment (Dane et al., 2012; Leybourne & Sadler-Smith, 2006; Zsambok & Klein, 2014). This may appear similar to the 'lazy' mental short-cuts of heuristics but actually involves intuition (Sinclair, 2010).

The effective use of heuristics in experts is theorised to result from intuitive processes that determine which heuristics are applicable to a situation and when rational analysis is necessary (Dörfler & Stierand, 2017; Kahneman & Klein, 2009; Sadler-Smith & Shefy, 2004; Sinclair & Ashkanasy, 2005). Naturalistic decision-making theory (NDM) emerged to describe this combination of intuitive expertise and focused rational analysis in the expert brain (G. Klein, 2008). Building upon observational work and theory from the mid-late 20th century (Barnard, 1968; Dreyfus & Dreyfus, 1980; Popper, 1963; Prietula & Simon, 1989), NDM provides a framework to clarify how non-conscious, tacit knowledge may be used in medical experts –as the driving forces behind understanding and construction a of decision event which facilitate spontaneous knowledge of a solution. As well as firefighting and military combat, it has been observed in business, chess, and construction supporting its generalisability as a theory of expert decision-making across domains (Connors et al., 2011; Dane & Pratt, 2007; Hammond et al., 1987; Simon, 1987).

When using tacit knowledge in the application of heuristics - described as a 'gut feeling' (Sadler-Smith & Shefy, 2004) - experts find the steps that lead to intuitive solutions difficult to articulate (Dörfler & Stierand, 2017). The solutions often manifest as 'Eureka' moments triggered by key information appearing as 'knights move' thinking to the external observer (Prietula & Simon, 1989). Analytical processes in the expert brain are shown to largely focused on exploration of intuitively drawn conclusions than undertake a comprehensive comparison of alternatives (Dörfler & Stierand, 2017).

Intuition not only supports the ready availability of tried and tested solutions (pattern-matching) but also supports the creative generation of novel solutions, and tacit knowledge of solutions for never-before-encountered phenomena termed ‘entrepreneurial expertise’ (Sinclair & Ashkanasy, 2005).

3.4.2 Summary of clinical decision-making literature

This section explored current knowledge of expert decision-making in clinicians that may inform the conceptual model of ESDM. It highlighted the paucity of knowledge in this domain compared with non-medical experts; however, experimental studies suggest that expert clinicians apply the same cognitive processes as non-medical experts. Studies reveal that expertise poorly translates across domains of usual practice. few studies relating to operational and/or remote decision-making in clinicians.

Theories of intuitive expertise and NDM were shown be useful in planning how ESDM may be studied to inform the SSM. As much expert decision-making appears to occur in the non-conscious brain, direct observation of real-life decision-events is likely to be crucial in knowledge generation.

3.4.3 Measuring the effectiveness of Early Senior Decision-Maker allocations

The standard metrics currently applied to determine outcomes of effectiveness are poorly evidenced and rely on levels of admission avoidance suitability in local populations that vary. They are not suitable to represent effectiveness in a SSM of the ESDM phenomenon in urgent care. Additional outcomes that represent health and efficiency are available to improve this for inclusion in a SSM.

3.4.3.1 Standard metrics in urgent care

There are several metrics applied to evaluate urgent care services, but few have been demonstrated to represent value for patients in AMU settings. As Table 3:4 shows, the measurement of success in urgent care largely centres on performance – time to disposition (admission or discharge), re-attendance after discharge, and non-waste of resources via enhanced utilisation of Ambulatory Emergency Care (AEC). These metrics reflect outcomes generated by a whole system (not urgent care specifically) and are assumed to represent quality in care and efficiency (NHS England, 2019; NHSS Director General, 2020). Their respective uses in a SSM are discussed below.

3.4.3.1.1 The access standard and breaches

The four-hour access standard and breach times are of limited benefit in understanding efficiency in urgent care areas beyond the ED. Acute Medical Units (AMUs) are designed to accept patients in whom a need for emergency resuscitative care has already been excluded (by the initial clinician review). Most AMU and AEC facilities are resourced with stationary beds and/or chairs to reflect this (Irvine et al., 2022; SAM, 2019). As these are not temporary trolley assessment areas, the four-hour access standard has little influence. (see Section 2.2.2). This is not necessarily a negative point as the time taken to deliver care for AIM populations differs to that of ED populations due to the nature of illnesses presenting (Atkin, Riley, et al., 2022; NHS Improvement, 2019). Indeed, clinical leaders in acute medicine are accepting of delays from arrival to medical evaluation of up to four-hours (NHS England, 2015; Society for Acute Medicine, 2020). Using the four-hour access standard as an efficiency outcome for ESDM in acute medicine would tell us little although it may provide information on how the efficiency of AMUs impacts efficiency in ED where patients are transferred between the two settings for admission.

Table 3:4 Performance metrics applied to UK urgent care settings

METRIC	DESCRIPTION	WHERE APPLIED	USE
Four-hour access standard[b,c]	New and unplanned return attendances should be seen and then admitted, transferred, or discharged within four hours. To be met in 95% of all attendances	Any urgent care areas where patients are assessed on a trolley	Primary indicator of performance in NHS Scotland Secondary indicator of performance in other UK settings
Eight and Twelve-hour breaches[b,c]	All patients waiting longer than 8 or 12hrs in ED areas before transfer to an in-patient bed.	Any urgent care areas where patients are assessed on a trolley	Secondary indicator of performance. Seen as an ED and whole system performance indicator
Readmissions[a]	Reattendance to urgent care within 7-days and within 30-days of discharge No set target, evaluated via cross-site comparison	Whole organisation	Whole system measure of quality
Mortality[a]	Death within 30-days of urgent care attendance No set target, evaluated via cross-site comparison	Whole organisation	Whole system measure of quality when standardised and compared across organisations
Utilisation of same day emergency care[b,c]	An expectation (rather than a target) to manage higher volumes all urgent care attendances via same day services/AEC Expectation of ≥30% increase in utilisation	Any area delivering urgent care	Indicator of performance in NHS England Level of importance not clarified at the time of writing

([a]NHS Digital, 2022; [b]NHS England, 2019; [c]Public Health Scotland, 2022b)

3.4.3.1.2 Readmissions

Readmissions are perceived to measure both efficiency and quality of care. Evidence of their suitability in reliably capturing either of these via large dataset analysis is poor (van Walraven et al., 2011; van Walraven, Austin, et al., 2012; van Walraven, Jennings, et al., 2012). Unavoidable readmissions reflect an unpredictable course of illness, the limitations of evidence-based care, or unanticipated external factors whereas avoidable admissions are defined as preventable errors in care delivery or diagnosis (Goldfield et al., 2008). Identifying avoidable admissions requires systematic analysis of the particulars in each case by multiple clinical experts (van Walraven et al., 2011). This is a resource intensive task and not possible to replicate via large dataset analyses of NHS data or the outputs of a SSM (van Walraven et al., 2011; van Walraven, Austin, et al., 2012; van Walraven, Jennings, et al., 2012).

In addition to their poor reliability in representing effectiveness when analysed at the population level, there is disagreement amongst clinical leaders about what patient readmissions tell us. Clinicians argue that readmission does not necessarily indicate poor quality care, or service inefficiency - each case warrants exploration before such conclusions can be made (Stangoe & Milne, 2012; van Walraven et al., 2011). Given the uncertainty inherent in urgent health decline, readmission may occur as a consequence of a system that seeks to increase utilisation of non-admission pathways for urgent care. The strategies adopted to keep COVID-19 patients at home with technology to detect decline suggests that providers and governments tacitly accept the readmissions risks of urgent out-patient care under some circumstances (Vindrola-Padros et al., 2021). The unusual circumstances present during the pandemic should not be underestimated – urgent care resources were not equipped to deliver ‘care as usual’. Nonetheless, the success of the strategies adopted reveal that readmissions rates are a tenuous indicator of care quality.

It may also reflect a failure of the elective system to meet demands once urgent illness has been addressed. Readmission rates in the UK vary widely (Friebel et al., 2018). Freibel et al. (2018) found many hospital saw increased or stagnant rates following emergency attendance over the time that facilities for admission avoidance have been increasing. When extracted from population level datasets, there is little granularity in readmission rates to detect health change, harm, or efficiency either within or across organisations (van Walraven et al., 2011; van Walraven, Austin, et al., 2012; van Walraven, Jennings, et al., 2012).

3.4.3.1.3 Mortality

Mortality is the most frequently applied metric to measures an individual patient's change of health, but it represents an extreme change in health and lacks sufficient context to have meaning in urgent care. The binary nature of the measurement of mortality facilitates detected in population datasets, but, as with readmission, the events leading up to death in urgent care are complex, multiple, and contextually nuanced (Rudge, 2019). As a solitary quantitative metric, it is unable to provide any indication of the effectiveness of care in a field of practice that deals with urgent and extreme ill-health. This is because it fails identify where conditions have declined but not led to death, where improvement has occurred, or where death was the natural course of illness (Mushtaq et al., 2021). That quality of life metrics include scales reflecting health states worse than death is a clear example of its limitations (N. Devlin et al., 2009).

Whilst mortality may be a reasonable measure of harm with context, other harms associated with admission avoidance – decline in health, side effects of medication - are not measured. Whilst it is logical to assume that admission prevention avoids the harms of the hospital setting (De Vries et al., 2008), if the alternative processes of care in the community are ill-equipped to meet a patient's needs, the risks of non-admission may outweigh those of in-patient care and harm may still occur (Fonarow, 2018). The use of mortality to measure harm as an output in an SSM would be insufficient to inform outcomes.

3.4.3.1.4 Utilisation of same day/ambulatory emergency care

Measurement of the utilisation of AEC services may provide evidence to suggest non-waste but assumptions of quality, health gain, or departmental efficiency cannot be inferred. The metric is reliant upon local system capabilities to avoid admission, i.e., the prevalence of AEC suitability. Measures of the utilisation of AEC services are assumed to represent in-patient admission avoidance and efficiency in urgent care resource use. This is because patients are more likely to realise discharge home after care in an AEC facility. This assumes that decisions to allocate patients to AEC intentionally select patients suitable for discharge and that services can support discharge plans. Measurement of the proportion of patients discharged from AEC services is not explicitly recommended by policy.

Utilisation of AEC is a ratio – patients starting care in AEC as a proportion of patients referred. As a ratio it is determined by both the numerator and denominator. This introduces the potential for high volumes of poor-quality referrals to mimic efficiency. Failures in primary care or elective services may lead to more non-urgent patients referred into the urgent system, an alternative form of gaming (Guilfoyle, 2012; Paddison & Rosen, 2022). For example, GP telephone triage systems introduced during the COVID-19 pandemic are set to remain in place in many parts of the UK (Royal College of General Practitioners, 2020). Removal of the initial clinician assessment (that the effectiveness of AEC services was founded upon) may make identification of suitable patients more challenging. Clinicians may err on the side of caution and recommend attendance until a face-to-face evaluation can occur. This will increase urgent care attendances and improve AEC utilisation without identifying waste in service misuse.

3.4.3.1.4.1 Why prevalence matters

For AEC utilisation to be of value, estimates of the local prevalence of ambulatory care sensitive conditions (ACSC) should be known (AECN, 2018). This prevalence will vary according to local resources, geography, and local disease patterns. Where prevalence is low, e.g., because there is poor access diagnostic investigations, AEC utilisation will be low and not reflective of waste. Ambulatory Emergency Care suitability is often, but not always, determined by recognition of an ASCSs, but populations commonly treated by ambulatory centres in the US and Canada (where the term originated) contain a narrower spectrum of illness and tend towards lower acuity than those seen in AEC populations in the UK (Llovera et al., 2019). Those seen in the UK AEC services are more akin to patients discharged from Emergency Departments in North American settings. For example, in the US, patients with chest pain are immediately redirected to their local ED whereas UK hospitals with acute internal medicine and/or emergency medicine frequently accept these patients to their local AEC facilities (Reschen et al., 2020).

There is a degree of nuance in recognising AEC suitability - the availability of resources, location, time of day, and biopsychosocial needs will also determine whether AEC is feasible and preferable to admission (S Purdy et al., 2009). Because of this variation, we have no consistent record of the volume of patients that may predictably be managed on an AEC pathway on any one site. Estimates of ACSC in Western populations ranges from 16-37% of all urgent care attendances depending upon the definitions, patient age, and context (Frick et al., 2017; Yang; Tian et al., 2012). The variation in access to resources seen in Scotland (likely to be replicated in other parts of the UK) will limit local teams' abilities to avoid admission via AEC services (Irvine et al., 2022). Thus, AEC utilisation in two different hospitals could both be 20% with one reflecting efficiency and the other waste.

National patient datasets are insufficiently detailed to estimate local prevalence. Prior to 2021, all UK national databases recorded only the patient's final diagnosis making quantification of the total patients attending urgent care with a suspected ACSC impossible to gauge. Of note NHSE have recently changed their national database coding to recognise patients managed on AEC pathways regardless of outcome (NHS Improvement, 2019). A more accurate appreciation of variation in prevalence that supports interpretation of AEC utilisation may be possible in the future.

3.4.3.2 Additional ways to determine effectiveness

The previous section described the limitations of currently used metrics for representing measures of effectiveness in an SSM of the ESDM strategy in urgent care. This section explored the evidence for other metrics that may augment existing ones. Three categories of outcomes were considered: departmental activity, patient-reported health, and patient experience. The literature search for urgent care outcomes was based on the missing elements of effectiveness: efficiency, safety, health, and quality of care experienced.

3.4.3.2.1 Departmental activity

Departmental activity relates to the volume of patients attending and how those patients affected the environment of care. It describes how patient movement within a system affects resources available and has many facets dependent upon the type of care delivered in the area evaluated (National Services Scotland, 2023). Not all are of significance in urgent care but bed occupancy, delays to care, and lengths of stay are arguably the useful to appreciate activity.

Bed occupancy is a reliable measure of activity and efficiency, but is more likely to provide a reasonable measure of efficiency in urgent care if measured over the course of a day rather than at a single point. Hospital bed occupancy provides an estimate of the available capacity in a system to accommodate care and react to fluctuations in demand (Bagust et al., 1999; R. Jones, 2011; A. C. Pratt & Wood, 2021). In the UK, hospital occupancy is captured at a single moment of the day (midnight for in-patient areas and 0800hrs in urgent care (NHS England; NHS Improvement, 2021). This metric is useful if predicted demand is manageable – e.g., by rescheduling planned activity or increasing capacity – something that is heavily influenced by the size and scope of the whole hospital site (Bagust et al., 1999; R. Jones, 2011). As a measure of departmental efficiency, a single daily estimate is less useful in urgent care areas as lengths of stay in urgent care areas alter over a timespan of hours and in-patient areas over days (A. C. Pratt & Wood, 2021). Additionally, as a measure of staffed beds only - not trollies or AEC facilities without beds - it paints an incomplete picture. Average hospital-wide occupancy rates may also be misleading as areas with less activity and fewer in-patients (such as specialist surgical services) may see low levels of occupancy that offset higher levels elsewhere in the system that do pose a risk.

Review of available literature and health services databases revealed no data to inform of real time occupancy rates in urgent care areas beyond ED settings. No recommendations for the collection of this data were found in the relevant professional body guidance. This may suggest that, as a metric, it perceived to be of limited use. However, previous predictions have shown efficiencies to reduce and patient harm to increase when occupancy levels breach an average of 85% (Bagust et al., 1999). This effectiveness tipping point may be colloquially referred to as 'crowding'. The 85% estimate is not a consistent for all settings as lower occupancy levels are likely to be required for areas where patient populations present heterogeneity in clinical need. For example, Pratt and Woods (2021) found internal medicine urgent care areas to realise inefficiencies with average occupancies ranging from 52 - 78% according to department size and tolerance of delays. As sustained high occupancy levels have implications for the health and well-being of staff as well as patients (Medley et al., 2012; Niedhammer et al., 2021; Virtanen et al., 2008), departmental occupancy levels present a suitable measure of effectiveness in urgent care systems with meaning to patients and providers.

Overcrowding (as opposed to crowding) may be described as departmental occupancy exceeding 100%. Attempts to define it beyond this are difficult as most urgent care departments function with safe waiting areas that will see occupancies breach 100% on a regular basis which they may not locally define as overcrowding. It is unclear if populations in designated waiting areas are included in hospital datasets. As discussed previously, heterogeneity in acuity and health need are shown to make occupancy levels <100% unwieldly in many settings (A. C. Pratt & Wood, 2021); overcrowding is thus a fluid and context-dependent term. When locally defined, it is correlated with poor patient and system outcomes (Higginson, 2012; McCarthy et al., 2009; Moskop et al., 2019). The immediate results of overcrowding – delays to patients accessing clinical spaces and starting care – are not consistently captured in centrally reported urgent care data. Patients forced to wait in unsuitable, non-clinical areas for AMU care (e.g., corridors) are not routinely recorded at an organisational level unless they have arrived via ED services.

Despite the known consequences of overcrowding in urgent care, few researchers have evaluated the impact of non-admission pathways on overcrowding beyond the early identification of minor illness or injury in ED and none look beyond ED settings (Davis et al., 2014; Jarvis et al., 2014). Locally reported quality improvement studies suggest a trend towards reductions in overcrowding following the introduction of AEC[6], but they

[6] 'AEC Programme: Case studies'. Available at https://www.ambulatoryemergencycare.org.uk/Programmes/AEC-Programme/Case-Studies

lack robust methodological techniques or freely available data to allow evaluation of their credibility. Including departmental occupancy levels in a SSM that explores ESDM will be of value in measuring effectiveness. Measuring lengths of stay and delays to care will provide context and meaning to bed occupancy levels to appreciate where inefficiency and harm may be occurring.

3.4.3.2.2 Health-related quality of life

Measurement of health-related quality of life (HRQoL) has been a feature of surgical care and clinical trials for many years (Calvert et al., 2013). Despite recommendations, HRQoL measurement is not routinely applied to in-patient care (Appleby et al., 2004; Kind & Williams, 2004). Many fields have developed HRQoL tools to measure outcomes specific to their patient populations but transferability to a generic index that allows comparison of health change across services varies amongst them (Longworth et al., 2014). The use of generic HRQoL tools, such as the EuroQol 5-Dimension 5-Level® (EQ-5D-5L) or the Health Utilities Index, is increasing, but their sensitivity to all domains of health change is a long-recognised problem, particularly in ophthalmic conditions (Longworth et al., 2014). There are also floor and ceiling effects when attempting to differentiate changes in patients who initially report health nearing the maximal or minimal scores (Brazier et al., 2004).

The generic tools available have comparable performances; choice between then is best determined by the intended use (Coons et al., 2000). Consistency between the outcomes of the EQ-5D-5L and condition-specific HRQoL measurement has been proven for some asthma and pulmonary embolism patients managed via urgent care (Chuang et al., 2017; Samuels-Kalow et al., 2017). The EQ-5D-5L has also been successfully applied to patients with obstructive airway disease, elderly patients without delirium, and cardiac presentations, all commonly seen in AMUs and amenable to admission avoidance via AEC (Boczor et al., 2019; Nolan et al., 2016; Ratcliffe et al., 2017). The lack of tool for all urgent care populations is acknowledged and there have been recent attempts to rectify this but emerging methods have not been validated (Marjolein N T Kremers et al., 2019; Mols et al., 2021; Vaillancourt et al., 2017). At present, the generic tools present the easiest way to capture and track patient health amongst heterogenous populations like those seen accessing urgent care services (Mols et al., 2021; Olofsson et al., 2012; Vaillancourt et al., 2017).

The EQ-5D-5L tool is currently the best generic HRQoL tool for use in UK urgent care populations. It is preferred by NICE for the purposes of economic evaluation and a validation dataset to interpret weight and meaning of results exists for the majority of the UK population (N. J. Devlin et al., 2018; NICE, 2019). Its insensitivity to chronic inflammatory disease needs to be considered in AIM populations as they include a large number of patients with chronic health condition decline (Efthymiadou et al., 2019). Insensitivity due to the ceiling effect in patients nearing wellness, such as physiological stable populations accessing admission avoidance via AEC is a risk to be considered when interpreting results and comparing between urgent care populations (Brazier et al., 2004).

3.4.3.2.3 Patient experience

Patient experience is poorly measured in urgent care settings as few tools exist to capture it. Existing NHS surveys provide the best way to capture experience in urgent care populations, but they are limited in their ability to captures experiences of patients on out-patient pathways or using AEC facilities.

Although the goal of an urgent care area is primarily the improvement in health outcomes, there is an increasing desire to incorporate satisfaction and patient experience into measures of performance and responsiveness of a service (Valentine et al., 2003). However, experience and satisfaction are different concepts with no currently available validated tools to inform quantification and useful comparison. Satisfaction and experience are connected, but the relationship between them in healthcare is far from straightforward (Bleich et al., 2009; Ng & Luk, 2019). Satisfaction suggests a pre-formed expectation, but such expectations may be formed by prior experience of care, internalisation of government-stated norms of care, media representation of healthcare, or personal attributes (Ng & Luk, 2019). Experience may be affected by both the meeting of expectations and the local system's response to ameliorate any dissatisfaction. Thus, patient experience may be only partially explained by satisfaction (Bleich et al., 2009; Donelan et al., 1999). If we accept Maslow’s (1958) appraisal that satisfaction is an isolated point in an evolving trajectory of human needs, then it may be only modestly affected by events in a local healthcare system or department; at which point, lived experience of care becomes a more useful measure to explore (Bleich et al., 2009; Ng & Luk, 2019). Studies of patient experience in urgent care are limited and authors often conflate experience with satisfaction (Doyle et al., 2013; P. Sullivan et al., 2013; Trout et al., 2000).

Formal measurement of patient experience is yet to be centrally mandated in the UK, largely because there are no agreed definitions of what such concepts mean or how they may be measured (Bleich et al., 2009). No tools have been validated for use across all settings. Experience surveys, the most frequently seen approach, may be used to collect data which to inform improvement in services or provide a measure of whether a pre-defined target was achieved (Albert & Tullis, 2010). No targets have been set for patient experience in urgent care. Of note, the results of patient surveys have been shown to be moderately correlated with those of staff in some UK locations so they may serve to understand the experiences of all stakeholders (Raleigh et al., 2009). One location-specific study of older patients reported higher experience ratings for care received via AEC services over in-patient care, but repeated attendances for follow-up and delays featured heavily in criticisms (Glogowska et al., 2019). In other urgent care settings, perceptions of waiting time, confidence in care, and symptom control are cited as key elements informing experience (Aaronson et al., 2018; P. Sullivan et al., 2013; Welch, 2010).

The absence of a validated tool has created a tendency to conflate tangible elements of healthcare performance, such as waiting times, with experience (Valentine et al., 2003). Surveys employing Likert scales experience the disadvantages of central tendency bias, non-reproducibility, and the potential for inappropriate researcher conclusions based on statistical analysis (Albert & Tullis, 2010; Hasson & Arnetz, 2005). They also restrict available responses to those offered by the provider as important rather than a qualitative exploration led by the patients' voices (Ng & Luk, 2019). Visual Analogue Scales – a response along a trajectory indicating preference between two opposing options - may be more sensitive, provide reproducibility, and provide more reliable results but they represent a summative assessment with limited data about where experience could be improved (Hasson & Arnetz, 2005; Voutilainen et al., 2016).

The UK NHS health systems measure experience via the ‘In-Patient Experience’ survey (Care Quality Commission, 2016). This is a structured questionnaire that provides a ‘snap-shot’ overview of user experience following admission to hospital. Review of reported findings suggest that the results are evaluated for directional trends rather than inter-organisational comparison (Care Quality Commission, 2023). It therefore represents summative assessment, with large sampling numbers affording a reasonable measure of central tendency about the current state of healthcare user experience in the NHS but limited useful feedback to allow departments to detect or create value (Care Quality Commission, 2016). The NHS tools have not been applied to specifically explore AEC or AMU care although NHS England have recently published an urgent care survey[7].

3.4.3.2.4 Summary of measures of effectiveness in urgent care

This section explored existing metrics to evaluate effectiveness in urgent care and revealed their insufficiency for the purposes of this research. It described how current metrics are exclusively focused on performance with little tangible evidence of how they provide measures of health change, quality, safety, or efficiency. Urgent care occupancy throughout the day and delays to starting care were suggested as useful ways to determine local efficiency. The impact of urgent care activity on the hospital system, as it emerges via early senior decision-making, may be better understood by exploring the volume and activity of patients admitted into hospitals beds from an urgent care area.

[7] not available at the time of research planning in early 2020

This section also explained that UK healthcare leaders' ambitions to incorporate patients' health and experiences into definitions of effectiveness were not possible via currently recommended metrics. Patient-reported measures of health and well-being using the EuroQol 5D-5L tool were shown to be useful in addressing this deficit, despite limits to sensitivity for patients nearing states of wellness. No validated tools for capturing patient experiences of urgent care were found, but established NHS surveys were presented shown to have credibility amongst UK healthcare leaders and useful for the purposes of this research. Their closed, structured format suggested that not all experiences would be adequately captured. Qualitative exploration of what constitutes good and bad experiences of care would be a useful adjunct to inform conceptualisation of how patient experiences emerge within the system and contribute to value.

3.4.4 Conclusion

This section revealed that knowledge of the decision-processes of individual clinicians (including influences), patient outcomes, and the urgent care decision environment was insufficient to inform an SSM of the ESDM strategy. Prospective data collection would be necessary to understand each element of the model, how entities interacted within the decision environment, and how internal/external events affected early decision and their outcomes. An ethnographic case study presented the most efficient way to capture such a wide variety of data and simultaneously understand the system to be modelled. A review of the evidence supporting case study and ethnography as chosen methods for this purpose form the final section of this literature review.

3.5 Ethnography and analytic autoethnography

Although several approaches could have been considered to inform the SSM, observational case study was found to be the most efficient approach. This section starts by presenting the evidence for case study research and ethnography as a method within case study research. Because of the potential for bias introduced by the researcher's clinical role, literature regarding the researcher as both a participant and observer is discussed before the novel method of analytic autoethnography is introduced.

3.5.1 Case study research

The case study has gained increasing recognition as useful method of exploratory, evaluative, and experimental research in social science (Yin, 2017). This is particularly so when the phenomenon under investigation involves human behaviours heavily influenced by context with the potential for generalisable features (Yin, 2017). Research into organisational behaviours at the system and/or individual level are particularly suited to a case study methodology when control of those behaviours to facilitate experimental research is not feasible as is the case in an urgent care setting (Yin, 2017; Yin et al., 1985). Case study research may successfully explore organisational decision-making in contemporaneous phenomenon as direct observation of events and interviews are possible (Carroll & Johnson, 1990; Yin, 2017). Regardless of format, the central tenet of data triangulation from different sources to support or refute the findings is a crucial part of validation (Yin, 2017).

Findings from a single case study face challenges when seeking to identify generalisable theories. A single site case study may only explore one community meaning efforts to generalise will rely on comparability of context, populations, and a sound analytical approach (Yin, 2017). However, generalisation of theoretical explorations (as opposed to quantifiable outcomes) is possible and of relevance to policy evaluation (Taber, 2000; Yin, 2017).

3.5.2 Ethnography and participant-observation

Case studies are a separate technique to observational or participatory research, but both observational ethnography and participant-observation may be embedded within a case study design (Brannick & Coghlan, 2007; Spradley, 1980, 2016; Yin, 2017)**.** The position of the author as both a researcher and a senior clinician in urgent care had advantages and disadvantages (Adler & Adler, 1987). In choosing this subject to research there was likely to be a pre-formed theory about decision behaviours that risked creation of an inaccurate model based on researcher's beliefs and recall (Polanyi, 2009). This created the potential for unconscious bias in data collection and analysis. That said, intimate knowledge of a language, environment, and culture that few researchers could access was beneficial for understanding the data that informants provided through shared language and experiences (Adler & Adler, 1987; G. L. Anderson et al., 2007; L. Anderson, 2006).

Shared knowledge and language of a researcher with inside knowledge facilitates a research space for participants to be candid about behaviours, influences, and motivations with a revelatory impact on findings (Adler & Adler, 1987; Van Maanen, 1979). The risks of recall bias and performative behaviours in participants is not removed however, and multiple sources of data are necessary to triangulate findings and differentiate between what is said and what is done (S. S. Coughlin, 1990; Van

Maanen, 1979). Empirical evidence generated via reflexive analysis of a participant capable of performing the ESDM role had the power to enhance the evidence generated by observation of others as an additional source of data for triangulation (L. Anderson, 2006; Brannick & Coghlan, 2006). As an urgent care clinician with over 10years of experience practicing at a senior level in hospitals across the UK, the researcher identified as an insider to the group under study. With an appropriate framework for reflexive analysis, deeper knowledge of the process involved in expert decision-making in the remote urgent care task could be achieved via analytic autoethnography.

3.5.3 Analytic autoethnography

Recognition of the value that an 'insider-as-researcher' may bring to organisational research has increased the popularity of participant-observation (PO) methods within organisations (Amabile & Hall, 2021; Brannick & Coghlan, 2007; Spradley, 1980). This has contributed to the creation of analytic autoethnography (AA) (L. Anderson, 2006). The use of AA in organisational research has expanded in the last few years (Amabile & Hall, 2021; Anicich, 2022; de Paiva Duarte, 2017; R. C. Smith, 2021). It enhances a traditional ethnographic approach via multi-source data triangulation of reflexive findings of the researcher, those observed, and information recanted by participants experiencing the same phenomenon (L. Anderson, 2006). Data external to participants (e.g., organisational communications or observed cultures) is also included in the analysis.

When research seeks depth and richness of understanding in complex, inaccessible phenomena, AA provides a framework for the creation of a unique body of data-transcending knowledge that is impossible to achieve with a detached, experimental approach (Amabile & Hall, 2021; L. Anderson, 2006). Intimate group knowledge affords reflexive analysis of the self, alongside the analysis of others, to authentically generate distinctive knowledge of the group as a whole (Amabile & Hall, 2021; L. Anderson, 2006). It contributes to debates of how knowledge is transferred from practitioners to the academics when real world practices are studied (Brannick & Coghlan, 2007; Rynes et al., 2001).

3.5.4 Ethnography in systems simulation modelling

As Section 3.3 described, systems simulation modelling has a rich history of using case study research for healthcare settings. Simulation of the processes of care and scheduled events is possible with hard data and stakeholder descriptions of culture and influencers without the in-depth analysis required by ethnography (Pidd, 2004). However, that which is said to be done is not always consistent with that which is done in large organisations (Van Maanen, 1979). This is arguably more relevant when a large number of autonomous, powerful, actors operate within the system. For example, senior doctors able to enact methods of care delivery which are consistent with their preferences but inconsistent with standard operational policies. Such behaviours will be less reliably captured if the presented views of stakeholders (obtained via informal discussion) are taken as a true reflection of operations in action.

Microscopic behaviours captured via ethnography naturally complement the methodology of ABM (An et al., 2021; Tubaro & Casilli, 2010). As Sections 3.5.2 and 3.5.3 explained, ethnographic studies enable the capture of microscopic behaviours - and their influences - which participants may be unaware of or unwilling to disclose. In this case of this research for example, high risk decisions made remotely to avoid admission that are not evidence-based making them difficult to justify on clinical grounds. In an ethnographic study, the researcher makes interprets observed and/or described behaviours, by reducing them into concepts of systemic/cultural behaviours via an iterative process of coding. The interpretative loop is closed by testing the hypothesized systemic behaviours against real-world data (where available), i.e., by validating their findings (Swiecki & Eagan, 2022). Tests of statistical significance will be limited when comparative data is small as may be the case in ethnography. Modelling hypotheses via ABM is a way overcome this as realistic data may be simulated to explore hypotheses further and test significance of outcomes observed (An et al., 2021; Swiecki & Eagan, 2022).

The resemblances between ethnography and the modelling of social systems via ABM are well recognised in social science (An et al., 2021; Dirksen et al., 2022; Tubaro & Casilli, 2010). In 'pure' ABMs, real data is not always necessary to inform the model parameters and agent behaviours may be abstracted upon (Tubaro & Casilli, 2010). This is a useful strategy when the entities being modelled cannot be directly interrogated (e.g., in bird flocking patterns). However, with human subjects, we may be able to interrogate them and observe behaviours as they occur. This empirical approach to ABM is, arguably, a more efficient way of generating hypotheses to inform the proposed SSM of early decision-making by staff (An et al., 2021; Tubaro & Casilli, 2010).

Ethnography's record of informing ABM for over 20 years supports its validity as a method for this research: Small (1999) applied observations from her own participatory ethnography to develop a model of kinship and marriage in Polynesian chiefdoms, Geller & Moss (2008) used qualitative fieldwork and interviews to model the emergence of local solidarity networks in Afghanistan, societal fragmentation, and conflict, Dirksen et al. (2022) used ethnography in collaboration with police researchers to study the organising principles cocaine distribution in the Netherlands and modelled previously unexplored supply-driven markets. These examples suggest that participatory observation is useful to inform an ABM that reproduces complex networks and emergent outcomes in previously unresearched phenomena.

3.5.5 Arguments against case study research

The validity of knowledge generated via case studies informed by insider knowledge has been criticised for limitations in validity, generalisability, and methodological rigor (G. L. Anderson et al., 2007; G. L. Anderson & Herr, 1999; Bonner & Tolhurst, 2002; Brannick & Coghlan, 2007). These are reasonable arguments to raise, but structured study design, transparency in data collection, and analyses, and triangulation of data sources all serve to counter them as shown in Table 3:5.

Amongst academics who practice traditional autoethnography, there are concerns of contamination of autoethnographic accounts by the accounts of others (Denzin, 2006; Ellis & Bochner, 2006). This is argued to dilute the richness of data. From the perspective of this research purpose, its weakness appears consistent with its strength – the creation of intersubjective knowledge that defies objective knowledge methods and is generalisable across experiences – i.e., the conscious and non-conscious decision processes involved in the ESDM task as discussed in Section 3.5.2 (L. Anderson, 2006;

Denzin, 2006). Concerns about bias and the validity of knowledge created outside of the realm of passive observation neglect to consider the role that researcher bias plays in subject choice, research design, analysis, and conclusions in all studies (Polanyi, 2009). This is connected to the restrictions that result from limiting knowledge to only that which may be deduced via tangible data and without consideration of what has not been captured or considered. This is discussed in greater detail in Chapter Four.

Table 3:5 Addressing the limitations of case study research

CRITICISMS	STRATEGIES TO ADDRESS CRITICISMS
Lack of rigor	Adherence to recognised methodology in design and delivery of case study research - for example Yin. Transparency in methodology and data collected
Validity of findings	Design in accordance with tenets of validity in social science research (where relevant): • Construct validity: multiple sources of evidence to establish a chain of evidence with review by key informants following completion • Internal validity: pattern-matching, explanation building in analysis, exploration of rival explanations in analysis • External validity: use of theory when performing single site case studies and replication of findings in multiple case studies • Reliability: creation and presentation of case study protocols and a database of evidence
Statistical constraints when generalising beyond the case site/s	A focus on analytical generalisability of theory over statistical generalisability of findings
Resource intensive with exhaustive findings	Design methodology relevant to the phenomenon of interest - focused ethnography and/or participant observation (where included in design) over lengthy field visits. Guided report presentation that focuses on the relevant points of the case and not a traditional, ethnographic narrative
Cannot be used to establish causal relationships	Use of case studies as complementary to experimental methods by providing rich explanations of how or why differences may be seen.

Adapted from Yin (2017)

3.6 Summary

The literature review presented in this chapter sought evidence supporting UK policymaker's assumptions of whole system efficiency and cost-effectiveness in the early senior decision-maker (ESDM) strategy for acute internal medical populations. No such evidence was found; however, a tendency for urgent care experts to identify patients suitable for admission avoidance in greater numbers when compared with non-expert staff decision-making was suggested by the research in this field. This supported the need for the novel research into the effectiveness of the ESDM strategy presented in this thesis.

Systems simulation modelling (SSM) was shown to be a useful method to address questions of effectiveness of ESDM when compared with other types of remote, early decision-making. Upon review of the literature on SSM methods for healthcare system research, combining methods provided the best opportunity for studying the emergent outcomes of autonomous agents interacting with and within a system that experienced stochasticity, regularly scheduled events, and the frequent emergence of queues. With these features in mind, a hybrid of ABM and DES held the greatest promise for successfully reproducing the proposed model requirements. Although combining ABM with SD would be an alternative approach likely to gain insight into system outcomes, the absence of discrete event scheduling and the low importance of stochasticity made SD less suitable for this particular work. It would be less capable of exploring the outcomes of decision-making in an environment with a large degree of stochasticity and regularly scheduled events informing agent behaviour and emergent outcomes.

By introducing individual agents into an event-orientated DES worldview it would be possible to create a model where entities 'listened to' (sensed) events occurring in their environment and responded according to their unique attributes and rules (S. K. Heath et al., 2011). Responses triggered could create movement through the model from one process to the next (e.g., arrival into the department, treatment commencement, exiting the department); queues could be created which triggered alter behaviours and movement amongst individual entities according to their unique attributes and/or rules as well as informing potential modelled outputs (delays to starting care and overcrowding).

Knowledge of how ESDMs occur, the influence of the environment, and the outcomes of care delivered without admission was necessary to inform the conceptual model and model building. However, this was largely absent from extant literature. Figure 3:2 summarises how the knowledge gaps fell into three related categories: knowledge of early allocation decision-making, of the decision environment, and of the effectiveness of decision outcomes.

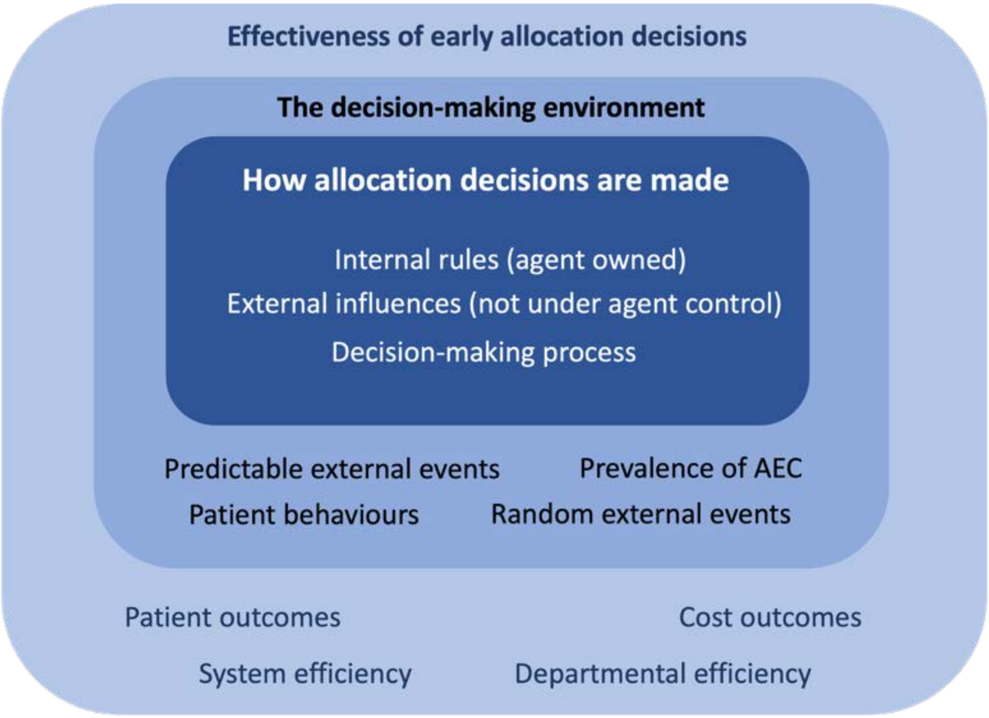


Figure 3:2 Knowledge of the ESDM phenomenon required for SSM

At the core of early senior decision-making (ESDM) is better understanding of the decision-making processes in senior and junior clinicians – the cognitive and externally available tools employed, internal motivators, and external influences. At the next level, elements of the decision-environment that are outside the control of staff may influence this process by altering the decision landscape in both predictable and unpredictable ways (e.g., removal of resources). Finally, the effectiveness of decisions to allocate patient to receive ambulatory emergency care (AEC) requires knowledge of the impact of admission avoidance on patients, the department, and the hospital system.

An ethnographic case study incorporating analytic autoethnography of ESDM in context was revealed as a useful and efficient method for capturing the data requirements described in Figure 3:2. Although infrequently applied, previous research revealed ethnography to be methodologically complementary to simulation modelling of social systems. This was particularly true of agent-based modelling. Analytic autoethnographic was perfectly placed to exploit the researcher's role as AIM clinical expert and modeller to conceptualise ESDM for the simulation model. An ethnographic case study of a typical AIM environment would provide the opportunity to study non-expert decisions, gain knowledge of the dynamics of the decision environment, and knowledge of organisational cultures that may influence ESDM or its outcomes. Ethnography would also facilitate the collection of patient-level data to inform model outputs. Few validated and/or credible tools existed for measurement of patient outcomes in urgent care populations. Generic health-related quality of life tools could be applied and non-validated measures of patient experience. Results would have to be interpreted with caution given their novel application in this setting. No reliable measures of efficiency nor safety were found in extant literature. Correlations between departmental occupancy levels and mortality supported using departmental occupancy levels to represent local safety, quality, and efficiency in modelled outputs. System efficiency would be challenging to represent holistically.

The nature of the evidence sought and how this influenced the research design, processes of data collection, and data analysis for each stage is discussed in the next chapter.

4 Methodology

This chapter summarises the methodological approach I adopted to reproduce the phenomenon of ESDM as it occurs in the complex social space of a healthcare delivery system and explore the outputs of different staffing strategies. It begins by explaining why the ontological nature of the research subject necessitated an ontological position of Critical Realism and a framework of complexity (Sections 4.1). Section 4.2 explains how the philosophical nature of the research question relates to the SSM technique – a hybrid ABM/DES – with Section 4.3 relating it to the chosen research design. Section 4.4 describes the data collection and analyses performed during the ethnographic and autoethnographic stage of the study when qualitative data on decision-making and the decision environment was collected. Section 4.5 describes the collection and analysis of the quantitative data collected during the case study. Section 4.6 explains how the results presented in Sections 4.4 and 4.5 were used to build the explanatory SSM and explains the process of sensitivity analysis and model validation. Section 4.6 ends by describing the final research stage predicting the outcomes of alternative staffing strategies.

4.1 Ethical approval

Approval for the study was granted via the Health Research Authority (UK) and the Regional Ethics Committee for East Scotland. A data management plan that ensured security of patient level data was approved by the University of Strathclyde. This included anonymization of all patient level data on the case site before transfer to the University cloud storage system in the form of password protected .csv files. Approval for use of the EQ5D5L tool was granted by the EuroQol Research Foundation.

4.2 Philosophical considerations

"The first step is to measure whatever can be easily measured. This is OK as far as it goes. The second step is to disregard that which can't be easily measured or to give it an arbitrary quantitative value. This is artificial and misleading. The third step is to presume that what can't be measured easily really isn't important. This is blindness. The fourth step is to say that what can't be easily measured really doesn't exist. This is suicide."

—The McNamara fallacy taken from Charles Handy, The Empty Raincoat, page 219

4.2.1 Knowledge and the object of research

The types of knowledge sought in this research varied in their format and ease of capture. Some aspects would be challenging to capture in an entirely objective fashion (e.g., the nature of expert decision-making) raising the potential for findings to be controversial amongst those in the domain of clinical practice. Consideration of how the nature of the knowledge sought informed its identification and capture – its ontological nature – was necessary. Once the philosophical nature of the research subject had been identified, appropriate research techniques, commensurate with a framework that reflected the epistemology, could be established. Acceptance of new knowledge in science relies on consensus amongst the society to which the knowledge is presented and their agreement upon the validity of the evidence used to generate it (Kuhn, 1970; Latour & Woolgar, 2013). Healthcare leaders will often consider evidence obtained through quantitative, positivist methodology as the gold-standard of knowledge formation in healthcare research despite the non-stable, complex state of healthcare systems and human behaviours (Alderson, 1998; Greenhalgh & Papoutsi, 2018; Mays & Pope, 1995; Starbuck, 2006). Knowledge created outside of the community's preferred framework risks non-acceptance (Kuhn, 1970).

This research sought knowledge of human decision-making and its outcomes when combining scientific and social knowledge in the socially constructed space of a hospital. In keeping with behaviours of knowledge acceptance in medical communities, new knowledge is more readily accepted by healthcare leaders when data is amenable to quantification and robust statistical analysis (Mays & Pope, 1995). This meant that creation of new knowledge in the ESDM task presented a challenge as data of social phenomena are less reliably quantified, validated, and reproduced compared with phenomena in the natural sciences (Starbuck, 2006).

Research objects held in the social realm, such as the non-conscious processes of expert decision-making, may still be studied and learned from. Attempts to coerce qualitative phenomena into quantifiable aliquots can be inaccurate and misleading as they force new knowledge into old ways of thinking (L. L. Wang et al., 2013). This may occur if there is ignorance of the fact that much of what we may understand as knowledge lies on a spectrum between knowable and unknowable, objective and subjective; some knowledge is easily quantified and agreed upon other types are not capturable using quantitative methods (Danermark et al., 2005). In complex phenomena, where knowledge is present but may be poorly articulated, patterns and tendencies may be the limits of external knowledge creation (Polanyi, 2009). Methodological frameworks applied to research in social science realms like healthcare delivery should acknowledge the limits of what is knowable and how the generation of new knowledge may occur despite perceived empirical barriers.

4.2.2 Studying the known, the knowable, and the unknowable

This research was carried out through the lens of Critical Realism as it presented an framework commensurate with the ontological nature of the knowledge sought. There are several positions that one may take when determining truth of the ESDM phenomenon:

- That singular truths are independent of human consciousness and all evidence must adhere to them
- That singular truths are independent of human consciousness but have multiple, context-dependent explanations
- That no singular truths independent of human consciousness exist – there are many truths entirely dependent upon perspective and/or context

Table 4:1 presents the objects of knowledge in the study of the ESDM phenomenon some of which may be reasonably agreed to be absolute points of truths independent of human consciousness (e.g., lengths of time), some singular truths with multiple explanations (external influences on the environment), and some non-singular (e.g., patient experience).

Table 4:1 Objects in the early senior decision-maker phenomenon

DOMAIN	OBJECTS
The decision-making environment	The clinical setting of decision-making The dynamics of the environment External influences on the environment (e.g., other parts of the hospital system)
Decision-making behaviours	The conscious and non-conscious processes of decision-making The influences on decisions Group versus individual behaviours in decision-making Existing differences between and within groups of decision-makers
Decision outcomes	Where patients are allocated to receive care How long patients wait for suitable resources Length of time in the urgent care system The experience of patients when allocated to care in different areas Health and well-being changes when allocated to care in different areas Outcomes of admission and discharge

Note that within even within agreed types of truths there are nuances and the perspective taken is important. A patient observed in a bed for ten hours overnight may perceive that they experienced admission whereas the provider may only perceive an admission to equate to a stay ≥24hrs; The scoring systems discussed in Section 3.4.3.2.2 transform health into an objective piece of knowledge comparable across populations despite the subjective nature of what it means to feel healthy (Karimi & Brazier, 2016). Similarly, definitions of expertise are shown to be context and task dependent (Patel et al., 1990; Shanteau, 1992).

The ontological nature of the objects listed in Table 4:1 were considered on a spectrum of knowable data (amenable to experience or capture in some manner) and objective data (measurable in a way that the truth of their nature may be agreed upon). Figure 4:1 presents a visualisation of objects on these spectra to appreciate the challenges in knowledge capture and analysis. A need for an epistemological approach that supported both easily quantifiable data and an abstraction of thought necessary to create knowledge of objects less amenable to capture was clear. Critical realism supported these requirements.

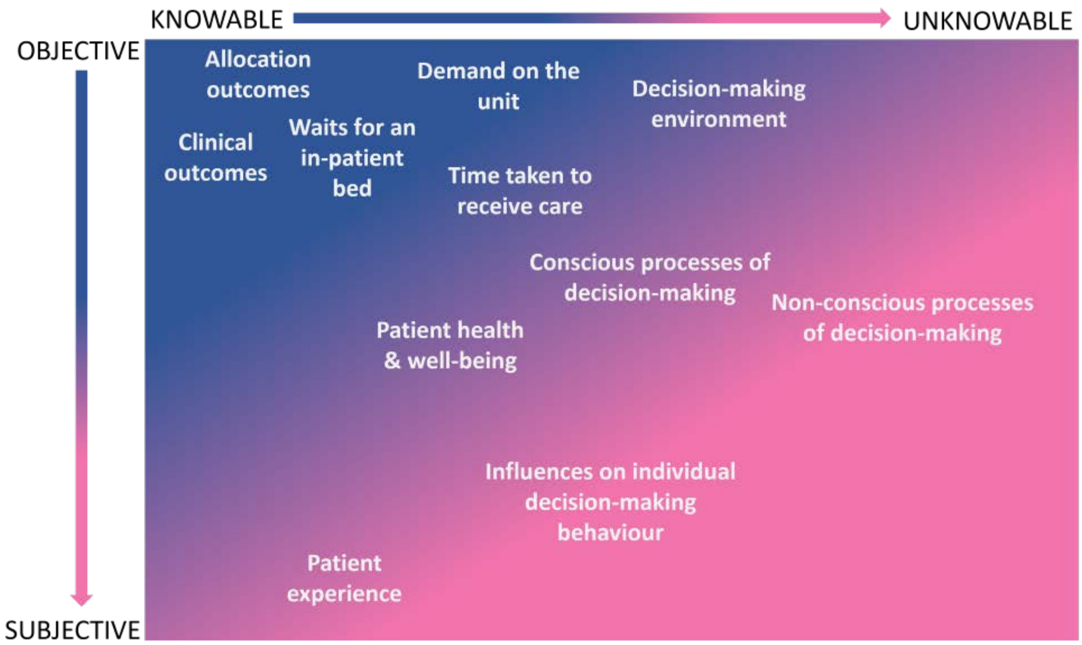


Figure 4:1 The nature of objects in the early senior decision-maker phenomenon

Knowledge identified as necessary to understand the research object were considered on spectrum of feasible knowledge capture and objectivity. Some elements presented an incontestable truth of early decision-making (e.g., place allocated to), some a truth that was entirely contextual and unique (e.g., patient experience). Many knowledge objects fell between theses extremes: easy to capture but in a state that may not achieve consensus on what it could be said to represent – e.g., the cognitive processes of decision-makers were difficult to capture directly but, where knowledge capture was possible it had the capacity to be reliable if consistently observed in independent contexts and subjects.

4.2.3 Critical realism

Critical realism is an approach that moves the emphasis of research and knowledge from an understanding of events as experienced (the empirical; the observed) to an understanding of the underlying mechanisms that generate events. It is a philosophical position that acknowledges a reality independent of human consciousness but understands it to be one that coexists with a dimension of our own socially influenced knowledge (Danermark et al., 2005). In establishing this school of thought, Bhaskar presented the world as existing in three strata as shown in Figure 4:2 (Bhaskar, 2013, 2014).

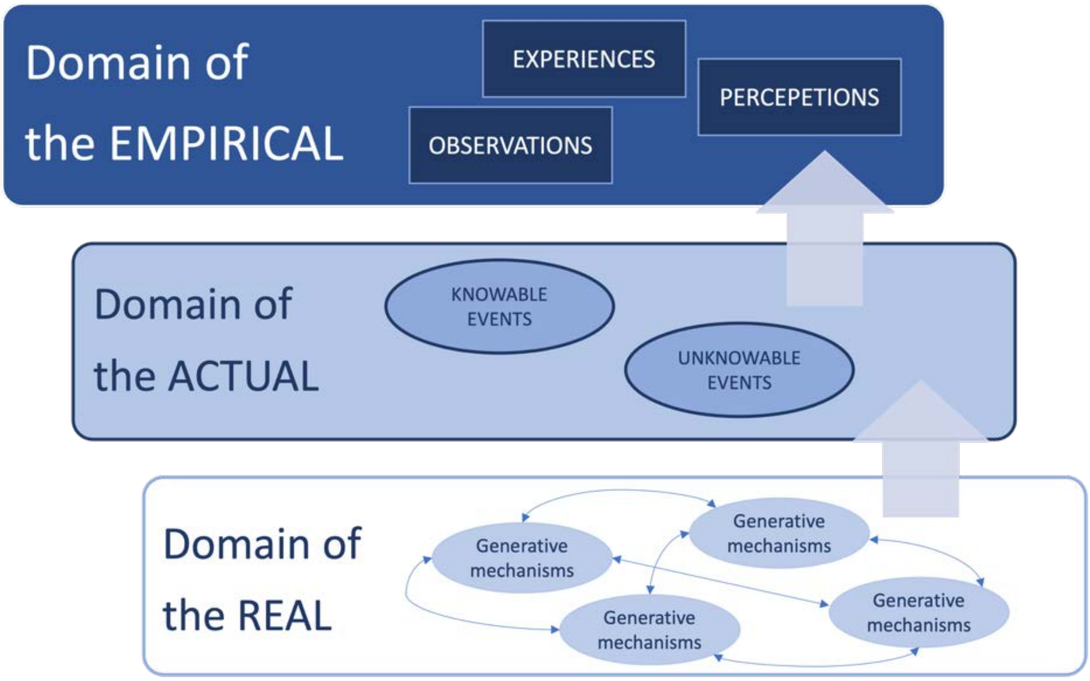


Figure 4:2 Domains of knowledge creation as proposed by Critical Realism

(Bhaskar, 2013; Danermark et al., 2005)

The underlying mechanisms of all events exist within an intransitive domain that may never be known or experienced only theorised upon. Within that dimension lie separate domains of generative mechanisms that interact between and within substrata, e.g., social, chemical, and biological. Interactions may be emancipating, enhancing, or inhibitory. Knowledge of the existence of generative mechanisms and their interactions may only ever be theories abstracted from the information experienced in the transitive domain of the empirical, itself a manifestation of the events that the generative mechanisms led to in the transitive dimension of the actual. Events in the domain of the actual may be knowable or unknowable – i.e., with no or ineffectual 'instruments' to facilitate capture. Despite being outside of human consciousness, unknowable events exist with the potential to be knowable in future (Danermark et al., 2005; J. Mingers, 2006).

Experimental conditions founded in a naïve realism (the belief in an objective, singular truth outside of human consciousness independent of context) seek to isolate generative mechanisms and control their interactions in the hopes of observing events in a pure form. This makes them ill-suited to study underlying mechanisms that exert influence but of which we are yet to understand or know. Appreciation of how empirical evidence emerges from the real, via the domain of the actual within a Critical Realist approach, highlights the limitations of naïve realism. As phenomena emerge from both known and unknown events via imperceptible interactions, a methodology that specifically isolates only known events creates incomplete knowledge. Reducing all knowledge to the domain of the observable places severe limitations what may be understood of underlying causes (Danermark et al., 2005). If we accept that we may never understand all mechanisms and events that lead to what is manifest in the empirical, additional analytical processes are necessary allow explanation in the face of our partial knowledge (Danermark et al., 2005; J. Mingers, 2006).

To address absence of full knowledge in generative mechanisms, Critical Realism promotes a form of thought experimentation (abduction) that theorises upon causes that may be reasonably said to underly a phenomenon. Theories may be valid if supported by evidence that has manifested in the empirical. It is through abduction that we may generate statements of knowledge about the interaction of mechanisms underpinning events experienced in the social world and about unknowable events (Danermark et al., 2005). Such statements of knowledge can only ever approximate truths, but some statements may be considered more 'truthlike' than others as knowledge is founded upon an intransitive reality that is socially influenced but not socially determined (Danermark et al., 2005; J. Mingers, 2000). Not all abducted statements are equally valid - methodological rigor in the retrieval of supportive evidence is required to differentiate between valid and less-valid truths (Danermark et al., 2005; J. Mingers, 2000). For example, triangulation of evidence via multiple sources, perspectives, and data formats.

Critical Realism eschews the existence of universal (causal) laws (Danermark et al., 2005). Under the influence of the social world, 'truthlike' statement are constantly subject to change – as we learn, the knowledge within our transitive domains is altered, along with our understanding of events and their possible causes (Danermark et al., 2005). Relationships theorised may only ever be tendencies which evolve in parallel with our knowledge (Bhaskar, 2013). Multiple explanations for phenomena may emerge reflective of our (always) partial knowledge of reality and the dynamism of social influence. This is consistent with established epistemological arguments of the limited role that predictive science has in the social sphere when we model behaviour on historical events and objective knowledge alone (Popper, 1960, 1979), for example predicting future ESDM outcomes from the outcomes of previous ESDM events.

4.2.4 Critical realism and complexity in healthcare system research

Many relationships in healthcare settings are non-linear (Plsek & Greenhalgh, 2001). Naïve realism applied to social science research may create non-useful or misleading knowledge (J. Mingers, 2006), yet research that seeks to understand and improve healthcare delivery continues to be unduly influenced by methodologies focused on linear causality amongst empirical data (Deblois & Lepanto, 2016; Gowen et al., 2012). Urgent healthcare settings display features of complex adaptive systems

(Fajardo-Ortiz et al., 2015; Plsek & Greenhalgh, 2001; Tsasis et al., 2012). Its processes are highly non-linear and capable of self-regulation via autonomous behaviours at the level of the individual, groups of individuals, and departmental entities (see Table 4:2). This influences behaviours and activity in other parts of the healthcare system (Tsasis et al., 2012). The complexity observed in healthcare settings means that predictions of future events and outcomes may only represent possibilities with the potential to be realised under some conditions. Taking a Critical Realist approach we may ask, '*given the knowledge we have, what alternative explanations, conditions, and outcomes may also be possible?'*.

Table 4:2 Manifestations of complexity in urgent care

FEATURES OF COMPLEX ADAPTIVE SYSTEMS	POTENTIAL MANIFESTATIONS IN URGENT CARE
Attractors: agents or processes which motivate systems to follow behaviours[a,b]	Clinical leadership from staff trained in urgent care Performance metric success encouraging other systems to mimic practices Organisational recognition of performance success leading to enhanced funding to develop services further
Emergent behaviour: new system paths emerge through unexpected events as a result of the connection of systems[a,b]	Regular communication between urgent care and specialist teams leading to collaboration and novel pathways of care Creation of non-admission pathway for one condition triggers consideration of the possibility of others Spontaneous generation of new pathways of care when resources are limited Temporary disruption to established processes due to demand leading to new ways of working
Networks: connected teams of agents	Centre-point between primary and secondary care services Professional bodies create networks of urgent care teams to learn from other areas with similar populations e.g., rural hospitals learning from other remote site practice at professional conferences Clinician leadership with executive influence in service planning and development
Self-management & self-organisation: the ability to react to internal and external influence and change[a,b]	Adaptation of pathways according to patient need, preference, and resource availability without executive approval Flexible design of services and processes to cope with periods of high demand and unstable patients Power to alter shift patterns and staffing at the departmental level on a daily basis
Entropy: barriers/structures breaking down and system elements homogenising[a,b]	Prolonged periods of departmental overcrowding causing assessment processes to break down: o senior staff assuming trainee roles and managerial roles to safely co-ordinate patient flow o other services attend urgent care areas to evaluate patient populations o ambulance staff prevented from transferring care and queues forming o clinical staff performing assessment in non-clinical settings (e.g., car parks)
Negentropy: elements in the system take energy from elsewhere to maintain heterogeneity and avoid entropy[a,b]	Senior clinicians removed from clinical roles when managing flow or performing trainee work Patients boarding causing cancellation of other services (e.g., elective surgery) Ambulance prevented from attending calls when forced to remain with patients without a safe space Development of barrier mechanisms to redirect patients to alternative services (e.g., hospital closure) Pulling of resources from other areas when overcrowded (e.g., staff redeployment or priority for diagnostic services Specialist attendances to urgent care to support admission avoidance reducing services in their areas
Fractals: identifiable similarity in smaller components of a wider system	Processes in one admission avoidance pathway are representative of other and general service processes Supportive & creative clinical leadership at the ward level representative of supportive & creative executive leadership
Chaos: small changes in one part of the system leading to fragile states or unexpected results[a,b]	Application of four-hour access standard in one area causing crowding in other where standard not applied Poor training in urgent care due to overcrowding leading to removal of trainees to the service by educational bodies Poor GP and social care access over weekends/public holidays leading to a build of demand transferred onto urgent care

([a]Fajardo-Ortiz et al., 2015; [b]Greenhalgh & Papoutsi, 2018)

4.3 How the research philosophy informed the systems simulation model

It would be impossible for an SSM to be a precise representation of early senior decision-making (ESDM) without abstractions or assumptions (Sargent, 2010). Modelling the entire hospital system would be logistically impossible and not necessary to appreciate emergence at the departmental level that could be said to have impact upon the wider system. The conceptual model need only consider reasonable explanations for decisions made in the ESDM (based on the empirical evidence) and determine which explanation was the most 'truthlike' and useful. From thence, predictions about potential futures could be made. Absolute accuracy is not the goal, the SSM need only be useful for answering the questions asked of it (Hunter & Kelleher, 2020):

1. How could the department have come to be in its current state as a result of early allocation decision-making by the staffing model currently in place?

2. How might the state and outcomes of the department differ with alternative staffing making early allocation decisions?

A hybrid of agent-based and discrete event simulation modelling was chosen for the research. This combination was capable of capturing all elements suitable for modelling ESDM in a complex social environment from a position of Critical Realism as shown in Table 4:3. As ABM functions in an aggregative fashion (as opposed the allocative nature of DES), outcomes could be driven by individual staff from the bottom up (Railsback & Grimm, 2019). As the bottom-up events were subject to regular events in time and altered states at the departmental level, DES was a natural inclusion. Combined they reproduced a real-world system in which individual clinicians had the capacity to react to events and alter behaviours accordingly with outcomes that had meaning at the departmental level.

Table 4:3 Comparison of SSM techniques for meeting research requirements

REQUIRED FEATURES	ABM	DES
Incorporate non-linearity in relationships	Yes	Poorly
Schedule events (e.g., staff shift changes)	Requires additional coding - may be time-consuming	Key feature of software means efficient coding
Model outcomes over time	Yes	Yes
Model autonomous decision-making	Yes	No
Incorporate external influences into decision-making	Yes	Requires additional coding - may be time-consuming
Create networks of queues	Requires additional coding - may be time-consuming	Yes
Model individual staff to respond to queues	Yes	Requires additional coding - may be time-consuming
Collect individual outcomes	Yes	No
Collect group outcomes	Yes	Yes
Explain decision behaviour	Yes	No
Identify emergent patterns for predictive purposes	Yes	Yes

Uncertainty present in the non-linear relationships of the ABM component would mean that hypothetical explanatory models of ESDM allocation behaviours could be explored in a manner that represented uncertainty in knowledge of how those allocation behaviours manifested in real-life (An et al., 2021). Consistent with the process abduction, this represented a ‘search for credible arguments based on computational experiments’ (Bankes, 2002). The depth of reflexive analysis facilitated by autoethnographic study of ESDM combined with evidence from the first-person perspective to corroborate informant descriptions and achieve intersubjective agreement about the cognitive processes involved in ESDM. This supported the creation of valid, truthlike statements about ESDM that could be applied to the SSM (Danermark et al., 2005; Fresco, 2021; J. C. Mingers, 1995).

4.4 The research design

An overview of how the ethnography, autoethnography, and case site observation serve to answer questions about the effectiveness of ESDM is summarised in Figure 4:3.

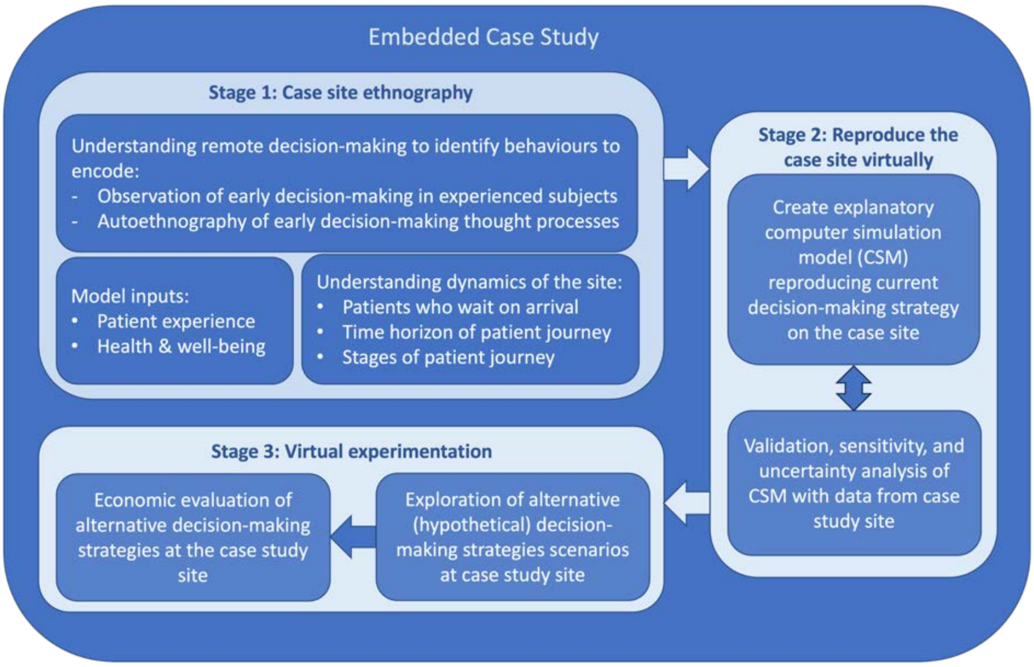


Figure 4:3 The research design: an embedded case study

A prospective study of the early senior decision-maker phenomenon, the nature of referrals into the local system, and the decision-making environment was required. This included understanding the behaviours and outcomes of patients managed in the system. Reproduction of the phenomenon and the environment via model conceptualisation and programming followed - an iterative process as verification and calibration fed back into the model design. Once validated, the model would be used to explore of the outcomes of alternative staffing models completed the study.

The policies promoting ESDM were explicit in their assumption that senior clinical staff made more effective decisions than other staff irrespective of context. This implied a belief amongst healthcare leaders and policymakers of a generalisable theory of senior doctors in the ESDM which could be generated via abduction if studied in the context of a representative acute medical unit environment.

4.4.1 Methodological bricolage

The unique nature of the research and variety of objects required a unique approach to research design that maintained rigor. Choice of appropriate methodology is a recognised dilemma in social science (Starbuck, 2006). The methodology chosen had to acknowledge the unstable nature of the social world and the subjectivity of interpreting individually experienced thought processes and decision-making (Starbuck, 2006). Phenomena anticipated to defy easy capture, such as the processes involved in non-conscious thought, required consideration of the different ways that data may be experienced and captured. Participant selection had to consider how research subjects formed a representative sample of the spectrum of early decision-making skills (Mays & Pope, 1995). In addition, patient activity, environmental influence, and outcomes had to be collected from a real system as there was no data to inform a hypothetical one.

Methodological bricolage has developed to address requirements of rigour in knowledge creation whilst recognising the nature of poorly quantifiable phenomena (M. G. Pratt et al., 2020). This approach acknowledges that research methods for social worlds need to be as unique and varied as the objects that form them and that methodological rigor must to be found beyond the forced application of ill-suited templates (Harley & Cornelissen, 2020; M. G. Pratt et al., 2020). This includes consideration of types of data accessible to a researcher, e.g., clinical settings, expert clinicians, and patients undergoing acute care. A bricolage that combined ethnography, autoethnography, and systems simulation modelling sufficiently represented the requirements of data necessary to answer the research question provided the processes of data collection and analyses adhered to the principles of each method. The remainder of this chapter describes those processes.

4.5 Qualitative data collection and analysis of early senior decision-making

4.5.1 Autoethnography of the decision-maker role

The researcher (author) performed the ESDM role as a paid member of the healthcare team and took contemporaneous notes during events. She was provided with a contract to perform clinical duties on the case site as a consultant in Acute Internal Medicine for 12hrs per week during the study period. No observation of others was performed during clinical duties. Observation of other participants occurred during non-clinical time. She recorded anonymised particulars of the decision-events and documented the sequence of events, behaviours, emotions, and clinical notes taken at the time.

4.5.2 Analysis of autoethnography

Contemporaneous notes were stored for later analysis. Handwritten notes were transferred to an electronic document at the end of each shift and underwent reflexive analysis upon completion of the observational study period. This involved exploration of alternative explanations for behaviours, emotions experienced, and the decisions taken via the process of bracketing - a method of reflexive analysis that forces the researcher to set aside their personal interests, assumptions, and pre-formed theories to view the data from a different perspective (Brannick & Coghlan, 2006; Fischer, 2009). Analysis via bracketing occurred in two stages: during the analysis of original notes and after the thematic analysis of observed participant findings (Fischer, 2009).

4.5.3 Participant selection

Consultant staff were assumed to be peer-recognised experts in the ESDM role consistent with the assumptions of expertise in the clinical studies cited in Section 3.4.1, Junior medical staff >4years post-graduate were assumed to be experts in training. As senior nursing staff (≥ Band 6) performed referral call-fielding on the site, and were known to do so in other hospitals, they were included in the case study protocol. Staff were excluded from observation if they did not consent or if they did not fit into the categories of consultant, trainee of >4yrs post-graduate training, or senior nursing staff. Observational activity and decision-maker participant recruitment was performed via convenience sampling. No decision-makers were observed 2200-0800hrs as staff in the overnight period were rarely members of the staff identified for recruitment.

4.5.4 Observation

Timed, contemporaneous notes of dialogue and actions during referral conversations were recorded. Due to the potential for (non-consented) identifiable patient information capture, all observation notes were taken by hand in research journals or entered directly into a secure computer database. All interview data post decision-making was recorded on paper to prevent capture of non-consented patient data during the discussion. On immediate completion of the referral, participants were asked to describe the interaction, their awareness, and timing of decisions, impressions formed, and solutions generated. This was followed by a short, unstructured interview guided by their recall of events, cross-referenced with the researcher's observational findings. Decisions were categorized by the researcher according to those shown in Table 4:4.

Table 4:4 Categorization of how urgent care solutions were made

DECISION TYPE[a]	DESCRIPTION	EXAMPLE
Option selection	Externally presented solutions (i.e., determined by referrer)	Referrer states that the patient needs to be placed in a bed
Procedural	Application of a pre-determined organisational rule	Patient suspected of contagious infection requiring placement in an isolated facility
Deliberation	Rationalisation of multiple options between colleagues or considered via analysis by the decision-maker alone	Admission avoidance via AEC allocation is suggested by the health need and the patient preference but there are logistical challenges to ensuring this is safe and feasible
Prototype	A standard approach to previously/often encountered dilemmas when cases seem to merge into one 'pattern'	Patient with a suspected cardiac event, who is pain free with normal initial investigation/s being allocated to AEC versus patient with ongoing pain or non-normal initial investigations being allocated to a bed
Constructed	Novel creations as solutions based on knowledge of previously seen or shared situations/solutions. Usually, a variation on prototype solutions adjusted to meet specific patient needs, resource availability, or geographical obstacles	Using community diagnostic facilities to support non-attendance – e.g., arranging an urgent blood test in the patient's location for remote review by the hospital clinician
Analogue	Use of another situation seen or heard about (applied in isolation and not incorporated in newly created solution)	Application of a solution because 'that is what is done here' or they've seen someone else do it without conscious consideration of why

[a](G. A. Klein et al., 1986)

4.5.5 Thematic analysis

A thematic analysis was undertaken by the researcher (Corley & Gioia, 2004; Gioia et al., 2013). Informant, first-order concepts were identified and progressively abstracted to form second-order themes which were used to form aggregate dimensions in an iterative process via the emergent inquiry of grounded theory (Charmaz, 2008; Corley & Gioia, 2004; Gioia et al., 2013). This included data collected during the observation of departmental activity and culture and the data generated via reflexive analysis of the autoethnographic findings. Findings of the thematic analysis were shared with the consultant participants and other consultants performing ESDM on the case study site. A focus group meeting led by the researcher was conducted over an online video service teams to determine representativeness of findings and conclusions drawn (validation of findings). All consultants working in the department were invited to attend. The focus groups was recorded with the permission of the participants with additional handwritten notes taken by the researcher.

4.5.6 Observation of departmental activity and culture

Between autoethnographic and participant observations, everyday activity, exchanges between staff (clinical and managerial), and departmental meetings were observed. Informal discussion about the general running of the ward with members of the senior medical and nursing team also occurred via convenience sampling. This was necessary to understand how the environment informed decisions, if/how the organisational cultured influenced decisions, and how the hospital system processes responded to high occupancy levels. Findings were then used in when conceptualizing the model: how culture influenced decisions, how patient movement through the system affected/was affected by variations in activity.

4.5.7 Analysis of departmental activity and culture

This data collected during departmental activity observation was included in informant first-order concepts of the thematic analyses described in Section 4.5.5 and the process of bracketing described in Section 4.5.2. Findings relating to local culture and influence upon decisions were validated via the local expert focus group discussion of the thematic analysis. Representation of departmental activity was validated via face-validation of model functioning and pattern-oriented matching of modelled outputs.

4.6 Quantitative data

This section describes the collection and analysis of three datasets: patient-reported outcomes (Sections 4.5.1); a hospital database of patient movements, allocations, and outcomes (Section 4.5.2); a dataset of the outcomes of consultant decision-maker events performed during a quality improvement project from 2015-2016 (Section 4.5.3). A single month (October 2019) of a handwritten dataset of patient activity was cross-referenced with the hospital server data to ensure accuracy of large dataset information.

4.6.1 Patient outcomes

This section describes the methodology for collecting data to inform the model parameters representing value to patients – health, well-being, and experience.

4.6.1.1 Participant selection and data collection process

All patient participants were identified and recruited by the researcher. Participants were approached within four-hours of arrival onto the unit. After gaining consent, they were assigned a unique participant number and asked for their preferred method of follow-up. Relevant contact details, age, gender, ethnic identity, and a clinical description of the presenting complaint were recorded. Excluded patients were: patients attending for follow-up; those with physiological instability (based on clinical observations and symptoms); those identified as having a planned/clear need for prolonged admission by the clinical team; patients with cognitive impairment. Participant details were stored on a password protected .xls file held in the University cloud storage. Participants were not selected on the basis of presenting condition/complaint and were recruited via convenience sampling during AEC working hours on days when I was not providing clinical duties.

Initial surveys of health and well-being and experience were performed at recruitment. Follow up surveys were completed 7-30 days after discharge. A minimum period of 7-days was chosen to allow for ongoing recovery or follow up. A maximum of 30days was chosen to mitigate the impact of new health issues or unrelated hospital attendances on the survey results. Follow up was predominantly via email and electronic collection (at the request of participants) but patients some chose to complete follow-up via telephone contact (with the researcher) or via post.

Only patients discharged from the AMU bedded or ambulatory emergency care (AEC) area within 48hrs of arrival were contacted for follow up to allow comparison of outcomes of those allocated to receive all care via urgent care in-patient with those cared for via out-patient services. This was determined for three reasons:

1. The role of ESDM is to enhance use of AEC services, therefore any patients admitted beyond the AMU were assumed to be unsuitable for AEC allocation

2. Patients transferred to other areas of care would be at risk of recall bias or conflating care and experience across all areas

3. A time frame of 48hrs allowed the inclusion of patients whose discharge from urgent care was delayed for logistical or process-driven reasons (e.g., delays to access transport home or delays to accessing clinical resources)

4.6.1.2 Patient experience

An adapted version of the NHS Scotland In-patient experience (IPE) survey was used to collect data about patient experience. Adaptation was necessary to reflect the unique setting of the AMU as an urgent care ward and not a general hospital ward. As the IPE was designed to capture elements of the in-patient experience, it was performed upon completion. To mitigate recall bias of the initial hours of care, an exploratory survey (non-validated) was performed at the time of recruitment. This asked about patient knowledge of how urgent care may be delivered, anticipated length of stay, and preferences for out-patient of in-patient urgent care. Both surveys are presented in Appendix A.

4.6.1.3 Analysis of patient experience data

The experience surveys underwent descriptive analyses according to the area of the department where patients described receiving the majority of their care. Differences in findings from each area were evaluated via Chi-squared testing against the null hypothesis. Where responses were too small for Chi-square testing, Fisher's exact was applied. Free text comments in the initial survey and the IPE were explored for themes not identified by the structured survey questions to inform how the conceptual model could meaningfully incorporate patient experience.

4.6.1.4 Health related quality of life

Health-related quality of life (HRQoL) was collected at recruitment (within four-hours of arrival) and on follow-up (7-30days post-discharge) using the EQ-5D-5L tool (Appendix A).

4.6.1.5 Analysis of health

The EQ-5D-5L surveys underwent descriptive analysis according to area of discharge recorded on the hospital database (TrakCare®). Survey results for each of the five levels were converted to a Health Index (HI) value for initial and follow-up survey for each patient and differences calculated. Health Index values were taken from the NHS England dataset as none was available for Scottish populations (N. J. Devlin et al., 2018). This assumed homogeneity between the populations of Scotland and England in values/weightings used to inform the value set. The visual analogue component of the survey was used to determine reliability of HI value calculated. Where change in HI was inconsistent with the magnitude or direction of change reported in the VAS, responses were omitted. Comparison of HI change for each area was performed using the null hypothesis using the Welsh Two Sample t-test which assumed a normal distribution of outcomes.

4.6.2 Departmental activity

Patient movement through the urgent care system was taken from the local site database (TrakCare®) as shown in Table 4:5. Data from October 2019 to February (end) 2020 were used to omit the effects of the COVID-19 pandemic which were assumed to be temporary. Data for patients arriving between 01/12/ - 31/12 was excluded as the Xmas holiday period and the week in the lead to this are known to display abnormal referral and activity patterns not seen at any other time of the year in the UK. This is anecdotally reported to be due to preference of patients to avoid hospital admission on Christmas Day.

Neither the local department nor the TrakCare® system recorded the patients who were referred but allocated to alternatives sites. Time of referral was not recorded in the TrakCare® dataset. The source for the TrakCare® dataset was the original departmental repository of contemporaneously data entry by handwritten by staff. This data was uploaded to TrakCare® via excel spreadsheet entry by non-clinical staff up to 24hrs after patient attendance. Comparison of the handwritten entries and the TrakCare® data was performed for patients attending in October 2019 to determine the accuracy of the TrakCare® dataset as the local Business Intelligence team had not validated the TrakCare® data. October 2019 was used to verify and calibrate the model outputs but not for validation.

Table 4:5 Patient activity data used to inform conceptual model, model inputs, and validation

Data	Source	Use in the model-building process	Rationale
Source of referral	TrakCare®: 01/10/2019 - 30/11/2019 & 01/01/2020 - 28/2/2020	Calibration	Capture population attendance times and identify populations for decision-maker programming
Arrival date/time	TrakCare®: 01/10/2019 - 30/11/2019 & 01/01/2020 - 28/2/2020 Handwritten records: 01/10/2019-31/10/2019	Verification Calibration Validation	Capture arrival patterns and length of stay
Area of care upon arrival	TrakCare®: 01/10/2019 - 30/11/2019 & 01/01/2020 - 28/2/2020 Handwritten records: 1/10/2019-31/10/2019	Verification Validation	Capture arrival patterns and activity in AEC and in-patient areas
Time placed into a bed (in-patient allocations only)	TrakCare®: 01/10/2019 - 30/11/2019 & 01/01/2020 - 28/2/2020 Handwritten records: 1/10/2019-31/10/2019	Verification Validation	Capture patients waiting for in-patient resource on arrival and length of wait
Departure date/time	TrakCare®: 01/10/2019 - 30/11/2019 & 01/01/2020 - 28/2/2020 Handwritten records: 1/10/2019-31/10/2019	Verification Calibration Validation	Capture length of stay
Outcome (e.g., discharged)	TrakCare®: 01/10/2019 - 30/11/2019 & 01/01/2020 - 28/2/2020	Verification Calibration Validation	Capture activity patterns on completion of care
Place after leaving the AMU	TrakCare®: 01/10/2019 - 30/11/2019 & 01/01/2020 - 28/2/2020 Handwritten records: 1/10/2019-31/10/2019	Verification Validation Validate hospital dataset	Validate the accuracy of the outcome record in the TrakCare® dataset
Reason for referral	Handwritten records: 1/10/2019-31/10/2019	Comparison with collected patient data	Compare with prospective data collected to evaluate representativeness of inputs for the model

4.6.2.1 Analysis of departmental data

The TrakCare® patient level dataset was anonymized on site, tidied, and analysed. Table B:5 in Appendix B summarises the assumptions made on analyzing the dataset and rules applied to manage missing values.

4.6.3 Historical data of decision-making on the case site

The quality improvement (QI) project recorded remote, early consultant decision-making for a six-month period from December 2015 - June 2016 (see Table 4:7). Contemporaneous notes were added to an .xls file by staff as they performed a trial of ESDM during the hours of 0900-1800, Monday to Friday. This included one trainee-consultant within 6-months of completion of training. As a member of staff on the case site during this period, the researcher's decision-making was also included in these findings.

Table 4:6 Data from local quality improvement project

Data	Description	Proposed purpose in the model
Time of referral	Time of urgent referral	Reproduce referral activity patterns not reliably captured in departmental data
Name of decision-maker	Staff taking the call	Identify years of clinical practice in the department to inform coding of decision outcomes
Decision taken	Outcome of the call: • AEC • In-patient area • Refer to another team • Stay in community	Inform conceptual model of decision-making patterns according to experiential learning

4.6.3.1 Analysis of historical data

Descriptive analysis was performed to identify trends in timing of referrals. Staff decision outcomes underwent logistical regression. This regressed AEC or non-AEC allocation as binary outcomes upon months spent working as a consultant on the case site as an assumed proxy for expertise. A predictive model to explore AEC allocation probabilities according to career length was generated using the results.

4.7 Creation of the systems simulation model

This final section of Chapter Four begins by explaining the framework used to create the SSM. It then provides an overview of the software (Section 4.6.2), the methods of verification, and validation (4.6.3). Techniques for validation of the decision-maker sub-model prior to its use in predictive modelling are discussed in Section 4.7.3.4. Section 4.7.4 describes the sensitivity and uncertainty analysis of the explanatory model. The chapter ends with a description of the methodology for predictive modelling and output analyses (Section 4.7.5).

4.7.1 Model building framework

My approach to reproducing the ESDM acknowledged that no model could ever be proven true in an absolute sense but may be considered true for the purpose it was designed for (Marino et al., 2008; Saltelli et al., 2019). Creation of a SSM requires a reductionist approach to decision-maker behaviours and the environment – identification of the salient features and removal of unnecessary variables that could impair the validation of findings, limit identification of the key factors, and challenge user understanding of the outcomes produced (Box & Draper, 1969). Adoption of the TRACE framework (Table 4:8) helped to achieve rigor in this process (Grimm et al., 2014). The TRACE framework informs the arrangement of Chapter Six where the results of the SSM validation are presented.

Table 4:7 The TRACE framework

Stage[a]	Description
1. Problem formulation	The decision-making context in which the model will be used, the question(s) that should be answered with the model, specification of model outputs; the domain of applicability of the model and any extrapolations
2. Model description	A detailed written model description including coded behaviours and data sources. This is presented in the form of an Overview, design, and development (ODD) protocol (Grimm et al., 2020) in Appendix C
3. Data evaluation	The quality and sources of numerical and qualitative data used to parameterize the model and of the observed patterns that were used to design the model structure. This is presented in Chapter Five. Assumptions about data and its use in the model are presented in tabulated format for ease of reading in Appendix D
4. Conceptual model evaluation	Simplifying assumptions underlying a model's design about empirical knowledge used and general basic principles
5. Implementation verification	Demonstration that the model functions as designed without programming errors. How the model may be used by clients or other interested future users who may wish to modify or amend it for another purpose
6. Model output verification	How well the model output matches observations and the extent of calibration required to obtain good fit
7. Model analysis	Analysis of the sensitivity of the outputs to changes in model parameters. Explanation of the emergence of model outputs
8. Model output corroboration	Comparison of model outputs to independent data and patterns - i.e., outcomes that were unused and preferably unknown during the model development. provides evidence of structural realism of the model to allow interpretation of predictions

[a](Grimm et al., 2014)

4.7.2 Model methodology

Based on the review of modelling methods (Section 3.3.2), a hybrid model of discrete event and agent-based simulations held the greatest promise for successfully reproducing the proposed model requirements - staff displaying autonomous decision-making under the influence of the dynamic state of the department, and patients movement within the department (also influenced by the dynamic state) subject to scheduled events (e.g., treatment starting, treatment ending, areas closing). Although combining ABM with SD would be an alternative approach likely to gain insight into system outcomes, the absence of discrete event scheduling and the low importance of stochasticity made SD less suitable for this particular work. It would be less capable of exploring the outcomes of decision-making in an environment with a large degree of stochasticity and regularly scheduled events informing agent behaviour and emergent outcomes.

By introducing individual agents into an event-orientated DES worldview it would be possible to create a model where entities 'listened to' (sensed) events occurring in their environment and responded according to their unique attributes and rules (S. K. Heath et al., 2011). Responses triggered could create movement through the model from one process to the next (e.g., arrival into the department, treatment commencement, exiting the department); queues could be created which triggered alter behaviours and movement amongst individual entities according to their unique attributes and/or rules as well as informing potential modelled outputs (delays to starting care and overcrowding).

4.7.3 Modelling and analytic software

Netlogo™ was chosen to create the SSM as it was specifically designed for ABM but has the flexibility and developer support to incorporate DES components (Wilensky, 1999). Within the Netlogo™ software, individual and group behaviours along were programmed with scheduled events such as peak hours of activity to mimic the case study site and collect data on queues as they formed. The SSM was run via the 'nlrx' package in R studio as the Netlogo™ analytic software was inadequate for the size of data collected due to Microsoft Excel limitations (Salecker et al., 2019). The 'nlrx' package was also used to perform the sensitivity analysis. Modelled outputs representing departmental activity were stored at the end of model time-step (occupancy levels) each and at the end of each modelled day (all other outputs). Individual patient outputs (delays, length of stay, HRQoL) were stored in the model in the form of lists and amalgamated into a .csv file for analysis at the end of model runs.

4.7.4 Explanatory Model analysis

4.7.4.1 Stochasticity

Stochasticity reflective of real-world events and activities in urgent care was built into the SSM (described later in Section 6.2.4 and Appendix C). The SSM underwent cumulative runs to identify the maximum number of runs required to detect significant change in outputs at a level of meaningful important difference (MID) determined at the 99% confidence interval (99% C.I.) (Hunter & Kelleher, 2020; Sargent, 2010). These values described the minimum change in outputs that healthcare leaders would consider having a significant impact on service performance. The final values chosen were determined after discussion with local experts on the case study site (Table 4:8).

The SSM was run an increasing number of times until the 99% C.I. around outputs was less than or equal to the MIDs.

Table 4:8 Minimal important difference in outcomes required

Outcome	Format	MID	Source
24hr discharges	99% C.I.	0.05	Modeller assumption and local expert opinion
Discharges from bedded area	99% C.I.	0.05	Modeller assumption and local expert opinion
Discharges from AEC	99% C.I.	0.05	Modeller assumption and local expert opinion
Admissions	99% C.I.	0.05	Modeller assumption and local expert opinion
Daily waits for an AMU bed	99% C.I.	0.10	Modeller assumption and local expert opinion
Proportion of transfers occurring overnight	99% C.I.	0.05	Modeller assumption and local expert opinion
Length of delay Bedded area	IQR	30 minutes	Modeller assumption and local expert opinion
Utilisation of AEC	99% C.I.	0.05	Modeller assumption and local expert opinion
Health Index (HI) change[a]	99% C.I.	0.070	(Henry et al., 2020; McClure et al., 2017, 2018)
Positive experience	99% C.I.	0.05	Modeller assumption and local expert opinion

[a]measured via the EQ5D5L tool

Studies of the EQ-5D-5L tool in UK populations estimated meaningful change in HI to lie between 0.037-0.069 whereas, in other Western populations, it ranged from 0.078 – 0.098. It is important to note that the MID value for HI change represented individual and not population change. As the SSM stored the total number of patients discharged, it was possible to calculate the mean HI change per person across the entire discharged population to compare with the MID.

As model runs created mean values, outputs over cumulative runs represented the means of means thus were assumed to be normally distributed as per the Central Limit Theorem[8]. The distribution of lengths of delay was assumed to remain skewed with a wide variance, hence MID was compared with the interquartile range.

4.7.4.2 Verification and calibration

Verification is the process of determining whether a SSM functions as intended (Sargent, 2010). The SSM graphical user interface (GUI) was designed to visually reproduce the AMU environment including waiting areas, patients due to arrive, and departmental occupancy levels. Face verification was carried out via the GIU as the model ran to ensure activity mimicked that observed during ethnography. Sub-models reproducing behaviours were tested by exploring extremes of parameter inputs to sensitivity, magnitude, and direction of any output change against modeller predictions. Data from October 2019 was used to verify and calibrate model outputs in an iterative fashion. Parameter inputs were adjusted until the distribution pattern of modelled outputs visually matched the historical data and the median values of modelled outputs fell within the interquartile range of the historical data (calibration).

4.7.4.3 Validation

Evaluating the usefulness of the SSM, relied on determining how well it represented the phenomenon under scrutiny - "homomorphism between one system and a second system that it purportedly represents" (Richiardi et al., 2006). The model was designed

[8] "the sum of a sufficiently large number of independent identically distributed random variables approximately follows a normal distribution" (AECN, 2018)

to mimic staff behaviours in response to stochasticity introduced by variation in clinical need, the dynamics emerging in the environment, and any barriers to model exit (e.g., poor hospital capacity). Test of statistical significance between the absolute values of the SSM outputs and validation dataset were assumed to be useful but not comprehensive - close mimicry would have forced the SSM to reproduce the exact moment in time seen during the dataset rather than provide a measure of potential outcomes. To support tests of significance in validation, a pattern-orientated modelling (POM) approach was taken (Grimm et al., 2005). This evaluated emergent outputs at multiple levels – decision-maker, patient, department, and system - and compared them with patterns of activity seen in the validation dataset such as relational and directional trends. The POM approach considered how outputs emerged and interacted to produce a pattern amongst outputs rather than exactly reproduce historical dataset values for the reason explained above. Patient level and urgent care system level outputs chosen to perform POM are shown in Tables 4:9 and 4:10. Decision-maker outputs for POM are described in the next section.

Table 4:9 Patient level outputs used to validate the SSM

Outcome	Description	Pattern validation
Length of delay (bedded area)	Time spent waiting for an AMU in-patient bed	Preferable: historical dataset within output IQR Acceptable: historical dataset captured within output range
AEC discharges LoS	LoS in the for patients discharged from the AEC area (minutes)	Preferable: historical dataset within output IQR Acceptable: historical dataset captured within output range
AEC admissions LoS	LoS for patient admitted from the AEC area (minutes)	Preferable: historical dataset within output IQR Acceptable: historical dataset captured within output range
AMU discharges LoS	LoS for patients discharged from the AMU bedded area (minutes)	Preferable: historical dataset within output IQR Acceptable: historical dataset captured within output range
AMU admissions LoS	LoS for patients admitted from the AMU bedded area (minutes)	Preferable: historical dataset within output IQR Acceptable: historical dataset captured within output range
Arrival patterns	Attendances per hour as proportion of daily total arrivals	Preferable: Non-difference from historical data on 'Goodness-to-fit' test via Kolmogorov-Smirnov testing of the null hypothesis Acceptable: Pattern-matching of output and historical ecdf
Departure patterns	Departures per hour as proportion of daily total departures	Preferable: Non-difference from historical data on 'Goodness-to-fit' test via Kolmogorov-Smirnov testing of the null hypothesis Acceptable: Pattern-matching of output and historical ecdf

AEC: Ambulatory emergency care, AMU: Acute medical units, ecdf: empirical cumulative distribution function,

IQR: interquartile range, LoS: Length of stay

Table 4:10 Departmental and system level outputs used to validate the SSM

Outcome	Description	Pattern validation
Daily attendances	Total number of patients entering the department in a 24hr period	Preferable: historical dataset within output IQR Acceptable: historical dataset captured within output range
24hr discharges	Proportion of patients discharged within 24hrs of arrival	Preferable: historical dataset within output IQR Acceptable: historical dataset captured within output range
Daily waits for AMU bed	Number waiting >5mins for an AMU in-patient bed	Preferable: historical dataset within output IQR Acceptable: historical dataset captured within output range
Relationship between attendances and bed waits	Pattern of daily waits seen with varying demand	Correlation pattern match
Utilisation of AEC	Proportion of patients allocated to AEC daily	Preferable: historical dataset within output IQR Acceptable: historical dataset captured within output range
AEC discharges	Proportion of AEC patients discharged back to the community	Preferable: historical dataset within output IQR Acceptable: historical dataset captured within output range
Admissions	Proportion of patients transferred into the hospital system	Preferable: historical dataset within output IQR Acceptable: historical dataset captured within output range

AEC: Ambulatory emergency care, AMU: Acute medical units, ecdf: empirical cumulative distribution function,

IQR: interquartile range, LoS: Length of stay

4.7.4.4 Validation of decision-maker behaviours

The first stage of validation concerned the conceptual model for decision-maker (DM) behaviours. This was presented to experts on the case study site for face-validation. The complexity of decision processes observed could not be adequately programmed into the SSM nor credibly tested; however, validation was possible via comparison of patterns of accuracy in remote decisions - sensitivities, specificities, and predictive values of early allocation decisions for different categories of staff. These tests are commonly applied to clinical tools that screen for the probability of the presence/absence of a specific disease (Altman, 1990). This allowed the assumption that staff to behaved as screening tools for identifying AEC-suitability (the 'disease') and calculated the positive predictive values (correct AEC allocation after the fact) and negative predictive values (correct bedded allocation after the fact).

Predictive values, sensitivities, and specificities provided a measurable emergent output that occurred via interaction of staff allocation decisions, the natural stochasticity, the dynamic environment, and patients' needs. Table 4:11 summarises the conditions to be met for validation. As the validation dataset contained few instances of trainee decision-making, I divided the staff into expert (consultants) and non-experts (all other staff) in the model outputs. Interquartile ranges were used for validation as outputs were assumed to have a large degree of variation due to unique DM risk profiles.

Table 4:11 Decision-maker behaviours outputs used to validate the SSM

Outcome	Description	Conditions
Expert sensitivity	Probability of correct AEC allocation by experts	Historical dataset within output IQR
Non-expert sensitivity	Probability of correct AEC allocation by non-experts	Historical dataset within output IQR
Expert specificity	Probability of correct bed allocation by experts	Historical dataset within output IQR
Non-expert specificity	Probability of correct bed allocation by non-experts	Historical dataset within output IQR
PPV experts	Predictive power of experts in determining AEC suitability	Historical dataset within output IQR
PPV non-experts	Predictive power of non-experts in determining AEC suitability	Historical dataset within output IQR
NPV experts	Predictive power of in-patient need by experts	Historical dataset within output IQR
NPV non-experts	Predictive power of in-patient need by non-experts	Historical dataset within output IQR

PPV: positive predictive power, NPV: negative predictive power

4.7.4.4.1 Identifying correct allocations

Measurement of sensitivity and specificity required a gold standard to test results against (Altman, 1990). As there is no agreed definition of a 'true' AEC patient, local and national expert guidance[9] were combined to create one for the purposes of analysis. This assumed a patient to be AEC suitable after the fact (a 'true' AEC candidate) if they met the criteria outlined in Box 4:1.

Box 4:1: Criteria for AEC success

1. Discharge outcome
2. Length of stay ≤10hrs
3. Arrival during a time when AEC services were available

Conditions in Box 4:1 indicated AEC suitability regardless of allocation – i.e., an AEC suitable patient allocated to in-patient care (bedded area) who met all three conditions would reflect an incorrect allocation decision to the bedded area ('false' AMU). Patients were identified as non-successful AEC if all three conditions were not met. This approach facilitated the creation of a matrix according to DM allocation at referral as shown in Table 4:12.

[9] NHSS Unscheduled Care Directorate workshop on AMU activity. Held 07/05/19 2019 at the Royal Society of Edinburgh, Edinburgh, Scotland.

Table 4:12 Matrix for determining success of DM allocations

	Meets all three conditions?	
Allocation decision	**YES**	**NO**
AEC	True AEC	False AEC
Bedded area	False AMU	True AMU

As the name/category of the DM was not recorded in the case site dataset, assumptions were created to identify the DM according to staff shift patterns and source of referral. The local AMU functioned with different DM staff for two distinct populations as shown in Table 4:13. Time of arrival and source of referral were used to identify the allocating staff member as the recorded of times of referral were not available in the dataset. This assumed a delay between referral and arrival according to source of referral.

Table 4:13 Assumed decision-maker according to time of arrival

Referral source	Time of arrival	Decision-maker	Assumption
Non-ED	0900-2200hrs	Consultant	0900hrs arrivals assumed to be delayed attendances (referred pre-2000hrs with 2hr arrival delay)
Non-ED	2201-0859hrs	Trainee	Junior staff call handling from 2000hrs of community patients. Allocate to AEC once open (at 0800hrs)
ED	Anytime	Charge nurse	All ED calls taken by senior nursing staff regardless of time of day

4.7.4.4.2 Sensitivity and specificity of decision-makers

The validation data had fewer instances of trainee decision-making compared with other types of staff. To overcome problems with small sample size, staff in the model were categorised as expert (consultants) or non-expert (trainees and charge nurses). The outcomes of decisions were used to inform matrices for experts and non-experts as per Table 4:12. Sensitivity and specificity for the two staffing groups were calculated using Eqns. 4:1 and 4:2 (Altman, 1990).

Sensitivity = True AEC / (True AEC + False AMU)

Eqn. 4:1 Sensitivity calculation

Specificity = True AMU / (True AMU + False AEC)

Eqn. 4:2 Specificity calculation

4.7.4.4.3 Predictive value of decisions

Predictive value calculation added an additional layer of POM for validation. In practice, sensitivity and specificity tell us little of the usefulness of the test unless the prevalence of the condition is also considered, and predictive values calculated (Altman, 1990). Predictive values combine sensitivity/specificity with the underlying prevalence of the condition to give us a better sense of the accuracy of a screening tool in local populations as shown in Eqns. 4:3 and 4:4 (Altman, 1990).

PPV = (sensitivity x prevalence) / [(sensitivity x prevalence) + ((1 – specificity) x (1 – prevalence))]

Eqn. 4:3 Positive predictive value

NPV = (specificity x (1 – prevalence)) / [(specificity x (1 – prevalence)) + ((1 – sensitivity) x prevalence)]

Eqn. 4:4 Negative predictive value

Although sensitivity and specificity were intended to validate the model only (and not of use for predictive purposes), analysing the SSM's ability to reproduce predictive values created an additional layer of POM validation for emergent outputs in the explanatory model. As discussed in Section 3.4.3.1.4, the prevalence of AEC suitable populations in any region is dependent upon the capability of an urgent care service to deliver due to resource and logistical challenges. These may also be assumed to vary over time (Irvine et al., 2022). Local prevalence of AEC suitable patients was not established on the case study site and was described by staff to vary daily – resource availability could alter, processes could experience delays, and discharge plans could change following evaluation. Calculation of predictive values required estimation of the prevalence in the local setting. The only data available to do so was the validation dataset; however, as historical prevalence values were not intended as SSM inputs, and no other reliable sources were available, estimation of prevalence from the validation data was an acceptable solution.

4.7.4.4.4 Calculating prevalence of ambulatory care suitability

Prevalence for Emergency Department (ED) and non-ED populations was assumed to differ for two reasons:

1. A higher probability of severe illness in ED patients (self-selection by patients and paramedic decision-making)
2. Assumed ability of ED teams to identify and discharge some AEC-suitable patients directly from the ED

Bayesian inference was used to create an informed prevalence for both ED and non-ED populations (Spiegelhalter et al., 1999). With this approach, use of Bayes Theorem provided an estimate of the probability of an event (AEC success) by updating prior information and/or beliefs (extant literature of probability of the event) with new data (evidence of the event in the validation dataset). The formula for this is shown in Eqn. 4:5 where A represents the prior knowledge of the event (probability (P) of AEC success), B represents evidence of the event from the validation dataset (probability (P) of success as evidenced), and P(A|B) the updated posterior value, i.e., our new event probability.

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$

Eqn. 4:5 Bayes Theorem (Koch, 2007)

Extant literature of the estimated AEC prevalence in the UK was used to inform priors for non-ED populations. Prevalence in ED populations was assumed to be half that of non-ED. Values were updated by identifying the incidence of AEC success per population in all available data from the case study site: October 2019 – February (end) 2020 exclusive of December. Although incidence - a measure of new cases - is not equal to prevalence (incidence factored by disease duration), duration of AEC suitability was assumed to be 1-day. This is justified because successful AEC patients will receive their complete urgent care evaluation and plan on the same day before reverting to non-urgent follow up. As shown in Eqn 4:6., this allowed the assumption that incidence in the available data equated to prevalence.

$$prevalence = incidence * disease\ duration$$

Eqn. 4:6: Calculation of prevalence (Altman, 1990)

The prevalence values extrapolated were applied to the priors to create posterior values using Bayes Theorem with the 'Rjags' package via R Studio.

4.7.5 Sensitivity analysis

The outputs of any model can only be as reliable as the model structure and parameter values chosen for the inputs (Iooss & Saltelli, 2017). Regardless of source, a degree of uncertainty will surround the representativeness of the data values chosen and the sensitivity of outputs to changes in those values. This is of particular importance when modelling events with stochasticity – e.g., AEC allocation decisions based on individual clinical need. This affects model outputs as described in Figure 4:4.

There was moderate to high uncertainty in many of the SSM's parameter values because they had not been previously studied (DM allocations) and/or because they were known to be highly context dependent (e.g., AEC prevalence). Sensitivity analysis (SA) afforded exploration of how that uncertainty could alter outputs. Out of the many sensitivity analysis methods (Iooss & Saltelli, 2017), the non-linear relationships in the SSM necessitated a method that allowed for multiple parameters to be explored collectively to reflect to determine how magnitude and/or directional change could emerge with different parameter value combinations (Marino et al., 2008).

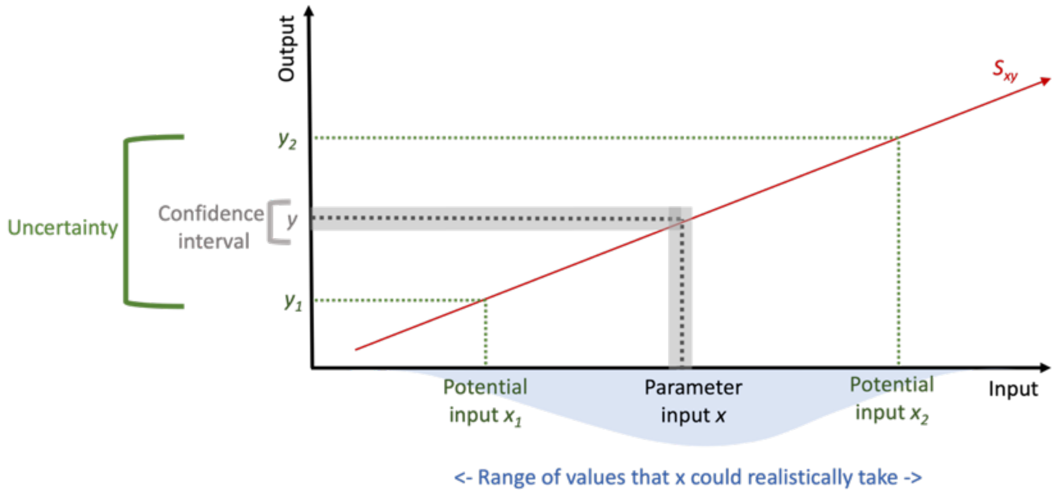


Figure 4:4 Relationships between parameter sensitivity, uncertainty, and model outputs

Value x represents the chosen model input that produces output y with an associated confidence interval (shown in grey). The range of values that parameter x could feasibly take includes x_1 and x_2 as shown by the probability distribution along the x-axis (shown in blue). Running a model with x_1 and x_2 will produce a range of outputs (y_1 to y_2) which includes y but extends beyond the confidence interval y. This range represents uncertainty in the model outputs relative to parameter x. The magnitude of the range is dependent upon the sensitivity of output y to changes in parameter x (the slope of S_{xy}). Thus, where the confidence interval provides a measure of stochasticity of a model's output for a given state of parameter x, the sensitivity analysis provides an understanding of the range in which real-life outcomes may lie (less likely but possible outcomes) based on the assumptions made in the model. Note this figure uses a single, non-interacting parameter for demonstration purposes. Sensitivities may alter in the presence of another interacting parameter.

A global sensitivity analysis (GSA) provided the best approach. A Latin Hypercube sampling (LHS) method was chosen for its efficiency over other GSA methods (Helton & Davis, 2003; Marino et al., 2008). The 'nlrx' package for R provided a platform to link analytic software with the Netlogo™ model software to perform LHS (Salecker et al., 2019). The significance of output changes to parameters with monotonic relationships to those outputs was determined via partial rank correlation coefficients (PRCC) using the 'epi.prcc' package for R. This technique was applied to provide a measure of the qualitative relationship (direction and relative magnitude) between parameter values (Conover, 1980; Marino et al., 2008). As data to inform the model parameters was sparse, uncertainty in the distribution of underlying true values was assumed to be moderate to large. Uniform distributions were applied to all parameters during for sensitivity analysis to account for the significant gaps in underlying parameter value knowledge and facilitate a full exploration of parameter spaces and combinations.

4.7.6 Predictive model analysis

The results of the explanatory model validation and sensitivity analysis determined which sub-model of DM behaviour best described the system in its current state. The chosen sub-model was then be used in the final SSM experiments to predict the outputs of alternative staffing scenarios. Important variables for measuring effectiveness that could not be validated in the explanatory model - PROMs and occupancy levels - were assumed to be valid provided the explanatory model successfully reproduced the case study site outcomes on the multiple output levels described in Section 4.6 The staffing strategies for predictive modelling were chosen to reflect strategies known to exist across the UK and to reflect health policy recommendations (Irvine et al., 2022). These are described in Table 4:14.

Table 4:14 Alternative staffing strategies explored using the predictive model

Scenario	Description	Rationale
BASELINE	- Consultants take non-ED referrals 0900-2000hrs - Trainees take non-ED referrals 2000-0900hrs - Charge nurses take all ED referrals	Current working model.
CONS	- Consultants take all referrals 24hrs per day	Reflective of recommendations to consider centralised referrals services run by expert staff only.
TRAINEES	- Trainees take all referrals 24hrs per day	Reflective of models of urgent care referrals services currently employed in the UK. Trainees learn decision-making under direct supervision during consultant working hours and support services at night when fewer AEC patients attend.
NURSES	- Nursing staff take all referrals 24hrs per day	Reflective of models of urgent care referrals services currently employed in the UK. Removes trainees from the early decision-making process to allow interrupted focus on training in the delivery of care and support the department.
CONS/TRAINEES	- Consultants take all non-ED referrals 0900-2000hrs - Trainees take ED referrals 0900-2000hrs - Trainees take all referrals 2000hrs-0900hrs	Removes non-medically trained clinicians from the early decision-making process. Trainees learn decision-making under direct supervision and support services at night when fewer AEC patients attend.
CONS/NURSES	- Consultants take all non-ED referrals 0900-2000hrs - Nursing staff take ED referrals 0900-2000hrs - Nursing staff take all referrals 2000hrs-0900hrs	Removes trainees from the early decision-making process to allow interrupted focus on training in the delivery of care and support the department.
TRAINEES/NURSES	- Trainees take all non-ED referrals - Nursing staff take all ED referrals	Trainees learn decision-making under direct supervision during consultant working hours and support services at night when fewer AEC patients attend

Nursing staff are all assumed to be of Band 6 level (charge nurse) or above. Trainee staff includes Advanced Nurse Practitioners and Physician Associates

4.7.6.1 Predictive model output analyses

Model outputs for the predictive SSM differed from the explanatory model to reflect its new purpose. As discussed in Section 3.4.3, standardised measures of efficiency for urgent care are few. The local AMU did not function with trolley assessment spaces and was therefore not subject to the four-hour access standard. Sensitivity, specificity, and predictive values were no longer required as the model's usefulness in reproducing decision outcomes had been shown. Daily discharges were used to measure disposition across the whole department rather than each area. This was because the conceptual model assumed outputs at the departmental level to have greater meaning to the whole system. The predictive model outputs covering efficiency, health, quality, and safety are described in Table 4:15.

Outputs with a normal distribution underwent tests of variance to explore differences between scenarios via Tukey's test against the null hypothesis. Statistical significance between strategies was determined via Tukey's test whereas meaningful difference was determined by the stated MIDs. Differences were assumed to be meaningfully significant if the lower bound of the confidence interval was not less than the MID.

Table 4:15 Measures of effectiveness to explore alternative staffing models

Output	Effectiveness captured	Explanation	MID
Median occupancy over 24hrs in each area	Local efficiency Quality of care	Occupancy levels are assumed to be skewed. Occupancy across the entire department assumed to masking overcrowd one area offset by waste in another	0.10 (modeler assumption)
Time per week spent with bedded area in occupancy 0.90 – 1.0 Time per week spent with bedded area in occupancy >1.0	Local efficiency Quality of care Safety of care Staff well-being	The local AMU routinely experienced high occupancy levels with staffing provision to manage this. A level of ≥90% (0.9) was assumed to reflect inefficiency due to crowding and >100% (1.0) to reflect inefficiencies and risks to safe care seen in overcrowding.	Both: 560minutes (Modeler assumption)
Daily bed waits	Local efficiency Quality of care Safety of care Staff well-being	Number of bedded allocates waiting for a clinical resource upon arrival	5 patients (Modeler assumption)
Length of bed wait (delay)	Local efficiency Quality of care Safety of care	Length of time (mins) patients wait to access bedded clinical resources	30minutes (modeler assumption)
Admissions	System efficiency	Proportion of patients referred who were transferred to an in-patient hospital bed. Impact on hospital capacity and shared bed resources	0.05 (modeler assumption)
Utilization of AEC per day	Local efficiency	Proportion of daily attendances allocated to AEC resources. Contributes to efficiency in local resource use	0.05 (modeler assumption)
Discharges within 24hrs	Local efficiency	Patients who complete their care in the AMU within 24hrs. Contributes to measures of efficiency in urgent care resource use	0.05 (modeler assumption)
Overnight transfers to hospital beds (2300-0800hrs) System efficiency	System efficiency	Stated organisational preference not to move patients out of hours due to disruption to patient rest, this was assumed to reflect departmental efficiency over the course of the preceding day	0.05 (modeler assumption)
Health Index change per patient discharged	Health generated	Heath change seen in all patients discharged. Assumes equivalence in conditions and need if care may be completed without transfer to an in-patient bed	0.070 (See Section 4.7.4.1)
Positive experience	Quality of care	Proportion of all patients leaving the AMU area with a positive experience of care.	0.05 (modeler assumption)

MID: Minimal important difference

To reflect the assumptions of policymakers advocating ESDM, the researcher hypothesized the following outcomes to emerge when ESDM was employed in whole or in part when compared with non-expert decision-making:

- greater utilization of AEC facilities
- fewer instances of crowding and overcrowding in urgent care beds
- fewer patients admitted to hospital following referral
- more patients discharged within 24hrs
- fewer patients transferred into a hospital bed in the overnight period
- fewer and shorter delays to accessing bedded resources upon arrival
- improved patient experience
- equivalence in health impact

4.7.6.2 Scenario testing

Uncertainty analysis provides an estimate of how confident we may be that a model's outputs provide a reflection of real-life outcomes as opposed to sensitivity analysis which focuses on how sensitive the outputs are to the uncertainty in the model inputs and its structure (Saltelli et al., 2019). To explore uncertainty in the predictive outputs, scenario testing included scenarios where the department was forced to remain in an overcrowded state. To reproduce this enforced overcrowding, each staffing scenario was run with maximum tolerated bedded-area occupancy of 100%, 115%, and 130%. This meant that reactive capacity creation (early transfer of patients into the hospital) was not triggered in the model until crowding reach the maximum level. Enforced overcrowding reproduced moments of very high hospital capacity that severely restricted the transfer of patients from urgent care into the hospital system[10].

Regardless of the enforced overcrowding levels in scenario testing, routine care processes (time to complete care, ward rounds, discharge/admission rules) were consistent. The ethnography revealed efficiency of care processes on the case study site during periods of high occupancy. This was achieved via the temporary redeployment of resources within the department and from other parts of the hospital area to meet patient needs and perform operational tasks (e.g., hospital management staff coordinating transfers). To mimic this, rules to rapidly create capacity for newly arrived patients (e.g., early transfer of patients identified for admission) were only triggered in the model if maximal overcrowding levels were breached. These rules are explicitly described in Chapter Six 'The systems simulation model' and Appendix C. They include rules representing realistic barriers to rapid capacity creation such as limits to how many patients may transfer early. As there was no empirical evidence of how outputs would change if occupancies experienced were extremely high (e.g., >150%), or if redirection of patients to other departments occurred (no capacity in beds or waiting areas), no additional rules to manage overcrowding or behaviour changes were created for these extreme events.

A global sensitivity analysis (GSA) for each staffing scenario was not performed. This is because the GSA of the explanatory SSM provided the model output's sensitivities to

[10] This type of tolerated overcrowding in urgent care has been observed in many settings since 2022 with some acceptance by healthcare leaders as 'a new normal' to plan services around (Campbell, 2022).

different categories of staff in the decision-maker role. For example, uncertainty in the allocation decision-making of charge nurses could be appreciated by exploring the GSA results for both charge nurse and trainee decision-making parameters as together they represented a spectrum of non-expert decision-making. That is to say, combined they represented uncertainty in the decision-making parameters of non-experts.

5 Findings: The ethnographic case study

My research question sought to compare the value generated when different categories of staff performed early decision-making via systems simulation modelling. To do so required knowledge of how these decisions occur and their influences. It also required knowledge of the behaviours of other (organisational and patient) entities in the decision environment and their role in the emergence of outcomes that measure effectiveness of care. The ethnographic study informed the conceptual model of the SSM and its parameter inputs by breaking my research question down into the four focused questions addressed in this part of the research:

> *1. What patterns of patient activity and staff behaviours exist in the AMU environment?*
>
> *2. What are the experiences of patients receiving all care via the AMU? (do they feel safe? listened to? Satisfied with their care?)*
>
> *3. What are the health outcomes of patients receiving AMU care via out-patient pathways?*
>
> *4. How do different categories of staff make allocation decisions at the point of referral?*

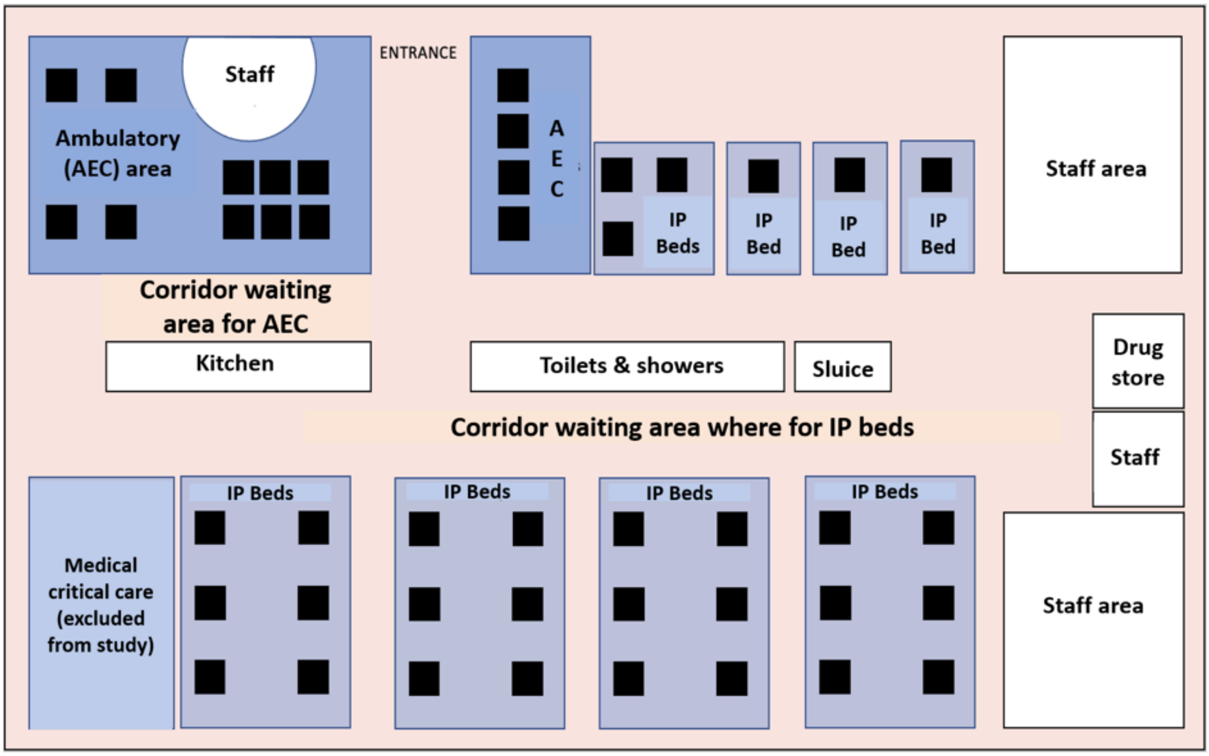
The chapter begins with the first question (Section 5.1.1: The decision environment). This presents an overview of the clinical environment, the organisational behaviours, and the patterns of clinical activity. The second and third questions are addressed in Section 5.1.2: Patient reported outcomes. Section 5.1.3 (Allocation decision-making) presents the evidence for the processes of allocation decision-making in different categories of staff. Section 5.2 (Discussion) is formed of four sections – a summary of my evaluation of the data for the purpose of systems simulation modelling followed by a detailed discussion of the findings for the questions outlined above.

5.1.1 The decision environment

The case site was a large university teaching hospital with approximately 700 in-patient beds. The hospital served a population of approximately 400,000 persons that was predominantly urban but with a significant rural component [11]. Figure 5:1 provides an overview of the AMU environment. The AMU had the capacity to deliver in-patient (IP) care for up to 30 patients and AEC care for up to 14 patients simultaneously – staffing was configured to support this level of occupancy. The waiting areas in the unit accommodated up to 20 patients but staffing resources were not configured to provide care for patients waiting.

The department functioned with a 15-bedded short stay area to accommodate patients with planned discharges within 48hrs. This ward was categorised as a hospital in-patient area because it did not directly receive patients for evaluation. It was excluded from the SSM.

[11] Between 26% and 49% of the population residing in a rural area as per the UK government urban/rural classification (https://www.gov.uk/government/collections/rural-urban-classification)



AEC: Ambulatory Emergency Care, IP: In-patient

Figure 5:1 Footprint on the case AMU environment

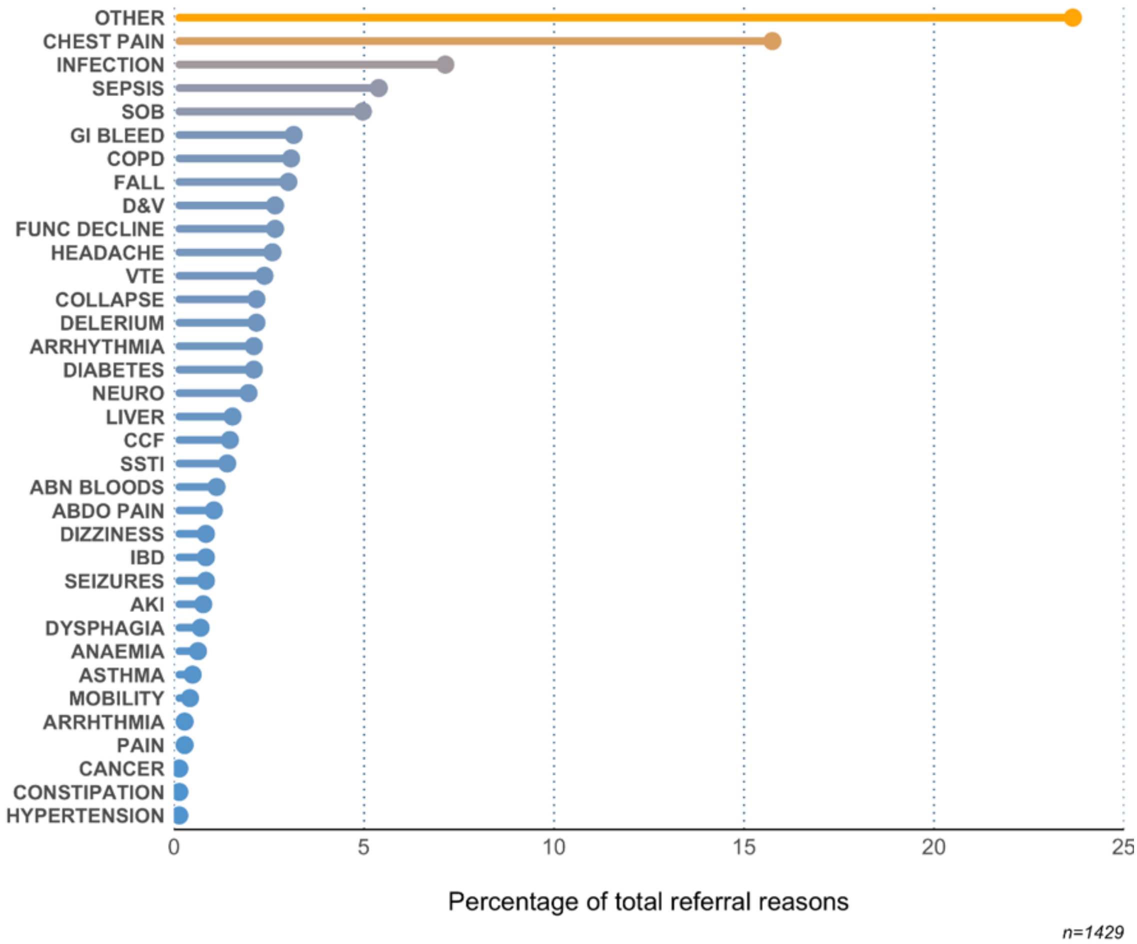
AEC resources consisted of clinic rooms, recliner chairs (with privacy curtains), and standard chairs that were used as a waiting area. Patients moved between clinic rooms, recliners, and chairs whilst undergoing evaluation. The waiting area for IP beds was in full site of the patients already placed in the IP beds. Patients would wait in this area on temporary chairs, wheelchairs, or trollies. Records of patients expected to attend following referral were kept in a staffing area with a duplicate list of AEC only patients in the AEC including planned returns or allocated to delayed AEC attendance the previous day.

The case site had three categories of staff making allocation decisions for different patients – consultants, trainee doctors, and senior (charge) nurses. Consultant staff consisted of a pool of specialists in acute medicine (n=7 including the researcher in an autoethnographic role) and medical specialists with an interest in acute medicine (n=12). They delivered a mixture of full-time and part-time service delivery. Trainee staff came from a pool of 30-40 staff with training in a variety of internal medical specialities. They rotated through the unit according to on-call and training needs with n=3 full-time acute medical trainees. Trainees ranged from three to seven years post-graduation. Charge nurses (n=8) worked exclusively in the AMU. Decision-maker staff were present in the AMU throughout their shifts and would frequently move between office and clinical space. Consultant staff would sometimes leave the AMU and work from their office off-site, but this was rare and only tended to occur in the mornings. Consultant DMs would form part of a team providing bedded area senior reviews from 1200-1800hrs whilst taking referral calls. They provided consultant reviews for AEC patients and shared IP senior review duties with high-level trainees and consultants from other specialties in the hospital. Other specialists only attended to review patients at two points in the day – mid-morning and at 1800hrs. This service was inconsistent amongst teams.

Referral calls were received 24hrs per day on all days. Bedded area facilities were always open, but AEC facilities were only available at 0800-2300hrs due to reduced staffing levels overnight. In exceptional circumstances of severe or prolonged overcrowding (not observed during the study), staff described using the AEC area to evaluate new patients in the overnight period. All Non-ED referrals were taken by consultants from 0900hrs-2000hrs and trainees at all other times. All ED referrals were taken by nursing staff.

5.1.1.1 Spectrum of referral reasons

As shown Figure 5:2, the spectrum of referred conditions was broad with the largest proportion of patients termed 'other' – i.e., the referred condition was either undocumented or outside of common acute internal medicine referral conditions (JRCPBT, 2012). Data informing Figure 5:2 were taken from handwritten notes made at or close to the time of referral. Referral categories were determined using the authors established knowledge of medicine and professional guidelines for acute medicine (JRCPBT, 2012). Where multiple conditions or symptoms were described in the data, the dominant referral reason was taken (e.g., 'delirium due to sepsis' was categorised as 'sepsis').



SOB: shortness of breath | GI Bleed: gastrointestinal bleed | COPD: chronic obstructive pulmonary disease
D&V: diarrhoea and vomiting | VTE: venous thromboembolism | CCF: congestive cardiac failure
SSTI: skin and soft tissue infection | IBD: inflammatory bowel disease | AKI: acute kidney injury

Figure 5:2 Reasons for referral to AMU (October 2019)

Data (recorded at the time of referral) was taken from the contemporaneous handwritten database held in the department. Some overlap of conditions is expected – e.g., patients referred with COPD will invariably experience SOB, but not all patients referred with SOB will have COPD; infections may be described according to site (e.g., SSTI) or severity (e.g., sepsis).

5.1.1.2 Prevalence of ambulatory care in the local population

Validation of the explanatory model required the calculation of the local AEC prevalence in ED and non-ED populations via Bayes Theorem (Section 4.7.4.4.4, Eqn 4:5). Local consultant staff provided values that informed the prior estimates. These were updated by applying the prevalence found in four-months of historical case site dataset values. This created a greater than three-fold difference in mean AEC prevalence between the populations as also shown in Table 5:1 ('Posterior values').

Table 5:1 Informed prevalence of AEC in local populations

Population	Prior estimates			Dataset values	Posterior values	
	Mean	Standard deviation	Distribution	Prevalence	Mean	Standard deviation
ED	0.15	0.05	ß (7,40)	0.066	0.067	0.005
NonED	0.3	0.05	ß (21,48)	0.211	0.213	0.007

5.1.1.3 Patients entering the system

Times to arrival (from referral) were challenging to gauge but observation revealed those arriving from ED and those allocated to AEC to have the shortest travel time. Time of referral was infrequently documented in the handwritten notes and not recorded in the Trakcare® database. Accurate analysis of referral times was impossible. Observation of activity in real time revealed that peak referral activity fell between 0900 - 1800hrs and that patient arrival occurred 60 – 360mins after referral. There were a few extreme outliers – a small number took up to 8hrs to arrive whilst those referred from other departments could take less than 10minutes. Those referred form ED arrived more rapidly. Those allocated to AEC from the non-ED sources arrived from 0900hrs onwards suggesting delayed attendance (from the previous evening) and/or rapid travel following referral. This may have been possible via private transport as clinical stability in AEC patients would remove the need for ambulance transfer.

The proportion of daily attendances referred from each source varied according to time of day. Most patients arrived on the unit between 0900 – 2200hrs. This would suggest times from referral to arrival of up to 6hrs as observed if the 0900-1800hrs window represented peak referral time. This 0900-1800hrs time window coincided with GP surgery hours on weekdays (no GP surgeries at weekends). There were also patients arriving onto the AEC who were scheduled from the previous day. Assuming arrivals from 0900-2200hrs represented those referred at peak, most peak referrals came from non-ED sources (Median 0.78). Off-peak referrals from ED and non-ED sources were evenly split (0.53 and 0.47 respectively). A full summary of the arrival times and sources is provided in Appendix B, Tables B:1-B:4.

5.1.1.4 Patients leaving

Departure patterns in the October dataset mimicked those of arrivals but lagged behind by 2 -3 hours. Observation revealed that patients movement from the unit was delayed during the morning ward rounds to allow for AIM consultant and specialist reviews (0800-1100hrs). Movement from the ward also reduced after midnight and appeared to more closely mimic arrival patterns. The overnight period saw fewer discharges home than the daytime period. Staff described transport challenges and safety concerns for frail patients as the key reasons. Arrival and departure pattern are compared in Figure 5:3.

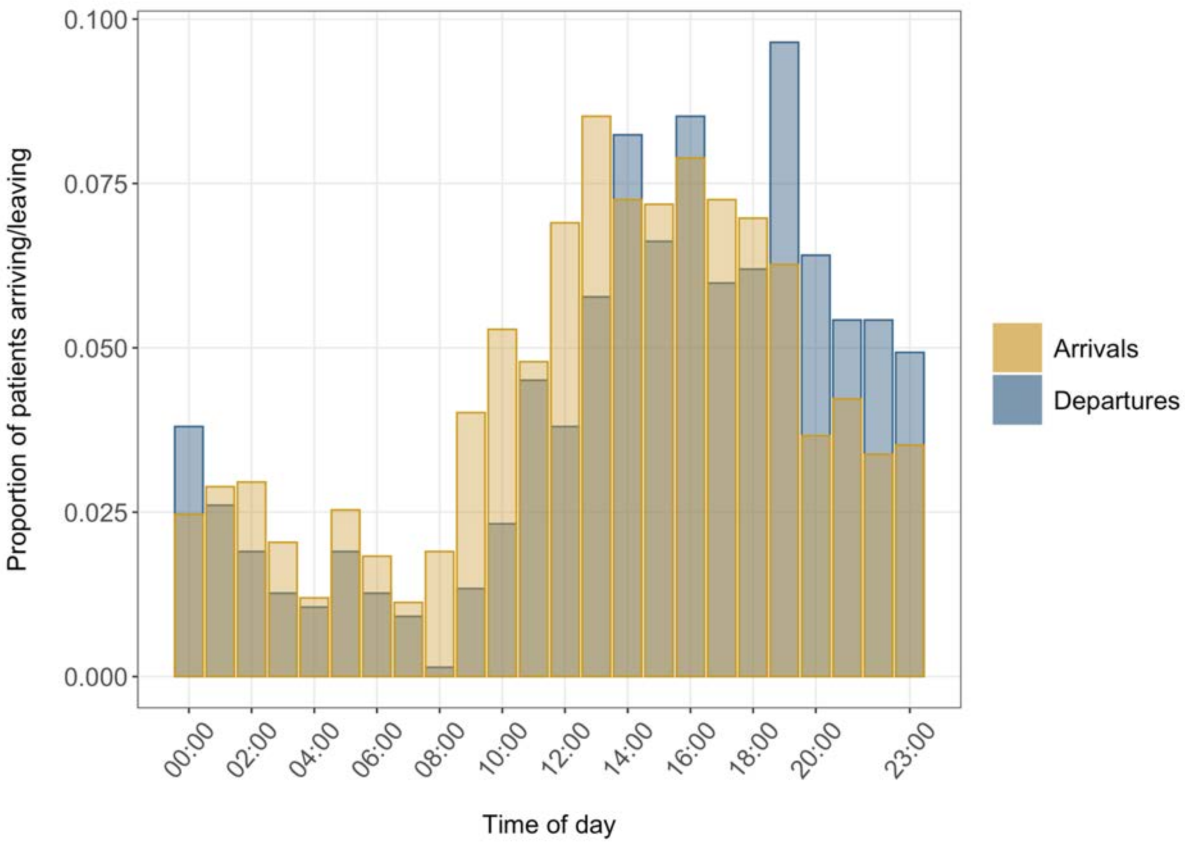


Figure 5:3 Case site patient arrival and departure times

The bar chart shows the proportion of patients arriving and leaving the unit at each hour of the day during October 2019. This is consistent with observed activity and the tendency for fewer departure after midnight and during the morning ward rounds/specialist reviews that occurred daily from 0800-1100hrs. Note the period from 0900 – 1800hrs when arrivals mostly exceed departures.

As may be appreciated by Figure 5:3, the time period between 0800 – 1900hrs saw more patients arriving than leaving. This was the time period most likely to experience overcrowding. Once patients had been identified as ready to leave, the time taken to arrange and wait for transport (for discharges), to await bed availability (for transfer), provide a clinical handover, pack the patients belongings, arrange for a porter to transfer the patient, and clean the bed space [12] added to the potential for overcrowding. Delays pending hospital bed availability were created by delays to patients being discharged from other parts of the hospital and/or the time taken to move a patient to another ward in the event of boarding.

5.1.1.5 Behaviours of non-decision maker actors in the system

The departmental culture was implicitly focused on admission avoidance with a preference to keep patients in the AMU to realise direct discharge. This practice was encouraged by hospital leaders via praise when data showed a reduction in hospital transfers from the AMU. Staff described using AEC services to avoid admission as equating to good clinical decision-making. Table 5:2 below summarises these behaviours. These behaviours (important for the conceptual model) had to be captured via observation as they were not possible to identify in quantitative data.

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[12] Note time to clean would be increased if the patient leaving the unit had been in a side room due to a transmittable infection such as infective diarrhoea

Table 5:2 System behaviours observed

BEHAVIOUR	OCTOBER DATASET	ETHNOGRAPHY	COMMENTS
Adherence to the four-hour access standard	No significant difference in delay time for ED and non-ED patients	Available beds were allocated to ED-referred patients prior to arrival but not to community patients until arrival	The 4-hr access standard was only applicable to patients referred from the ED. Locally the ED team strove for a 2-hr target. This was recorded until the moment a patient was placed into bed (if allocated). Patients arriving from the community or allocated to AEC at referral were not subject to an access standard
Tolerance of overcrowding	No data recorded	There was supported proactive capacity creation in reaction to overcrowding but this varied daily. Occupancy levels in hospital medical beds were frequently reported as >90% in the daily sitreps (although only captured at 0800hrs). Periods of overcrowding were tolerated. If the AMU was felt to have sufficient resources to cope, transfers would be delayed.	Patients were frequently moved to AMU from the ED despite insufficient resources – patients placed in the corridor. The AMU staff would create capacity by arranging early transfer of patients identified for admission. Proactive management of resources in anticipation of new arrivals was limited by other areas of the hospital and staff co-ordinating activity: - Protected mealtimes (3 times per day) - Time taken to free resources in the preferred ward (delayed discharges, infection control measures) - Freeing of resources in non-preferred wards (boarding patients) - Availability of staff to transfer patients
Preference for no transfers in the overnight periods	Majority of transfers between 1100-2200hrs	Patients identified for admission would remain in the AMU overnight unless overcrowding occurred	This culture appeared to stem from concern about disruption to patient sleep for both the transferring patient and the patients in the receiving ward who would be disturbed by the activity of a new arrival. If remaining in the AMU overnight, patients would wait until after the morning ward round before transfer to ensure a clinician review as they may miss the ward round on the receiving ward
Breakdown of clinical and non-clinical roles, increased risk-taking during overcrowding to maintain efficiency	Consistent departmental efficiency outputs.	Periods of overcrowding were short-lived when they occurred. Consultant staff were seen to adopt junior staff and some nursing to limit unnecessary investigations and manipulate admission avoidance in bedded patients before information gathered	Consistent with the framework of complex adaptive systems, when the department was on the edge of chaos (overcrowding), there was breakdown of barriers and roles to mitigate loss of efficiency and system failure (entropy). This could prompt the pulling of resources from other parts of the system to support the staff in AMU (negentropy). This was successful but described as mentally exhausting

The preference to keep patients in the AMU co-existed with a contrasting fear of departmental overcrowding. This was frequently discussed between nursing and consultant staff. Although overcrowding was not tolerated in the ED, there was an explicit organisational acceptance of overcrowding in the AMU. To meet the four-hour access standard and mitigate ED overcrowding, patients attending via the ED would be moved to the AMU regardless of whether a bed was available - if none were, they would be placed in the corridor waiting area. This deliberate overcrowding was assumed by hospital leaders to encourage AMU staff to be more efficient in departmental capacity creation – the physical presence of an unsafe patient creating a desire to create capacity quickly and reduce additional workload[13]. Overcrowding was not tolerated in any other areas of the hospital and transfers to other wards were frequently delayed maintaining this (see Table 5:2). This kept the AMU bedded area at high occupancy levels and at risk of overcrowding particularly in the overnight period when fewer patients left the unit. Fewer overnight discharges and a whole system preference to not board patients into non-medical wards overnight to accommodate new AMU patients contributed to overcrowding risks.

5.1.1.5.1 Reactive behaviours

Consistent with a complex adaptive system, overcrowding led to entropy and negentropy in the hospital system. Clinical and managerial roles broke down to maintain efficiency in care and structure of urgent care services. For example, the charge nurse coordinating patient movement and transfers would be forced to take on

[13] This assumption was based on a local quality improvement project performed several years earlier by the local ED team. This showed a shorter times to AMU bed placement for ED patients if patients waited for a bed in the AMU corridor rather than in the ED

nursing duties if patient were placed in the corridor waiting area (entropy) with managerial staff (tasked with managing several areas of the hospital) forced to remain in the department and assume coordination duties. When overcrowding occurred during working hours, speciality staff were asked to attend earlier in the day and for longer to see more patients thus removing this staffing resource from other parts of the system (negentropy). In very busy periods, diagnostic services would be asked to prioritise AMU patients to expedite discharge decisions monopolising hospital diagnostic resources (negentropy).

5.1.2 Patient reported outcomes

The results of the patient outcomes collected during the ethnography are presented in Appendix B. Here I present a summary of the findings as they pertain to informing the model inputs

5.1.2.1 Patient experience

Seventy-eight completed in-patient experience surveys were included in the analysis: n=61 AEC patients and n=17 Bedded area patients. There were no significant demographic differences between the groups (Appendix B, Table B:6). As the intention of the model was to explore differences in experience between the two areas of the AMU, responses were analysed for statistical significance between groups. Patients were grouped according to their main area of care as stated by them in the survey. There were no significant differences between the two groups in any of the categories of care explored (Appendix B, Figure B:2). The final ratings for overall patient experience are shown in Figure 5:4. Only 9 patients experienced waiting in the corridor area of the department all of whom received care in the AEC.

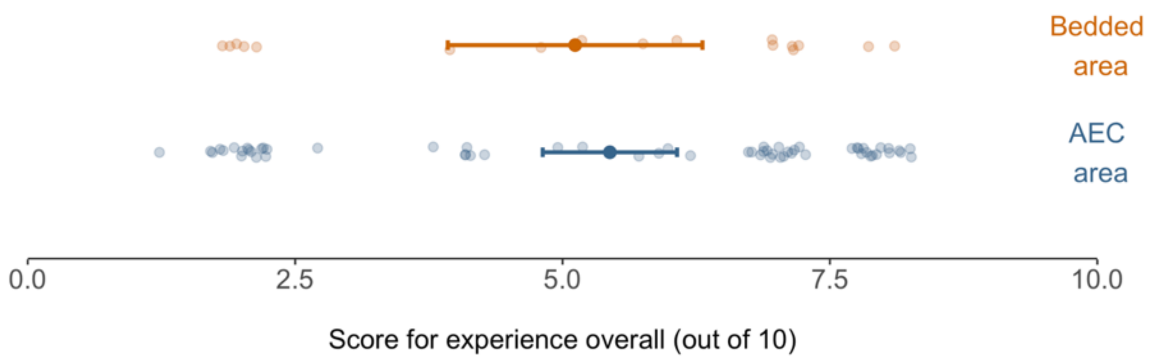


Figure 5:4 Patient experience ratings according to reported area of care

The final question in the survey asked for an overall score out of 10 reflecting the experience of being in the department. Individual scores are represented by the data points with the 99% confidence intervals with means represented by the bars. The means are close and the 99% confidence interval for AEC scores is entirely contained within the 99% confidence interval for the Bedded area. Note there are fewer data points for the Bedded area explaining the wide variation about the mean.

5.1.2.1.1 Free text comments

The patients' free text comments provided them the opportunity to elaborate upon responses or identify areas not covered by the structured component of the survey. Most comments were complementary to staff. Outside of staff comments there were two themes:

1. Dissatisfaction with time spent in the department either waiting to start care and/or receiving care in the AEC facilities
2. Variability in preference for admission avoidance in both populations

Examples quotes as evidence for these themes are provided in Table 5:3. No patients expressed satisfaction with the amount of time taken to receive care in AEC.

Table 5:3 Free text feedback of patients' experiences

TIME SPENT IN AEC	ADMISSION AVOIDANCE
"Nobody told me how long I need to wait till someone will assess me" AEC patient	*"The AMU ward area was better environment after waiting in the [AEC]"* Bedded area patient
"Less time waiting for [other specialty] doctor - AEC stuff complete at 1130 then waited until 6pm to see the [speciality doctor] and [then] told to go home with meds and out-patient follow up. If this decision had been made sooner this would have caused less anxiety and discomfort" AEC patient	*"I received treatment during the day and was allowed home which has helped my recovery massively, rather than being admitted for this treatment."* AEC patient *"Not inconvenient to come back and forth to get investigation and treatment"* AEC patient
"I understood that I would have to wait in the unit for a long time but did not expect it to be 10 hours" AEC patient	*"Travelled to AEC several times in one week… this would have been impossible without family transport or 1hr on the bus"* AEC patient *"asked to attend early next day and never got scan that day. Had to wait again. Unacceptable travel back and forth"* AEC patient

Responses suggested many patients understood that time to receive care could be long, but AEC populations described feeling uninformed about how long this would be. The October dataset reveals that >50% of patients experienced a LoS that exceeded expectations (Table 5:4). Of note, whilst most patients experience a higher LoS than anticipated, only AEC patients raised this as a point of dissatisfaction.

Table 5:4 Expected LoS reported by participants upon arrival

	Patient reported values		October 2019 values	
	Median LoS (hrs)	n	Median LoS (hrs)	n
AEC	4	27	4.8 (3.0, 7.4)	247
Bedded	10	4	14.9 (8.7, 22.6)	1177

Length of stay (LoS) is presented in hours with the 2nd and 4th quantiles in brackets. This reveals that most LoS exceeded patient expectations. n = number of patients

Patients' preferences for care setting varied according to their perceived level of illness, their ability to travel for follow-up attendances, and their trust in the hospital environment's care. Responses were unprompted and a suggest preferences for admission avoidance is context-dependent.

5.1.2.1.2 Observed patient experience

Patients mostly expressed a positive experience of care when observed interacting with staff in the unit consistent with the survey results. Both populations regularly expressed understanding about the uncertainty in outcomes and were tolerant of delays. That said, observed dialogues between staff and patients suggested a limit to this tolerance with discontent expressed if they had present in the AEC for several hours. Occasional complaints of discomfort with waiting area furniture, lengthy waits being unsatisfactory when feeling unwell, and feeling "forgotten about" were overheard in the waiting areas.

5.1.2.2 Health-related quality of life findings

Health related quality of life (HRQoL) surveys received fewer responses than the IPE survey upon follow up. Only n=57 were suitable for analysis: n=47 in AEC and n=10 in Bedded. There were no significant differences between the demographic characteristics of participants in each group with the exception of referral condition upon follow up. This was not the case at recruitment (Table 5:5).

Table 5:5 Distribution of health conditions for study populations

	Baseline			Follow-up		
Referral category	**AEC** (n=93)	**Bedded** (n=61)		**AEC** (n=47)	**Bedded** (n=10)	
Anaemia	0	5	Difference between populations[a] p = 0.289	0	3	Difference between populations[a] p <0.001
Arrhythmia	0	8		0	1	
Chest pain	43	19		27	0	
Venous thromboembolism	13	3		5	1	
Collapse/dizziness	2	2		0	1	
Electrolyte disturbance	3	1		0	1	
Gastrointestinal bleed	2	1		0	1	
Gastrointestinal upset	1	2		0	0	
Headache	11	6		6	2	
Acute neurology	11	3		0	0	
Shortness of breath	2	4		0	0	
Skin/soft tissue infection	2	2		1	0	
Urinary tract infection	2	4		1	1	

[a] Fisher's exact test with simulation

AEC: Ambulatory emergency care

n=number of responses

The Health Index (HI) provided a cumulative value equivalent to Quality Adjusted Life Years (QALYs) gained/lost. Values were calculated from each patient's responses to the five level questions in the EQ-5D-5L survey using the English population dataset as described in Section 4.6.1.5. Health Index at baseline and at follow-up were calculated. The Visual Analogue Scale component of the EQ-5D-5L asked patients to score their health out of 100. Baseline and follow-up scores for the VAS were visually compared with the direction and magnitude of change seen in the HI.

There was no statistically significant difference in health gain between the two groups of discharged patients although large difference in the Bedded area responses compared with AEC should be noted (Table 5:6).

Table 5:6 Health Index scores across each group

Health Index sample	Area receiving care			
	AEC (n=47)	Bedded (n=10)	Difference*	95% C.I
Initial	0.719 (sd 0.209)	0.737 (sd 0.171)	-0.018	(-0.151, 0.109)
Follow-up	0.787 (sd 0.225)	0.848 (sd 0.145)	-0.061	(-0.178, 0.057)
Health change	0.068 (sd 0.117)	0.111 (sd 0.131)	-0.043	(-0.139, 0.051)

*Welch Two Sample t-test

Histogram of the HI changes seen revealed that no change in HI was the most frequently observed findings in both groups and a rightward skew in the Bedded area participants. This skew was assumed to result from the small sample size. The mean and standard deviations for each group were used to create empirical probability distributions for HI change shown as an overlay to the histogram in Figure 5:5.

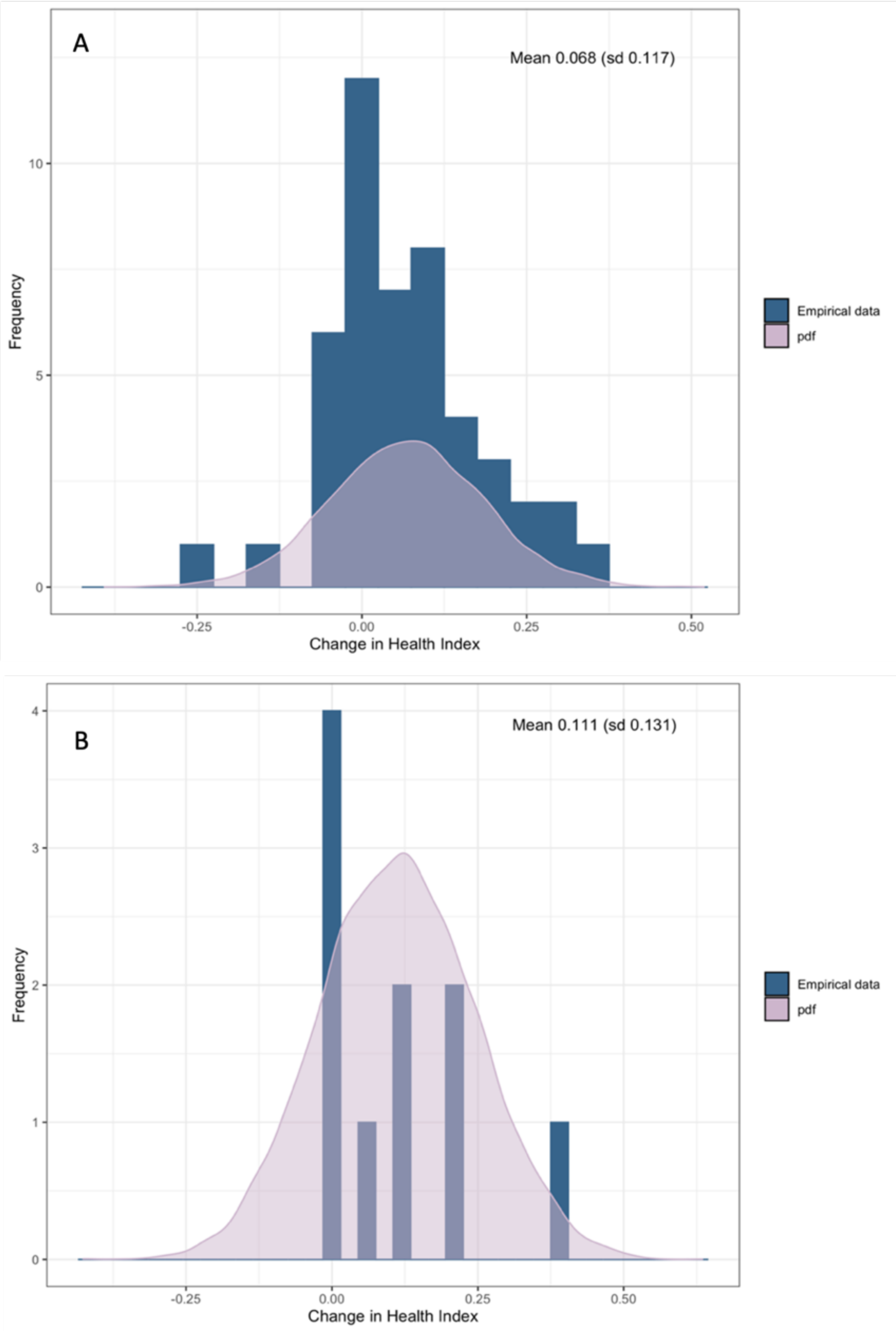


Figure 5:5 Distribution of change in health index in the AEC and Bedded areas of care

The empirical data is shown alongside representative empirical probability distribution (empirical means and standard deviations). A is the ambulatory emergency care (AEC) data, B is from the in-patient population. Note the leftward skew in the AMU-bedded area data (B). This was assumed to be an artefact of the small sample size of n<30

5.1.3 Allocation decision-making

This section provides the findings of the observed early decision-making events. It begins with a summary of the commonalities observed amongst different categories of staff, where behaviours deviated, and a qualitative appraisal of the observed patterns of decision types in each staff group. Section 5.1.3.4 presents the conceptual model of consultant (expert) decision-making with supporting evidence from the results of the analytic autoethnography. Section 5.1.3.3 describes observed influences in decision-making. The final contains analysis of the quantitative data from the historical quality improvement project that collected the outcomes of consultants early decision-making on the case site.

5.1.3.1 Decision-making behaviours common amongst staff

All staff were aware of the referral conditions or categories of patient need that were commonly managed via AEC with locally available guidelines for clinical management (Box 5:1). Allocation of patients with these suspected conditions/symptoms varied amongst the different decision-maker (DM) categories. Consultant DMs tended to allocate more patients to AEC than other staff. Consultants working in the department for the more than five years tended to allocate more patients to AEC than newly qualified staff. Consultant AEC allocations usually fitted with patterns of patient need and urgency that the consultant had encountered before and successfully managed via AEC using the local guidelines and their own clinical knowledge and judgement. Nurse DMs were observed to allocate fewer numbers of the common AEC patients to AEC. Their allocation decisions combined their knowledge of usual practice, judgement of patient need, and the opinion of the ED nurse referring the patient. Trainees DMs allocated fewer patients to AEC than consultants but more than nurses. Trainee AEC allocations were informed by accessible guidelines and clinical need only. All staff were observed to recognise when referrals were not medical in nature and would divert callers to other teams in the hospital (e.g., abdominal pain to the acute surgical team).

Box 5:1 Conditions with accessible out-patient guidelines

- Chest pain for exclusion of cardiac event (with a normal heart tracing)
- Suspected venous thromboembolism
- Headache
- Minor stroke
- Anaemia
- Suspected lower respiratory tract infection/pneumonia not requiring oxygen
- Minor upper gastrointestinal bleed
- Skin/soft tissue infection
- Ascites in patients with cirrhotic liver disease

5.1.3.1.1 Observed deviation from common behaviours

Consultants stated that considering conditions beyond those in Box 5:1 allowed more patients to be allocated to AEC and mitigate bottlenecks in the bedded area. It also had the advantage of creating the potential for fewer admissions if clinical expertise could be applied and available resources manipulated to create unique pathways of care. They explained that although avoiding admission in non-usual patients was not always possible it should be considered by allocating to AEC in the first instance. Consultants reported greater use of this strategy when overcrowding was present or anticipated.

Consultants also identified patients who were not urgently unwell. No other member of staff was observed to do this. In these instances, the processes of allocation decision-making were observed, but the clinical impression and solution offered were for the patient to remain in the community for treatment and/or investigation via elective out-patient services. One trainee was observed recommending an urgent GP review of a community patient referred by a paramedic crew to determine if attendance was required. This suggested that the trainee had some experiential learning in recognition of non-urgency, but as final decision remained risk averse this skill was not yet fully developed.

5.1.3.2 Types of decisions made

Staff were observed using different decision-making strategies according to their training. Consultants mostly applied 'previously tried' (prototype) and 'never before tried' (creative) solutions. Trainees also used prototypes but had a smaller pool to choose from. Nurse DMs used option selection and analogue solutions. This was a choice from amongst two or three solutions described as *"what we usually do here"*, but influenced by judgement of nursing needs, e.g., allocation to a bed if the patient had recently received morphine[14]. Consultants decisions demonstrated movement between concerns for individual patients (microscopic) and patients at the group level (mesoscopic). Prioritisation altered according to immediate context (e.g., high demand). Holistic decisions – consultants only - incorporated individual and grouped patients'

[14] Concern that the patient could be drowsy as a side effect of the drug and unsuitable for an out-patient seating area

needs, and departmental efficiency. Travel, resource availability, patient preferences, and staff workloads were all observed/described by consultants during and/or after decision-events. Nursing and trainee decisions focused on the individual patient only. A summary of decision types and behaviours is presented in Table 5:7. A tabulated list of the decisions may be found in Appendix B, Table B:8.

The only procedural solution applied was an organisational rule about placement of suspected COVID-19 patients upon arrival. Most participants applied the organisational rule when COVID-19 was suspected and reported satisfaction with these decisions. Two consultant participants were observed trying to exclude COVID-19 during referral calls despite an inability to confirm/refute this before testing upon arrival. During this, they displayed deliberative decision-making that was rarely present in their other observed events. Both expressed a desire to take a 'fair share' of work because the COVID-19 area staff felt the organisational rule was poor and argued that too many patients were being diverted. Those not applying the rule described their deliberations as good decision-making but expressed anxiety about introducing infection into non-COVID areas via poor decision-making. Both spent considerable time weighting up costs and consequences of COVID-19 decisions during and after calls and chastised themselves if COVID-19 was subsequently detected when they felt they had successfully excluded it over the phone.

Table 5:7 Summary of decision behaviours according to staff category

Staff	Decision processes used	Frequency of solution types observed	Recognition of a non-medical problem	Recognition of non-attendance	Ambulatory-suitability recognition	Patient-related influences	Environment-related influences	Trends in outcomes observed
Consultant	Intuitive decision-making enhanced by rational analysis. Varied according to time spent as a consultant in the local setting	1.Prototype 2.Creative 3.Procedural 4.Deliberation	Good	Good	Good	Clinical need, social factors, psychological factors	Current resource availability, anticipated resource need, time of day Regular review of patients attending and hospital occupancy levels	High proportion of ambulatory-suitable patients allocated at referral Small increase in ambulatory allocations as temporary measure to mitigate of prevent overcrowding
Trainee	Rational analysis enhanced by moderate us intuitive decision-making according to level of medical training	1.Prototype 2.Procedural 3.Deliberation	Good	Poor	Low-moderate	Clinical related to medical need. Occasional consideration of social factors (e.g., geography)	None	Low – moderate proportion of ambulatory-suitable patients allocated at referral No increase in allocations beyond own clinical comfort.
Charge Nurse	Rational analysis enhanced by intuitive decision-making in matters relating to nursing care	1.Option selection 2.Analogue 3.Prototype 4.Procedural	Good	Poor	Poor	Clinical only related to immediate nursing needs. Incorporation of immediate functional needs (e.g., mobility)	Regular review of patients attending and hospital occupancy levels Responsibility for movement of patients from the AMU to other areas	Low proportion of ambulatory-suitable patients allocated at referral Assumption that admission avoidance would be determined after evaluation

Summary of the observed referral events in consultants (47 allocation decisions), trainees (20 allocation decisions), and charge nurses (40 allocation decisions). Recognition of ambulatory suitability, non-attendance, and non-medical problems were qualitative judgements based on the researcher's expertise (their own intuited decisions which spontaneously occurred during observations) and the final outcome of the patient (whether bed allocations were admitted into hospital following consultant review). Consultant decisions were frequently consistent with the researcher's and fewer of their bedded allocations were discharged following consultant review. Trainee and charge nurse recognition was graded relative to consultant recognition, i.e., fewer decisions consistent with the researcher's and a greater number of discharges following consultant review

5.1.3.3 Conceptual mode of expert allocation decision-making

In consultants, remote allocation decisions were complex processes that applied non-conscious (system one) and conscious (system two) thought to a series of interconnected decisions to create holistic plans. Figure 5:6 presents the processes of allocation decision-making. From the outset of a referral, consultants would receive a large stream of information about a patient (usually delivered over a brief period of time) that fed into a framework of assumed urgent illness that formed from the outset of the referral dialogue. The acute clinical condition/symptoms initially described by the referrer would be used to build this framework into which all other data would be subsequently fed. The framework of assumed urgent medical illness would then be used to identify key data for creating a clinical impression and solution.

Impression formation and solution acceptance could be an iterative process as shown in Figure 5:6. Clinical impressions would intuitively manifest via pattern-matching heuristics via key data. Impressions, once formed, were spontaneously accompanied by solutions which were then accepted or rejected as viable by conscious tests of the compatibility of each impression with the data used to form it, the solution that manifested, and the current/near future state of the external environment (e.g., availability of necessary resources). If a solution was rejected, another solution would manifest for testing. This pattern would repeat until a solution was determined as non-refutable, or no more solutions were available.

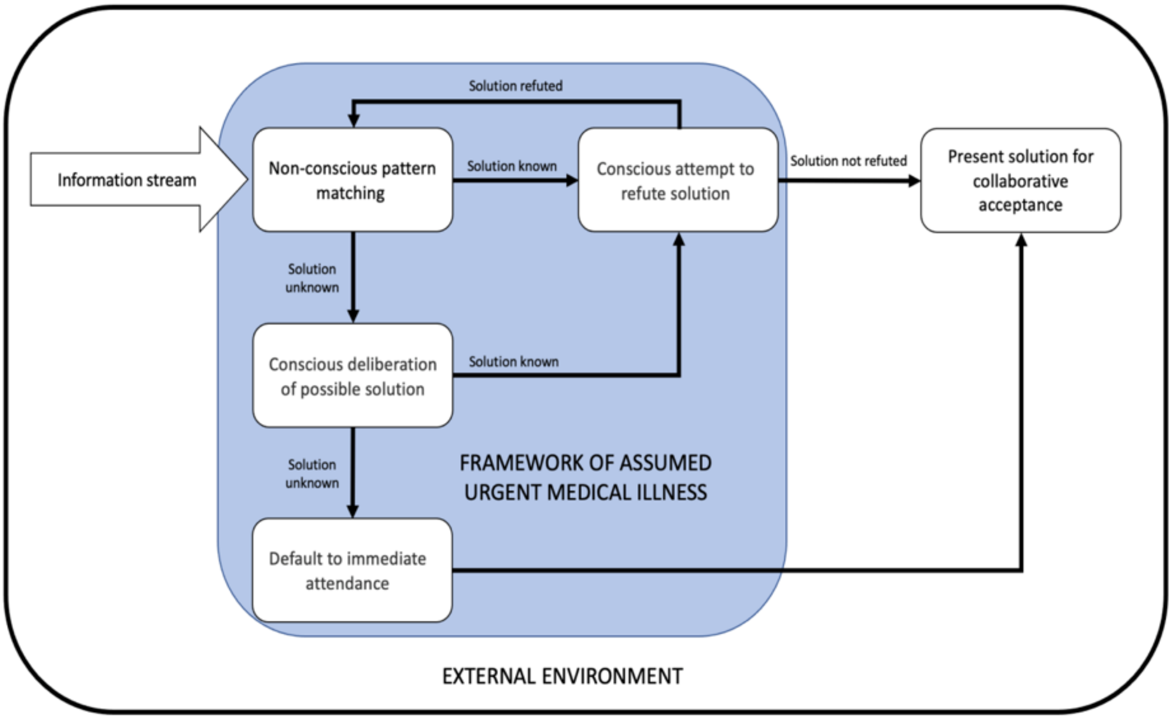


Figure 5:6 Conceptual model for expert remote allocation decisions

In remote early decision-making, initial information about the urgent health decline generated a framework in the decision-maker's (DM) brain within which all subsequent information was appraised. This framework existed within the context of the urgent care environment at that moment which was observed to influence the DM's emotional state and their decision-making. Information streams presented to DMs could be auditory and/or visual. The recognition of key data was largely performed by the non-conscious brain augmented by conscious processes ('sense-checks'). Key data triggered both the frame and the spontaneous appearance of solutions. Conscious attempts to find error or fault in the solution (tests of refutation) were observed in/reported in some senior trainee decision-events suggesting that the process described emerges via experiential learning in an environment with regular allocation decision events and feedback

Recognition of key data within the information stream was intuitive but could also be consciously sought. If sufficient key data were not forthcoming consultants would revert to direct questioning of the referrer or would search the electronic database to increase the size of the information stream. Some data would be immediately sensed as important when it entered the framework and would be held within the frame; other data was allowed to flow out (rejected as non-useful). The context informing the framework of assumed urgent medical illness, although held within the wider context of the external environment, specifically concerned the clinical needs of the patient referred.

Solutions were also intuitive and would become available immediately upon formation of a clinical impression. At this point, the consultant would mentally test the viability of a solution to determine if it was likely to fail. The external environment was frequently (but not always) observed to influence solution formation, but consultants were largely unable to recall moments of deliberation prior to solution manifestation. Once available, solutions would undergo intentional (conscious) testing of their viability. This took the form of a mental check that the solution would not fail due to patient or environmental factors (e.g., non-availability of resources). Consultants were aware of this mental check of the environment as part of solution testing. Once a solution was determined viable, it was accepted as correct, and presented to the referrer. Consultants were not observed to deliberate between multiple solutions simultaneously. The first non-refutable solution that occurred was accepted as the correct one.

The full thematic analysis of observed and reflexive evidence is presented in Appendix B, Figure B:4. By way of supportive evidence, a rich description of observed allocation decision-making is provided in the following sections. This is presented according to the key aspects of decision-making in expert staff: framing and hypothesis creation, key data triggering, the multiple rapid decision-events underlying allocation decision, and viability testing. This starts with an example of a referral experienced by the researcher. Consistent with the reporting and presentation style of ethnography, the researcher describes herself and her own decision events in the first person for the remainder of this section.

5.1.3.3.1 Example

The referral phone rings. I answer it by introducing myself and my role.

> *Paramedic: "Hi doctor, this is [xxx] one of the paramedic crew in [xxx] today. Can I talk to you about a patient?"*
>
> *Me (thinking): "Well yes, obviously… be more specific"*
>
> *Me (aloud): "Sure. Can you give me a name and a hospital number or date of birth?"*

During their opening statement I am aware of nothing beyond impatience for immediate information and a slight anxiety about a potentially unwell patient, and a busy day. The patient particulars allow me to access their electronic record. This is done in anticipation of the need to retrieve key data once an acute concern is presented. It also presents a way to usefully occupy myself, remove the impatience, and anxiety whilst I waited for the information I need to appear in the dialogue. I am keen to make a decision and move on to my other duties.

> *Paramedic: "We're with a 42-year-old woman. We were called out to see her because she was having chest pain…"*

I have an immediate and spontaneous impression of non-urgency. I have no conscious awareness of a specific diagnosis, but I have a sense of non-attendance that seems to be based on a pattern-match: the patient's age (young for concerning illness but not unheard of), the tone of the paramedic's voice (relaxed), their language ('*was* having chest pain" i.e., pain-free now), the very fact that they were phoning and not immediately transferring the patient to the Emergency Department (standard practice for concerning chest pain). As they are talking, I scan the sections of her medical records. I am aware of consciously looking for information that may alter the spontaneous hypothesis of non-urgency that presented itself: has this happened before? Any known illness or risk factors in her record? What other health conditions does she have? As I do this I am listening to the paramedic talk. I am aware that I am mostly looking for reasons to prove my initial hypothesis wrong.

The presented narrative is convoluted. It switches between present and past information and is interspersed with polite conversation. It is difficult to follow, and the disjointed information causes my attention shift between the records (intentional searching for 'clues') and the dialogue which catches my attention when key phrases appear: *"ECG normal", "had this before", "lasted 10 minutes", "radiated to her back", "pain-free".* Data feels like it is flowing towards me at high-speed form the conversation and the computer screen. As each piece registers I am conscious of rejecting it or not. Some of the dialogue feels muted and I am unsure if this is because I have rejected the information or not listened. Any relevant data is held in the front of my head as if the words are floating there waiting to be used. I actively try to remove non-relevant data to prevent it from settling there. I feel as if I am trying to 'unknow' things that I think may be of no use or negatively influence the decision.

I find an attendance from two months prior and read through it. The text refers to a normal ECG and pain radiation to the back. I experience a slight relaxation and a sense of a pattern; reassurance that this is unlikely to be a serious health threat. The impression of non-urgency, until now experienced as a vague shapeless sensation in my body, feels to be solidifying. Suddenly "ACS", "PE", and "Dissection" spontaneously appear as if typed on the inside of the front of my skull. I cannot fully hear the paramedic talking. These diagnoses need to be addressed either now or upon immediate attendance. No other urgent illnesses concern me. I rescan the attendance letter specifically searching for evidence of their consideration the last time. As I am reading, “ACS” and “PE” disappear, but “Dissection” remains. I feel confident that this was excluded the last time based on the investigations, but I feel unsatisfied. I immediately know I need to look at her X-ray for the final piece of data. I access it, I look at it for a couple of seconds and then feel physically relaxed. The paramedic conversation is now very audible:

> *Paramedic: "... so we called the GP, but the GP said we just needed to bring her in"*

I ask the paramedic team to repeat the history of the presentation today and ask them to check with the patient if the symptoms today are the same as the last attendance. They confirm an identical pattern and patients concurrence. I advise non-urgent investigation via the general practitioner (GP) with worsening advice if it recurs.

5.1.3.3.2 Framing, hypotheses, and impression formation

"I mean, [the GP] may have considerable experience in dealing with this. She has the patient in front of her... She only wanted me to exclude [acute coronary syndrome] as an ambulatory case, but the minute I heard the story, I thought 'needs admission'" ***Consultant 1***

Senior clinicians stated a preference for the early use of a framing heuristic to make sense of the information presented and identify key data. I preferred the reason for referral to be the first piece of data presented to me. In my own mind, this led to the immediate formation of a framework or a mental pinboard within which all new information could be understood. Frames were then used to generated hypotheses about the patients' illnesses and solutions. As the example scenario above revealed, I required a framework to pin all the data onto form the very beginnings of the conversation. Non-acute information prevented framing the referral and delayed the decision-making. Once the urgent concern was known to me, the framework of 'acute chest pain' was created. A hypothetical impression was also spontaneously and immediately present in my mind influenced by the style of the conversation and the age of the patient within reference to this framework. With another framework (e.g., 'unexplained fever'), another hypothesis would have formed.

Frameworks based upon symptoms and not diagnoses were preferable to me, possibly because diagnoses presented an additional (but non-helpful) bias into the decision process. For example, if the referrer opened a conversation stating a wish to exclude a suspected pulmonary thromboembolism (PTE), I would use the patient's symptoms to create the frame thus keeping my impression and solution-creation open to alternative explanations. I became increasingly aware of an intentional desire to use the framing heuristic as the study progressed. This awareness emerged by the act of studying my own decision events, but was supported by the observations and interviews with other consultants participants.

Interviews revealed the use of framing devices from the earliest moments of a referral in all other consultant participants. This supported its ubiquity in the allocation decisions of expert clinicians and triangulated the findings of my own reflexive analyses. Consultants described using information about the acute illness to set the immediate context for all allocation decisions. They expressed frustration when referrers commenced their conversation by listing prior medical illnesses consistent with my own preference to receive a patient's background history after the framework had formed. The consultants observed described background information as a source of data that helped to firm impressions, trigger decisions, or test hypotheses. All participants were wary of the potential for framing to introduce negative biases when used poorly.

Consultants described rapid hypothesis formation about patients' needs within the opening sentences of referral dialogue which continued to form and then suddenly solidify, marking the end of the allocation decision. Initially formed hypotheses were felt by all to be insufficient for solutions to be final unless hypotheses described a condition not normally managed in their department (e.g., a surgical presentation whereupon the allocation decision would end with advice to speak with the surgeons). Like me, subsequent data from the information stream would lead to hypotheses taking a more complete shape. This transition was frequently triggered by the emergence of a single piece of data in the dialogue or in the electronic patient record like a final jigsaw puzzle piece. My own hypotheses (or impressions) could manifest as a collection of typed diagnoses, as vivid images of an unwell patient, or sensed as indistinct, fluid shapes that solidified as conversations progressed. Other consultants did not explicitly describe these experiences but did describe a sense of having partial information and feeling uncertain at the beginning of hypothesis formation, with a sense of completeness and confidence building as data were gathered. My own mental imagery may have been an artefact of the act of self-observation, but could reflect known variations in mental imagery and sensory experiences amongst humans (e.g., aphantasia, synaesthesia). Certainly, a transition from incomplete knowledge and uncertainty to confidence triggered by key data was a common finding amongst the group.

5.1.3.3.3 Key data triggering

Data gathered during the referral would be immediately accepted or rejected for usefulness using the initial framework, but some data led to rapid resolution of the decision-making processes when they appeared. The appearance of a key piece of information could trigger a 'eureka' moment of knowledge and confidence about an intuited solution. Key data were not sought with the intention of reaching a diagnosis during consultant referral conversations although this could happen (a patient's symptoms could be the hallmark of specific pathology, e.g., neck muscle spasm after taking a particular drug). Rather, key data were mostly desired to create an impression of what may or may not be an urgent medical decline requiring attendance. In the example provided, my search for data was intended to determine if the impression of non-urgency could be refuted. Key data in the records to refute this was not found but data in support of non-urgency was.

Awareness of what key data was or could look like before it became known varied. Key data could be a specific piece of information actively sought or could unexpectedly occur in as important. In example given, I was initially searching for evidence of previous heart conditions or risk factors in the example patient's medical records but found the previous admission and realised key data within it. Whilst observing a consultant participant, the referrer's description of patient vomitus triggered the decision-maker to determine a non-medical emergency and advise referral to the surgeons. This was despite their initial hypothesis of immediate attendance for a likely medical complaint. Upon description of the vomitus, they experienced a sudden jarring sensation as the new information clashed with the framework they had created. *"I don't like upsetting people"* they explained, *"but this just didn't sound like an upper GI bleed*[15]*".* Of note, moments of key data triggering were observed in the most experienced trainee suggesting it is an element of decision-making that emerges in clinicians as their experiential learning in urgent care progresses.

5.1.3.3.4 Multiple spontaneous decision events

Allocation decisions comprised of several different decision-events which consultants were often unaware of performing. Decision-events concerned urgency, suitability for a

[15] Gastrointestinal bleed

medical department, and safety in admission avoidance. The order and timing of these decision-events was often hard to distinguish. They would frequently appear and be answered together via the appearance of a prototype solution in the DM's consciousness. Late one evening during the study, I was referred a patient with a low phosphate level who had recently discharged themselves against medical advice with this dyscrasia. The patient had refused to stay in hospital due to alcohol addiction but, as the referral came in the early evening, treatment would require an overnight stay. Multiple questions about the risk and logistics of care occurred and were answered in what felt like a simultaneous moment. Broken down post-event they may summarised in a logical sequence that encompassed consideration of the urgency, anticipated treatment, and feasibility of delivering treatment in context (Figure 5:7).

Although they appear as a logical sequence in Figure 5:7, they did not clearly occur in this order. Some were already made and appeared in my conscious mind as completed decisions and others I recall consciously asking myself. Non-urgency and a solution of attendance the next day for treatment appeared to me immediately, but this was then followed by a second check of whether we could feasibly complete care tonight. The decisions events included an assumption that the patient would not wish to remain overnight if they did attend that evening.

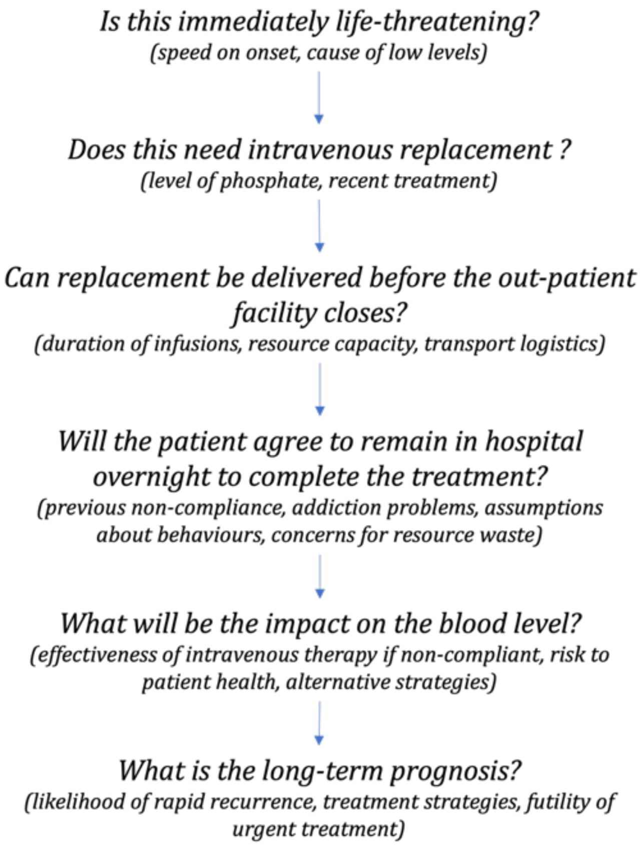


Figure 5:7 Example of rapid decision events

An example of a logical sequence of decision event questions and their context for considering answers (in brackets) is presented. This relates to the in-patient or out-patient allocation decision for a patient referred with a low phosphate due to chronic alcohol addiction. The allocation decision had to consider the risks to the patient but also the effective use of resources in a patient who had an explicit preference to avoid in-patient care. In theory, a very low phosphate level presents a high risk of arrhythmia. In practice, many persons with long-term, heavy, daily alcohol use have a very low phosphate levels due to a chronic poor nutritional state. This poses no emergency risk if their health is otherwise stable. The patient referred had been in hospital the week before for another reason and the low phosphate level found on a routine screening. They had elected to leave hospital against the wishes of their doctor despite treatment for alcohol withdrawal because they did not like the hospital environment and wishes to continue alcohol use. They were re-referred as a medical emergency because the community doctor providing follow up and monitoring was concerned about the risk of arrhythmia in the context of ongoing low levels despite oral replacement

Of note, this allocation decision reveals the holistic approach to decision-making in consultant allocations as well as the potential for harm with system one decision-making. The assumed patient preference for out-patient care was a heuristic – a decision based (partially) upon a pattern of patient behaviour in urgent care settings in the presence of addiction. This could be perceived as a negative bias that denied the patient the option of in-patient care. Alternatively, as a sympathetic and holistic decision informed by experiential knowledge of how persons with addictions frequently find healthcare settings to be antagonistic, overly regimented, and difficult to engage with. Consideration of efficiency in the allocation of resources also influenced the decision - non-completion of treatment in the event of self-discharge would have made starting treatment futile. This was explained to the referring GP when presenting my solution who did not disagree with the assumption. When observed in other consultant staff, allocation decisions involving complex psychosocial situations frequently displayed deliberation in decision-making alongside heuristics like the one described.

The simultaneous, rapid, and interconnected nature of the multiple decision-events that formed a single allocation decision belied what appeared, on the surface, to be a simple, single operational decision. Consultant referrals observed frequently took less than three minutes to complete. However, Figure 5:7 reveals the amount of information being processed. This would not be possible without the applications of heuristics based upon clinical and social knowledge. A stark difference in the time taken for trainee allocation decisions compared with consultant staff largely made this clear - trainee referrals that did not employ operational decision-making were frequently in excess of 5 minutes. This resulted from a longer time spent gathering information, and the frequently observed deliberation over potential diagnoses, and consequences of alternative allocation strategies in collaboration with the referrer. This out loud thinking may have been an artefact of the research process induced by an observing senior clinician. By way of contrast, consultants were rarely observed deliberating unless managing a patient outside of their domain of expertise (e.g., COVID-19 referrals).

5.1.3.3.5 Tests of refutation

Immediately upon the awareness of a solution in a consultant decision-maker, a conscious test of its suitability would occur. If it passed, it was accepted with no other solutions considered. If it failed another solution was immediately known to them and tested in the same manner. Trainees frequently verbalised multiple solutions to the referrer and deliberated them out loud, before settling upon a final one. Consultant participants and I were aware of this reflexive process of analysis. This was specifically a form of test to see if the solution we had generated could fail. For example, a prototype plan to attend for a diagnostic scan via AEC the next morning was tested by reviewing the availability of scans. If no scans were available (test failed) but were available the following day, then this new solution was tested for usefulness – e.g., the safety of a 36-48hr delay for that patient. If no solutions were acceptable, immediate attendance at the in-patient area was accepted by all as default. Solution tests could happen whilst data was still being gathered or once the requisite amount of key data had been realised.

5.1.3.4 The influence of the immediate environment

Staff were present on the unit during their shifts and had care responsibilities for all patients on the unit. The AMU environment had an observable influence on consultant allocation decisions. Consultant would allocate more patient to AEC when overcrowding was present or threatened. They would also allocate more to AEC if there were few patients expected in AEC that day, or if there was an inadequate ratio of staff to patient in the bedded area.

In some moments, awareness of a new referral could trigger anxiety. I was not always conscious of this but did sense it if referrals came through in quick succession or at busy moment in the day. Four possible explanations emerged upon analysis. Firstly, it may have signalled a personal fear about poor task management. Secondly, it may have been fear of encountering a condition that I had little experience in managing. Thirdly, a fear for patient safety in the department if it became overcrowding. Fourthly, an instinctive response to the alert tone of the referral phone and/or pager specifically designed to catch attention. It is likely that each of these reasons was involved in some form and at different times. This anxiety could be removed by acknowledging and addressing it. This could be achieved by inspecting the level of crowding and/or by answering the call and focusing on the decision task. When I was not responsible for allocation duties but still performing clinical duties, the sensation of anxiety rarely occurred. During the focus group, other consultants confirmed the same anxiety with some but not all calls. Most attributed it to a fear of demand exceeding resource capacity that day. All described dissipation of the sensation within the first moments of the referring dialogue.

"When the pager goes off, I have this immediate dread, like, I know this is another referral and I think 'Shit, what is this? Can we cope?' Or is that just me? [laughs] Does anyone else just assume this is another admission?" Me

"No, this is me too, I always assume that the patient will need to be admitted…" Consultant participant 1

"You do get this feeling of panic, but it disappears as soon as you start taking the call" Consultant participant 2

Referrals calls that occurred when resources were scarce or when occupancy levels exceeded 100% tended to prompt observed consultant DMs to allocate more patients to the AEC facilities. This included patients for whom in-patient care was intuited. Not all referrals would be allocated to AEC when occupancy levels were high. These decisions tended to be openly deliberative focusing on the consequences for departmental efficiency and patient safety. Conversations could include an explanation to the referrer about why AEC was being used and the high likelihood of admission and delays. One consultant was observed allocating a patient with a suspected diabetic ketoacidosis (life-threatening) to AEC to mitigate resource waste. As the necessary blood test to determine illness severity was immediately available in the AEC facility, this solution was made to create an efficient care pathway for the diabetic patient and prevent the unnecessary occupation of an AMU bed should the patient need to be transferred to critical care. Fear of overcrowding was a contributing factor in my own allocations. This included decisions to place 'non-usual' patients in AEC. This would usually be accompanied by a 'gut feeling' that this plan was unlikely to be realised; however, providing initial care via AEC meant that the staff workload could be fairly distributed, and beds would remain temporarily available for physiologically unwell patients arriving.

Increasing AEC allocations when crowding emerged was also perceived by consultants to meet assumed populations preferences for admission avoidance. One consultant arranged a delayed AEC attendance for a suspected pulmonary embolism in a high-risk patient because the patient stated a preference for non-admission. Increasing AEC allocations beyond the guidelines was also assumed by consultants to identify new categories of patients in whom admission avoidance may be realised with the potential for new guidelines to emerge. For example, in patients referred with decompensated congestive cardiac failure.

5.1.3.5 Quantitative data of decision-making in consultants

The quality improvement (QI) study of early senior decision-making in the local setting revealed a tendency towards increased AEC allocations as time spent as a consultant in the local department increased. This is apparent when a logistical regression of the AEC versus bedded areas allocations made by each consultant in the QI study is performed. As Figure 5:7 shows, there is a positive relationship between the time spent delivering care as a consultant in the department and the probability of a patient being allocated to AEC. Predictive modelling of the data (not shown) revealed the probability of AEC allocation by staff with no consultant experience neared but did not reach zero. Both the trends for increasing probability of AEC allocations with consultant-time served and the predicted allocations of staff with little-to-no consultant experience (e.g., nurses) echo the allocation behaviours observed during ethnography.

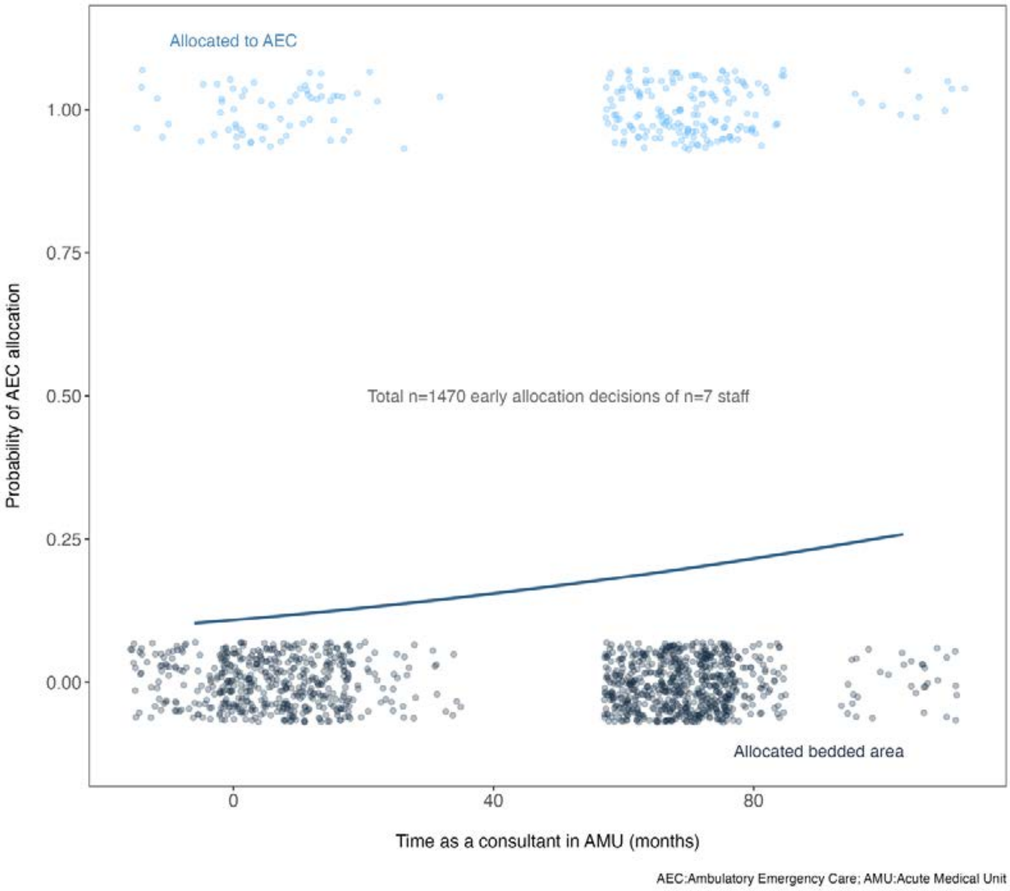


Figure 5:8 Predictive model of AEC allocation according to time as a consultant

Logistical regression of the data available from the quality improvement project is shown. The probability of AEC allocation is modelled according to time spent as a consultant in the location. 1407 decisions taken by seven staff (six consultants and one trainee) are shown as single data points (displaced for visual ease). Each data point is a decision to allocate a patient referred to AEC (1.0) or the Bedded area (0). The number of months the decision-maker in each instance had worked as a consultant in the local setting is shown on the x-axis. This included a trainee within six-months of completion of training (-6months). The regression model (line) shows a tendency to allocate more patients to AEC as time served increases.

Predictions of consultants who have worked in the setting beyond the time captured in the QI project are challenging - the proportion of suitable AEC patients will have a natural limit set by the local resource capabilities and evidence of safe care for non-admission.

5.2 Discussion: Evaluating the data from the ethnographic study

This section presents a discussion of the findings and their suitability to inform a systems simulation model (SSM) of early senior decision-making in a representative urgent care unit. This represents stage 3 of the Trace framework for model building (Section 4.7.1, Table 4:7). An ethnographic study was necessary to appreciate how a SSM could reproduce allocation decisions, their outcomes, and the dynamic environment in which they occur. Evaluation of the usefulness of the data collected had to consider the single site nature of the case study in representing local and generalisable features of ESDM and acute medical unit (AMU) environments. It also had to be mindful of the character of historically observed events which are not necessarily representative of all decision-events or potential outcomes (Popper, 1960). The discussion is split into three sections beginning with the data informing reproduction of the decision environment, followed by critique of the usefulness of the patient-reported outcomes collected as model inputs. The chapter concludes with a discussion surrounding the complexity found in early allocation decision-making of expert staff compared with others, and how this new knowledge may be applied to reproduce staff decision-making in an SSM.

5.2.1 Activity in the environment and influences

Departmental activity demonstrated consistent daily patterns at the mesoscopic level with stochasticity contained with observable ranges. Patterns of arrival were dependent upon the time of day and source of referral. Patterns of departure emerged from delays to starting care and the length of time required to complete care. As completion of care was finalised by senior doctor review, departure patterns were influenced by external factors, notably hospital resources and transport home overnight. The regular scheduling of influential events (ward rounds, AEC closure, reduced resources access overnight) would be possible via the discrete event component of the model. Observed stochasticity in, for example, patients' clinical needs, and plausible extreme events such as very high hospital occupancy could be incorporated via realistic parameter distributions informing the model inputs.

5.2.1.1 Patient arrivals

Patient arrival patterns could be reliably reproduced by combining the data of referral source, observations about arrival rates at different points of the day observed during ethnography, and creating assumptions about the timing of referrals assumptions (Karnon et al., 2012). Emergency Department arrival times were found to be adherent to the national access standard on the study site with a local goal to transfer patients within two-hours of ED arrival (NHSS, 2015). Analysis of data and observed activity revealed that the majority of patients were referred by their GP (median 65.9% were non-ED referrals) meaning surgery hours of 0900-1800hrs were a suitable range to estimate referral times for most patients. Arrival patterns would be straightforward to validate via the historical dataset, but would need to be modelled to emerge via referral times and parameters representing the observed times taken to travel to the AMU. Data to inform travel time from the community came had to be estimated from the ethnographic observation. This was an acceptable approach given the limited data available (Karnon et al., 2012). The parameter inputs chosen reflected the observed tendency for most patients to arrive within six hours of referral with the potential for outlying values of up to ten hours reflective of plausibly extreme delays.

Modelling arrival patterns on the case study setting risked limiting generalisability of the SSM and its findings. Not all urgent care systems are designed to accept patients without accessing ED services first. Of those that do in the UK, not all are adherent to the four-hour access standard. However, as direct referral to non-ED services is the preferred model of UK policymakers and healthcare leaders (NHS England, 2019; Urgent and Unscheduled Care Directorate, 2022), it is reasonable to assume that most hospitals currently have or are planning to have model of service that bypassing the ED for non-emergency patients. This may not be possible in very small centres of care (e.g., remote settings such as the Highlands and Islands of Scotland) or in those without dedicated AEC facilities. Arrival patterns may vary greatly in these settings and limit generalisability of the SSM and its findings.

5.2.1.2 Occupancy levels

Occupancy levels throughout the day were not recorded meaning validation of modelled outputs would be challenging. Reliable reproduction of occupancy levels throughout the day in the SSM was necessary due their influence on some decisions and the potential for harm and inefficiency with overcrowding (Bernstein et al., 2009; Iacobucci, 2021;

McCarthy et al., 2009; Morley et al., 2018). During the four-months ethnographic observation, occupancy levels in excess of the recommended levels were consistently seen in the department (A. C. Pratt & Wood, 2021). It was possible to identify days and times when overcrowding occurred in the historical dataset as it captured patients delayed in accessing a bed. Thus, patient delays (numbers per day and lengths of delays) provided the only means to validate occupancy levels in the modelled outputs

Modelling emergent occupancy levels would require inclusion of organisational behaviours that perpetuated crowding and overcrowding in the AMU. Consultant staff reported adjusting their allocation behaviours in response to anticipation of overcrowding, yet overcrowding still emerged. This heavily implied that urgent care overcrowding was poorly managed and even tolerated to some degree within the organisation. Trends of increasing delays to transferring patient from urgent care areas to in-patient beds observed across the UK suggest that the case study site is unlikely to be unique with respect to this phenomenon (S. Jones et al., 2022; McLellan & Abbasi, 2022). Evidence supporting assumptions of poor capacity management on the case study site were to be found in the observed barriers to proactive capacity creation (e.g., limiting overnight transfers) and adherence to the ED access standard that saw patients deliberately placed into the AMU corridor area regardless of ED occupancy levels. To realistically reproduce occupancy levels emergent in the department, the observed behaviours of actors outside of the AMU would have to be reproduced in the model. These behaviours and their underlying assumptions are listed in full in Appendix D but may be summarised: delays to transferring patients when overcrowding emerged, limits to the number of patients permitted to transfer to reduce occupancy levels, and unobstructed transfer of patients from ED to the AMU.

5.2.1.3 Patient activity

Acute internal medicine is involved with the delivery of urgent care to a wide spectrum of clinical conditions affecting persons over the age of 16years (Acute Medicine Task Force, 2007). However, patient needs extend beyond the clinical to include functional and psychological aspects of health (Mead & Bower, 2000). Time taken to deliver care for each patient therefore varies in urgent care, but delays to starting an evaluation and delays to leaving the unit once initial care is complete also contribute to length of stay. Thus, urgent care departmental activity emerges from the stochasticity of patient needs, the availability of resources to address needs, and any factors that influence movement from the unit. These were difficult to identify in the datasets available. This section describes how the data gathered during the ethnography was used to inform how patient care was modelled.

5.2.1.3.1 Patients' needs

Patient needs at referral could be usefully represented by a single continuous parameter. The breadth of clinical conditions observed on the case study site was consistent with other sites delivering acute medical care (Atkin, Riley, et al., 2022; De Silva et al., 2019). In addition, non-clinical elements of care affected how and where care was delivered. This meant that representation of patients' needs in the SSM using a discrete categorical variable reflecting medical conditions would be insufficient. A continuous parameter indicating each patient's clinical condition was determined to be the best way to represent patient need in the model. Overly complicating the model to include all possible permutations of patient needs would introduce significant computationally burden that was unnecessary to represent how patients underwent care on the case study site. In addition, creating three variables to represent the clinical, psychological, and social needs of patients and inform AEC suitability required strong assumptions about non-clinical needs which lacked sufficient available data to inform. Creating a continuous parameter to represent patient need was determined by the researcher to better represent a continuum of health needs. Assigning a value from 0.0 to 1.0 to represent states of poor health from well (0.0) to severely unwell (1.0) facilitated calculations of AEC suitability using the local prevalence values estimated from the data. Patients could then be modelled in groups according to area of care and disposition outcomes reducing the computational burden of the model without compromising representations of patient activity.

Processes of care could be modelled at the mesoscopic level by grouping patients. An individual patient's holistic needs were observed to be important for remote allocation decision-making, but proved less salient upon arrival provided the patient was placed in the allocated area. This was assumed by the researcher to be because the initial evaluative processes observed were the same for each patient according to their area of care. This homogenisation of patients into groups according to how care would be delivered on the unit was an intentional strategy by the local team to reduce variation and maintain consistency in outcomes (Calderwood, 2016; NHS England, 2019). Patients complied with the evaluation processes in the passive manner observed in other hospital settings (Shaffer & Sherrell, 1996).

5.2.1.3.2 Lengths of stay

Dataset records of patients' lengths of stay on the unit were insufficient to inform parameters that could combine to produce emergent outcomes, but could be used to validate modelled outputs. A parameter representing the intended length of treatment was better placed to represent processes of patient care in the SSM. The stochasticity of presenting conditions amongst patients observed in the study meant that lengths of time to complete evaluation and treatment in the initial stages of care varied between patients. Observation of day-to-day activity on the site confirmed this, but lengths of treatment time were difficult to isolate within datasets as only arrival and departure times were recorded. Treatment time was also observed to vary due to delays in accessing medical staff in the AEC and because of early transfers to create capacity. Using the dataset-derived LoS to reproduce treatment time risked misleading results in the predictive modelling scenarios. The research question hypothesised that delays varied according to allocation decisions and thus the category of staff in the decision-maker role. Creation of a parameter representing time taken to receive urgent treatment presented a useful way to allow lengths of stay in the department to emerge as a result of delays to care and moments of early transfer that may be triggered by overcrowding. These could be modelled according to patients' clinical need parameters and the allocation decision as the modeller's own knowledge of urgent care, her observations, and dataset analysis (Appendix B, Table B:4) revealed variation in lengths of stay according to patient need and area of care.

The findings from the ethnography meant that the SSM created assumed that AMU capacity levels had no direct influence upon treatment times. This could have limited generalisability of findings. As explained in Section 2.3.1, high departmental occupancy levels have an inconsistent effect on time taken to deliver care. An assumption that processes of care would be delayed when high occupancy levels were present lacked supportive evidence from the ethnography. The observation that patients would be managed in any available space when overcrowding occurred made modelling changes in treatment time (beyond early transfer for necessary capacity creation) difficult to justify. For example, when delays were long or there were many patients waiting for a bed, some would temporarily transfer to the AEC facilities and start care there, transferring back when a bed became available. This movement was poorly captured in the Trakcare and the handwritten records.

5.2.1.3.3 Final disposition outcomes and AEC prevalence

Observed consistency in available resources to facilitate non-admission meant that stochasticity of daily discharges existed within a predictable range. This could be usefully reproduced in a SSM. Decisions to discharge occurred at the end of care in the AMU. This was a shared task between AMU consultants, senior trainees, and visiting specialist staff. This feature of care delivery facilitated a consistency in decisions regardless of occupancy levels – i.e., if the AMU consultant was very busy discharge decisions would still be made. Discharge outcomes were subject to the types of patients presenting and resources available that day hence day-to-day variability. The evidence to support this relative stability in a range of outcome over time was strong enough to directly apply to model parameters. Other hospitals may have less support in discharge decisions and witness greater variation in disposition outcomes from AMU/AEC areas.

This may limit generalisability of the SSM and its predictive results to settings with similar access to other senior staff and similar discharge resources.

The predictable range of discharges included patients whose disposition plans changed as their care progressed. These events were not captured in the dataset meaning assumptions about a change in discharge plans were based on observations alone. Allocation to AEC provided some indication of the decision-maker's discharge predictions but as was shown, allocate to AEC could occur in the presence of anticipated admission. In addition, some patients presented with unexpectedly high or low levels of illness meaning discharge outcomes altered upon completion of care. Finally, if transfer to another area was delayed, a patient could remain in the AMU long enough to improve and realise discharged directly. An additional layer of stochasticity was required to represent these events. In the absence of quantitative data, weak assumptions about a small proportion of patients whose disposition outcomes changed were required.

5.2.2 Patient reported outcomes in the location

This section is divided into two sections to discuss health outcomes and experience outcomes observed. Measurement of patient-reported outcomes (PROMs) is rare in urgent care (Section 3.4.3.2.2). Valid tools to collect PROMs in urgent care populations were few and responses obtained in the study were small. However, with no other data to inform the SSM, the researcher determined that the data obtained would be useful to include for exploring possible trends and to understand any limitations of their use in urgent care research. The following two sections provide a critique of the findings and explain how they were applied use in the SSM.

5.2.2.1 Health outcomes in the location

Differences between the health outcomes of populations whose urgent care is managed via out-patient and via admission is unknown (Section 3.4.3.2.2). Analysis of health changes reported by patients upon completion of care was useful to inform the parameter distributions from which health outputs could be drawn in the SSM. The key concern with basing HRQoL on the Health Index (HI) change detected was the small sample size obtained in the study.

The difference in mean HI at baseline between patient groups was non-significant suggesting that the two groups experienced similar degrees of ill-health upon arrival. Comparison of the referral reasons and demographics of the two groups also revealed no significant differences at recruitment. However, clinical conditions did differ between AEC and bedded area patients who completed follow up. The mean change per patient was non-significantly higher in the bedded population: 0.111 (95% C.I. -0.151, 0.373) vs. 0.068 for AEC patients (95% C.I. -0.166, 0.302). However, this small difference introduced the potential for a large cumulative difference when modelled as QALY gains over time. Because different conditions necessitated different treatments, improvement could not be attributed to the area of care (nor the decision to allocate to that area). In addition, the AEC group may have represented a larger number of stable clinical conditions with little room for improvement – the ceiling effect of measuring HRQoL via a generic tool as discussed in Section 3.4.3.2.2 (Brazier et al., 2004). Had there been less variation in between group referral conditions, observed mean HI may have been similar across the patient groups. It also possible that the bedded area group may have experienced the same improvement in health had they received care via AEC.

The problems identified in the underlying data created severe limitations in interpretation of modelled outputs relating to health. However, for the purposes of exploring what may occur and to inform usefulness for future studies, they were included in the final SSM. With no other data available to inform the model, sampling distributions were created using the HI change data for each population.

5.2.2.2 Patient experience

Experiences of out-patient versus in-patient urgent care are largely unknown but reveal satisfaction with out-patient care in some settings and in some patients (Glogowska et al., 2019). The in-patient experience (IPE) survey on this site revealed no difference in most experiences of care between the AEC and the Bedded area, e.g., staff attitude, facilities, privacy. This may be assumed to reflect the co-location of the two facilities, the shared staffing, and shared culture as staff would regularly rotate between the areas. Free text responses and observation of the unit revealed two aspects of patient experience omitted from the structured surveys – dissatisfaction with long periods of time spent in the AEC area and dissatisfaction when forced to wait for a bed. Both warranted inclusion in the model to reflect patient experience as there were no other discriminating factors identified.

Poor experience of care in the AEC facility emerged from long periods spent waiting for and/or receiving care. This was consistent with poor patient experience in other settings and could be incorporated in the SSM (Glogowska et al., 2019; Huang et al., 2018). The free text responses in the IPE shed light on aspects of care that were emergent from departmental activity – delays to starting care and time spent in out-patient settings. The responses that referenced time came largely from AEC patients. This reflected their expected LoS when interviewed (4hrs). Dataset analysis revealed this to be close to the observed median LoS of 4.8hrs (3.0, 7.4) in the October 2019 dataset. Expectations may have been influenced by awareness of the four-hour access standard or may have arisen from sense-making in the environment. For example, being placed in a clinic setting rather than a bed may have prompted a patient to assume they were not unwell enough to warrant being in hospital all day. This conclusion may have made patients less happy to take time away from other duties (e.g., work). As this facet of poor experience emerged from delays and individual lengths of stay (LoS), it was possible to use both delays and (LoS) to inform a model output representing patient experience using values could be informed by the data collected.

Patients in the bedded area did not complain about time taken to complete care but dissatisfaction at waiting for a bed was observed. As an emergent phenomenon, this too could be incorporated to reflect poor experience when it occurred. Allocation to a bed created an expectation a longer time receiving care than allocation to AEC (10hrs vs. 4hrs). This may be because a bed allocation suggested a long time in hospital; or possibly patient sensed being more unwell than AEC populations despite differences between the mean health index scores upon arrival being non-significant. A perceived need to be in a bed could have generated dissatisfaction when one was not available. Experiences of waiting could have been worsened by the waiting area location - a narrow corridor opposite the bedded area with no facilities to deliver care, no capacity for infection control, and no privacy. This was also a crucial corridor for staff movement around the ward as they delivered care; waiting patients became a physical obstacle to staff. In this space, patients may have felt ignored or forgotten (O'Cathain et al., 2008). A poor experience of care in this context was a reasonable assumption to include in the model.

The reliability of the survey findings may be questioned if we consider respondents awareness that clinical staff would be reviewing results. This may have affected findings in two ways:

1) having little choice of healthcare provider in future episodes of ill-health patients may not want to appear 'difficult' (Shaffer & Sherrell, 1996)

2) patients were aware of the challenges faced by staff due to the COVID-19 pandemic and wished to be supportive rather than honest about poor aspects of care

Poor sensitivity of the instrument applied and/or the structure of the questions may also have limited detection of differences. It is also important to note that there was no observed overcrowding in the bedded area on the days that patients were recruited.

5.2.3 Processes involved in allocation decisions

Early allocation decisions had never been studies and knowledge of clinical-operational decisions was poor meaning there was little literature with which to compare the findings. That said, the decision-making behaviours displayed by the consultants bore close resemblance to those described in studies of expertise in comparable domains. Reproduction of this complex process was not possible in a systems simulation model

(SSM). However, basic the trends of decision outcomes and their immediate influences could be represented by simplifying rules of decision-making and allocations according to levels of expertise in staff.

5.2.3.1 Representing the spectrum of expertise in the allocation task

The conceptual model of early senior decision-making (ESDM) described in Figure 5:6 (Section 5.1.3.3) was simplified for the SSM. Although important to understand in development of the conceptual model, complexity observed in ESDM events was unnecessarily to include to answer the research question. Trends in allocation according to level of expertise were clear and could be represented by simplifying assumptions about the volume of patients a particular grade of staff may allocate to AEC given the information available at the time of referral. Feedback loops to represent altered decision behaviours in response to the environment could be included without making the allocation decision sub-model overly complicated.

Triangulating of findings from the autoethnography, the observation of staff, and the focus group discussion supported the trends observed amongst different categories of the staff on the case study site. These trends were to be found in the local quality improvement (QI) project and published observational studies of remote decision-making in other AMU departments (Reschen et al., 2020; Westall et al., 2015). The studies cited revealed greater use of admission avoidance strategies by consultants compared with other staff. Other work has found variation in comfort with the risks of non-admission amongst consultants according to domains of expertise (Beckett et al., 2018). The theory of intuitive decision-making supported by focused rational analysis was consistent with other models of rapid, expert decision-making in dynamic, high stakes situations that evolve from experiential learning (Kahneman & Klein, 2009). It was also consistent with theories of human decision-making, and trends seen in studies of expert and non-expert clinician diagnosing (Durning et al., 2015; G. A. Klein et al., 1986; Lesgold et al., 1988; Patel et al., 1990; Popper, 1963).

Tendencies to allocate patients to AEC could be modelled as a continuous parameter with increasing allocation as expertise developed. Consultants on the case study site were at different stages of their consultant career. Their expertise varied according to time spent in the department as a consultant decision-maker. A lesser degree of expertise was seen in trainees, again on a continuum according to time spent training in acute internal medicine (AIM). Decision-making could be modelled on a continuum amongst medically trained staff reproducing a tendency for clinicians to allocate different proportions of patients to AEC according to staff category with intra-category variation reproducing variation in time spent in the AMU. Trainees demonstrated some moments of decision-making that paralleled consultant decision-making. To reflect this, it was assumed that a greater variation of expertise occurred amongst individual trainees than in consultants. Those nearing completion of training were assumed to allocate patients to AEC at volumes consistent with early career consultants. Influence of the environment on trainee decisions was not observed so was assumed to be absent.

Nurse allocations could be represented by group behaviour in the model. The charge nurse group demonstrated no intra-group variation in decision-making, nor clinical expertise in allocating, nor trends towards development of expertise in medicine.

Firstly, as non-medical clinicians their scope for learning and feedback about clinical medicine was low. Secondly, there is a clear distinction between the roles and tasks expected of nursing and medical staff in the delivery of urgent care. Thirdly, charge nurses were responsible for multiple, simultaneous complex tasks leaving little mental bandwidth to devote to allocation decisions. Finally, they were observed to follow the same rules for allocating and allocated patients to AEC in consistently low numbers. In this respect, they demonstrated group-like and not individual variation in decision-making. This could simplify the model programming. There are exceptions to this in the form of advanced nurse practitioners (ANPs). As ANPs are trained clinicians, this researched assumed them to exist on continuum of expertise alongside trainee doctors. No ANPs existed on the site to study and confirm this assumption.

5.2.4 Summary

This chapter presented the results of the ethnographic study. It argued that data and findings were sufficient to reproduce staff allocation decision behaviours, the decision environment, patient activity, and organisational culture influencing outcomes of ESDM. This required simplification of a complex processes of human expert decision-making for modelling purposes. Departmental and hospital system outcomes at the mesoscopic level were successfully identified to inform model outputs with meaning to providers and staff. The data collected to inform patient outcomes representing health, well-being, and experience were few; however, they provided sufficient information to explore patterns in patient outcomes in the predictive SSM with some strong assumptions applied.

The application of the ethnographic findings as model inputs required strong assumptions that may limit internal validity and contribute to a limited generalisability of the SSM to other settings. The staff and system behaviours in response to overcrowding may differ in moments of very high occupancy or sustained overcrowding which were not observed. The resources available to assist with admissions avoidance (e.g., daily specialist staff reviews) may not be available in some hospitals. Other hospitals may prefer to promote rules and behaviours that mitigate overcrowding in AMU over adherence to urgent care access standards. Finally, the same degree of expertise in acute internal medical (AIM) may not exist in other teams delivering care. As a representative site, many features of the local department are likely to found in other hospitals. There are several reasons supporting this conclusion. Firstly, training in AIM and the development of acute medicine as a specialty evolved in a collaborative fashion across the UK. Secondly, clinician training and service development were collectively managed by the Royal College of Physicians and the Society for Acute Medicine. Thirdly, the philosophy and practice of safety in non-admission pathways for urgent medical populations arose from collaborative practice across the UK and flourished according to the local context.

6 The systems simulation model

This chapter summarises the systems simulation model (SSM) created to reproduce early senior decision-making (ESDM) on the case study site. The structure of the chapter follows the TRACE framework presented in Section 4.7.1. The first stage, 'Problem formulation', has been covered in detail in Chapters One and Two. The remaining stages of the TRACE framework are in presented in the order outlines with the exception of the evaluation of the conceptual model which has been presented first to to ease of understanding of the technical components of the model description. The design and development of the model are summarised in this chapter. A full technical description may be found in Appendix C. Key assumptions will be discussed throughout the chapter. A complete list of the assumptions is held in Appendix D.

6.1 Conceptual model evaluation

This section discusses the assumptions underlying the model design. Assumptions were predominantly generated via the ethnographic findings and the modeller's own knowledge of urgent care systems. All assumptions are presented in full in Appendix D. Only the key assumptions are presented here. Consistent with the ontological position of Critical Realism, the conceptual model was created to reproduce truth-like statements about ESDM events in different categories of staff. A balance between accuracy of representation and simplicity computational burden needed to be considered (Railsback & Grimm, 2019; Robinson, 2011, 2013). An overly simple approach could fail to usefully reproduce the object of study for the purposes of learning or prediction (Shannon, 1998); an overly complicated approach could render the relationship between parameters, emergent events, and modelled outputs impossible to extricate and accuracy of findings (Robinson, 2022; Shannon, 1998). The observed allocation decisions and the decision environment demonstrated many features of a complex adaptive system (Section 4.2.4, Table 4:2), e.g., self-management and self-organisation. Explanations for the observations could be abducted upon but not established as irrefutable facts commensurate with the philosophical lens of Critical Realism. Trends observed were sufficiently consistent with external studies to assume that simplifying the SSM to reproduce decision outcomes and immediate environmental influences via a simple 'if/then' logic would be sufficient for the purposes of the research.

The research sought to understand how the system came to be in its most recently known state as a function of allocation decision-maker behaviours. This required representation of the relationships between activities that lead to the emergence of the outcomes on the case study site. These are described in Figures 6:1 – 6:3. An overview of the entities and agents captured in the SSM is shown in Figure 6:1. Staff displaying individual allocation decisions (consultants and trainees) and those that display group behaviours (nurses) operated at the microscopic level. Their decisions led to emergent outputs at the micro- and mesoscopic level. Patients interacted with the system at the microscopic level upon referral and arrival, but formed collectives and generated outputs at the mesoscopic level.

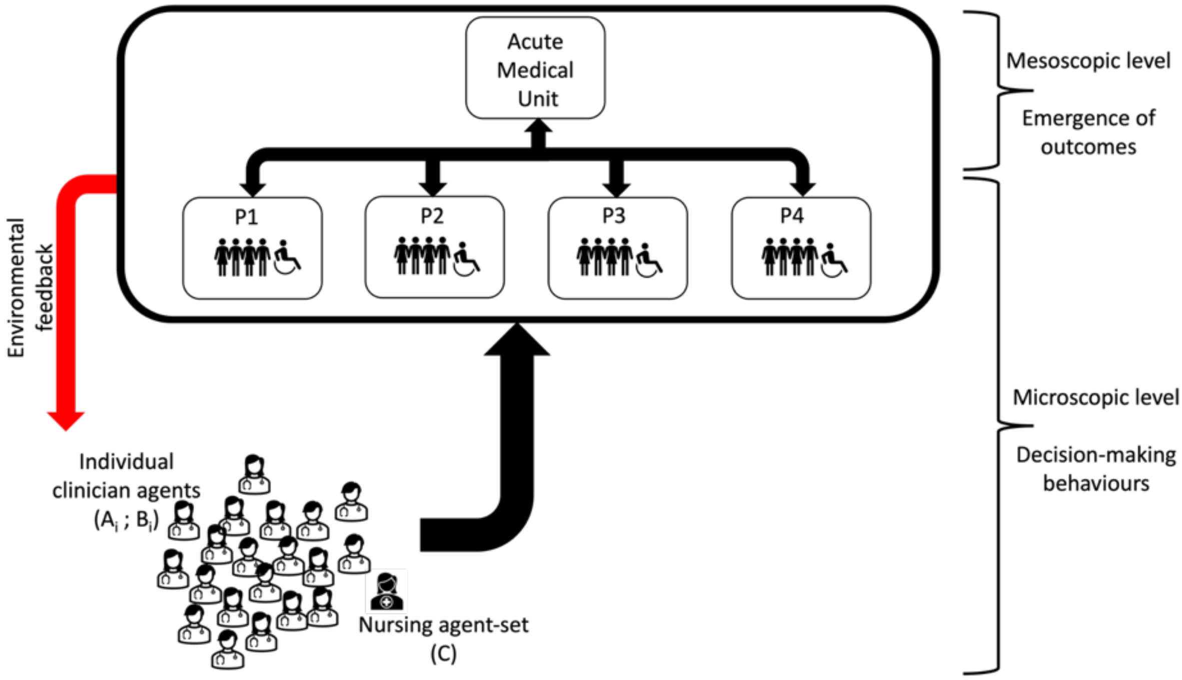
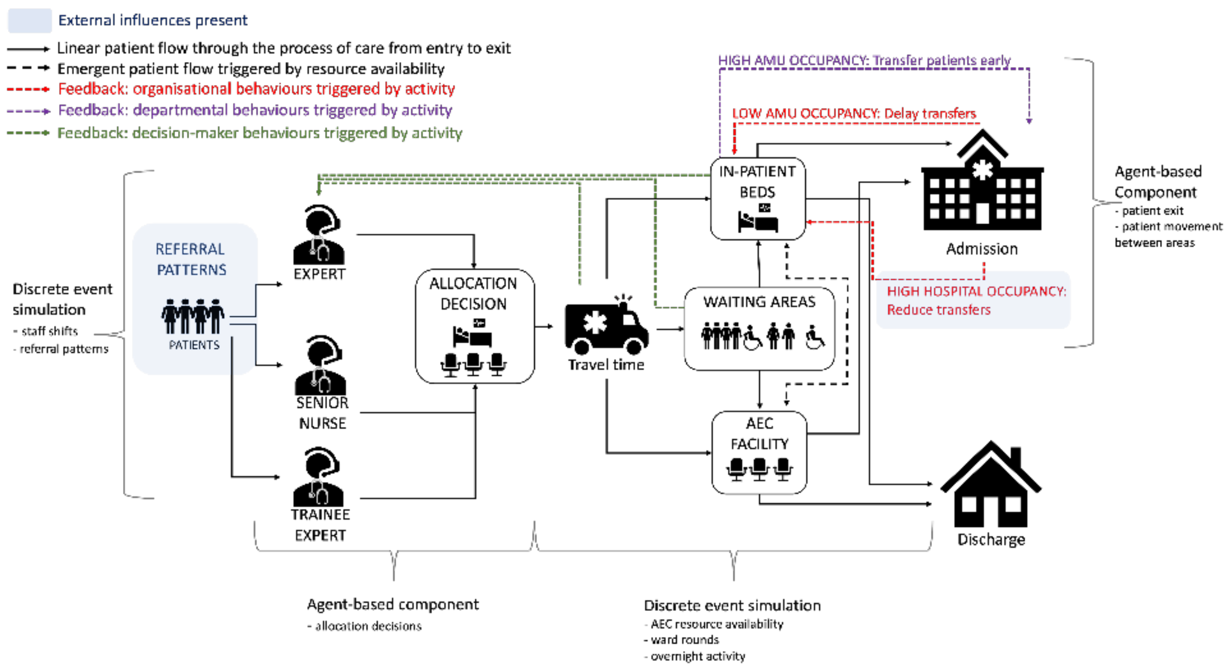


Figure 6:1 Microscopic and Mesoscopic levels

The model reproduced the influence of the microscopic behaviours of agents (grouped A - C according to staff category) on the microscopic agent-sets of patients whose behaviours are grouped according to area and outcome (P1-4). Patient activity and outputs provide the landscape of the department at the mesoscopic level. The number of agents in the expert and trainee-expert groups (A_i, B_i) is determined via the model user interface. Nursing staff (C) are programmed to display a fixed group behaviour throughout a model run and are represented by a single member of staff.

Figure 6:2 provides an overview of the flow, feedback, and external influences in the SSM. Patient entered the system and were allocated to a decision-maker (DM) according to source of referral and time of day. The DM then made an allocation decision about the patient's AEC suitability based on clinical need; however, if the DM was an expert, then the number of patients already in the department and anticipated arrivals was also considered. Patients were then delayed in arriving at the unit by their travel time (e.g., ambulance transport). Upon arrival, they access allocated area; if not available, they waited near that area until resources were free. If a bedded area allocated patient waited more than one-hour, they moved to any available AEC area to commence care before moving to a bed where available (indicated by the green dashed arrows). Once their treatment was complete a final disposition plan was enacted - transferred for hospital admission or discharged home.



AEC: Ambulatory emergency care

Figure 6:2 Flow and feedback created

An overview of patient movement through the modelled system is shown. The main agent-based and discrete event sections are highlighted. Patients enter the system with need determined at random. An allocation decision is made by their assigned decision-maker. Patients then wait to arrive at the system, before moving to their allocated area (the waiting area if no resources are available). Upon completion of care, they exit the model to the community (discharge) or transfer to a downstream hospital bed (admission). In periods of high occupancy, patient transfers may be inhibited or promoted depending on the area experiencing high occupancy. If a patient is placed in the wrong place for care, they will seek to relocate (emergent behaviour). This includes patients in the AEC at closing time. Allocation decisions of experts are influenced by departmental occupancy and expected arrivals.

Barriers and enablers to completing care and exiting the model were created (red and purple dashed arrows in Figure 6:2). These were triggered by emergent and scheduled events. Scheduled events not presented in the figure for ease of visualisation included morning ward rounds and overnight rules of reduced transferring. High AMU occupancy triggered identification of patients suitable for admission to transfer early, but high hospital occupancy (influenced by both AMU activity and activity external to the department)limited both the timing and the number of transfers from AMU.

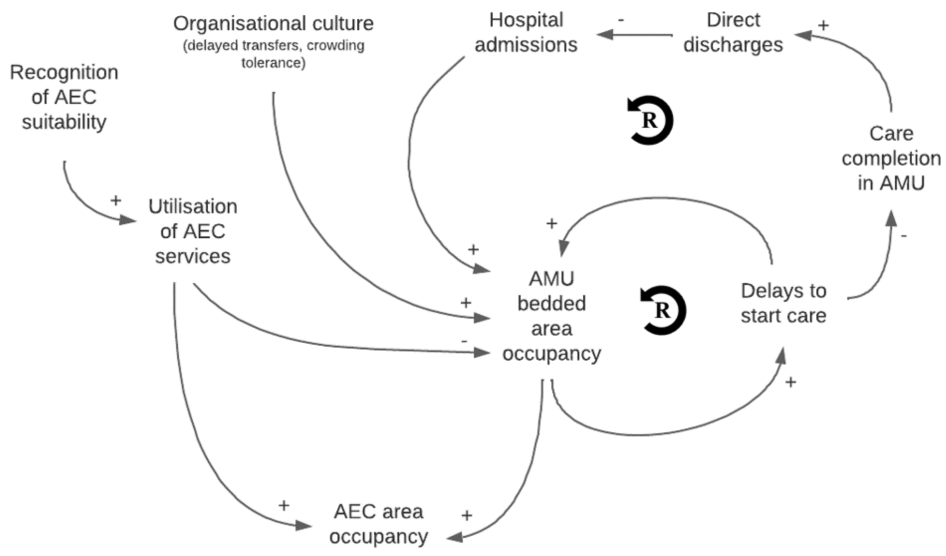
Figure 6:2 also provides a broad overview of how the ABM and DES components were integrated within the SSM; methods frequently overlapped to reproduce behaviours and movement. Patient arrival into the system was determine by DES (days and hours of peak activity are scheduled events in the model) but their presentation to a DM used ABM as they sought an alternative DM if the preferred one was not available. The presence of an expert DM was determined by the scheduling of staff at different times of the day, but their allocation decisions were an 'if/then' logic informed by patients, prevalence of AEC, their individual risk-profile, and emergent activity in the model (experts only).

Process of care were almost exclusively reproduced using DES methodology as were queues of patient represent occupancy levels (overall occupancy and in waiting areas). However, patients were modelled to autonomously decide when they were ready to leave the unit upon sensing care was complete. They also had autonomy in movement between areas during care, e.g., to access a bed if care was started in the AEC due to delays. Finally, some elements of the 'top-down control' approach of the DES elements adopted an if/then logic. For example, if there was a need to move patients early, then suitable patients were identified by a global entity in the model that altered the patients' variables to complete care early. The global entity also sensed how many patients were identified for early transfer to limit movement in unrealistically large batches.

A final element of the conceptual model not included in Figure 6:2 is the small volume of returning AEC patients. Returning AEC patient outcomes (including delays and lengths of stays) were not collected in the model. They were created to reproduce realistic competition for AEC resources between 0800 – 1600hrs per day as observed during the ethnography.

6.1.1 Emergence of inefficiencies

Section 2.3.1 (Figure 2:1), described how inefficiencies may arise from urgent care and in-patient hospital area interactions. Most notable was the emergence of overcrowding in the AMU when high hospital occupancy was present. The healthcare policies promoting ESDM wish to enhance utilisation of AEC via early expert decisions. This is intended to reduce AMU bed occupancy and mitigate the inefficiencies caused by overcrowding. The causal loop diagram in Figure 6:3 describes how recognition of AEC suitability is conceptualised to influence the environment and patient flow in the model. Poor recognition of AEC-suitability increases AMU bed occupancy, delays care, and whole system pressure via the transfer of patients who are yet to complete their AMU care episode (early transfer). Increased early transfers means fewer direct discharges (more hospital admissions). Because the hospital functions with consistently high occupancy levels, increasing transfers for AMU reduces bed availability for future AMU transfers. Because of this sequence of events, an organisational culture exists that seeks to keep patients in the AMU long enough to complete care and maximise direct discharges. This increases the risk of crowding/overcrowding emergence. Local AMU staff are complicit in this culture and use available AEC capacity to offset the risks of crowding/overcrowding in the bedded area.



AEC: Ambulatory emergency care, AMU: Acute Medical Unit

Figure 6:3 Emergence of inefficiencies in the conceptual model

The figure depicts the modelled emergence of inefficiency as a function of AEC-suitability recognition. Polarity indicates if an increase in the phenomenon at the start of the arrow increases/decreases the phenomenon at the head. As the figure shows, high AMU occupancy emerges via poor utilisation of AEC and an organisational culture that seeks to hold patients in the AMU long enough to complete care to realise direct discharge. As occupancy increases, delays to initiating care emerge as staff are overwhelmed. This reinforces high AMU occupancy (annotated via 'R' loop). To reduce AMU bedded occupancy, staff transfer some patients before care is completed. This action seeks to balance out the high AMU occupancy but leads to increased hospital admissions because the hospital constantly functions at high bed occupancy levels, limiting the capacity to transfer future patients in a timely manner, and creating a second reinforcing loop.

6.2 Model description

The overview, design, and development document (ODD) in Appendix C is a detailed outline of the rules and logic to behaviours in the SSM programming (Grimm et al., 2020). This is a highly specific document that outlines the rules and behaviours within the model, much of which is unnecessary to detail in full here.

6.2.1 Purpose

The model's purpose was to reproduce the outcomes of decisions to allocate some patients to AEC facilities at the point of referral into an acute medical unit. The case study site was chosen as a representative acute medical unit serving urban populations and urban with significant rural populations[16]. The model design was based on the findings from the ethnographic study of clinician decision-makers on the case study site (Chapter Five). Outcomes reflect efficiency in the local environment (departmental bed occupancy, delays to starting care, non-waste in AEC resources), and outcomes that impact efficiency elsewhere in the system (hospital transfers, transfers outside of usual working hours). Outcomes also reflect effectiveness of care via overall patient experience of receiving care in the department and the production of health in patients discharged from the department. The model was then used to explore how outcomes could change if staff with varying levels of clinical expertise were employed to make allocation decisions. The predictive modelling was intended to test healthcare policymaker hypotheses that expert decision-makers will realise the greater effectiveness in urgent care outcomes than non-expert decision-makers.

[16] Between 26% and 49% of the population residing in a rural area as per the UK government urban/rural classification (https://www.gov.uk/government/collections/rural-urban-classification)

6.2.2 Entities, state variables, and scales

A large number of entities and variable were required to programme the model to perform autonomous behaviours in agents, global organisational behaviours that impacted upon patient movement according to the environment, and scheduled events according to model ticks. This included global variables representing the organisational culture (e.g., tolerated level of overcrowding) and scheduled events (e.g., peak activity periods, opening and closuring times of the AEC facilities). For ease of presentation, all variable and entities are provided in Tables C:1 to C4 in Appendix C, The ODD protocol along with the landscape and high-level entities (e.g., beds and waiting spaces). Only low-level entity variables relating to decision-making, and patients are presented here.

Low-level entities within the model are decision-makers, decision-patches, and patients. Decision-makers (DMs)are created in one of three categories: consultant, trainees, and charge nurses. Each of these categories reflects a degree if expertise in acute internal medicine (AIM) and the staff most commonly involved in accepting patients referred into AIM systems. All DMs are created with variable reflecting their expertise in identifying AEC suitability in patients referred plus an additional risk-level variable that reproduces their comfort with allocating non-AEC suitable patients to AEC to mitigate overcrowding in the department. These variables reflect the allocation behaviours identified in the ethnographic and auto- analytic ethnographic study of decision-making (Chapter 5). Decision-patch variable are created to reflect the variables of the DM on shift at that moment for allocation decisions.

Patient entities have a large number of variable set and updated throughout the model run. They are assigned variables describing their health needs, source of referral, and time of referral set at creation. Other variables indicate their status in the model to facilitate their movement through the department and collect patient reported outcomes. For example, their anticipated time of arrival, delays experienced, their time to receive treatment time, and their disposition outcome (admission or discharge). Table 6:1 describes variables of the low-level entities in full.

The model ran with one tick (time-step) equal to one minute. Each of the scheduled processes was performed every minute. The use of one-minute time steps was justified by the rapid nature of change seen on the unit – time steps >5mins would have poorly reproduced the nature of activity and failed to adequately capture outcomes such as brief moments of overcrowding. One minute was chosen to ease programming of multiple scheduled events over 24hrs and seven days periods. The model was designed to run over a four-month period. The time horizon was limited by computational burden. Four-months was assumed by the researcher to be an adequate time frame detect trends in activity in the department based on her observations on the unit and her professional knowledge of urgent care delivery.

Table 6:1 Entities and state variables included in the model

VARIABLE	DESCRIPTION	FORMAT; NATURE; RANGE
	DECISION-MAKERS	
expert-adjust	Proportion of patients that a decision-maker determines suitable for AEC relative to population prevalence of AEC conditions	Rational number; static; 0.0 – 3.8
max-AEC-risk	Additional proportion of patients allocated to AEC when overcrowding is sensed.	Rational number; static; 0.0 – 0.15
	DECISION-PATCHES	
high-risk-adjust	Variable that allows a patch to adopt the max-AEC-risk profile of any decision-maker on that patch	Rational number; static; 0.0 – 0.15
expert-adjust-local	Variable that allows a patch to adopt the expert-adjust value of any decision-maker on that patch	Rational number; static; 0.0 – 3.8
	PATIENTS	
condition	Variable representing probability of an individual patient's condition being suitable for AEC	Integer; static; 0 - 1 uniform distribution
AEC-ok?	Variable that indicates suitability to attend the AEC area for care	Logical; static; true/false
ed	Variable indicating if patient has been referred from the emergency department	Logical; static; true/false
expert-dm	Variable indicating if the allocating decision-maker was a consultant or not	Logical; static; true/false
time_referred	Variable indicating model time when patient entered the model	Integer; static >0 (model ticks)
time_arrived	Variable indicating anticipated time arrival into the department	Integer; static >0 (model ticks)
aec-possible	Variable indicating if patient arrived during AEC opening hours	Logical; static; true/false
treatment_started	Variable indicated when patient started receiving care	Integer; static; >0 (model ticks)
treatment_time	Variable indicating time required to undergo investigation and care according to area and initial for-discharge value	Integer; static; 30-2150 (model ticks)
los	Variable indicating model time spent in the department from arrival to model exit	Integer; dynamic; >0 (model ticks)
delayed	Variable indicating model time spent in waiting to start treatment	Integer; dynamic >0 (model ticks)
time_complete	Variable indicating model time when care expected to finish	Integer; dynamic >0 (model ticks)
complete?	Variable indicating if patients is ready to leave the area	Logical; static; true/false
for-discharge	Variable indicating route of exit from the model	Logical; dynamic; true/false
final-area	Variable indicating area where care was predominantly received	Binary; dynamic; 0 or 1

6.2.3 Process overview and scheduling

The full schedule, including patient variable updates, is presented in Appendix C, 'Schedule'. A brief overview of the steps is presented below:

1. Model time check (overnight period and new day detection) to update resource availability, staff changeover, daily demand, patient plans according to resources availability, and ease of patient transfers
2. Patient creation and presentation for allocation decision at a rate determined by mean daily demand, time of day, and source of referral
3. Allocation decision according to patient variables and current state of the model (time of day, occupancy levels)
4. Patient progress through the model:
    a. if referred but arrived: countdown until arrival
    b. if waiting to start: look for a space and time delayed
    c. if arrived and allocated space available: start treatment and set end of treatment time
    d. If started treatment in the wrong place due to delays: find allocated resource
    e. if undergoing care overnight: adjust care plan to reflect reduced resources overnight and ward round reviews the next day
    f. if completed care: final disposition decision (admission or discharge)
5. Model exit process: store individual variables for model outputs and record outcome
6. Departmental occupancy check to detect system failure and redirect new arrivals

6.2.3.1 Scheduled events in the model

6.2.3.1.1 Patients' scheduled events

Patients underwent scheduled events that were influenced by the environment but not directly determine by them. Much of the patient progress was performed by a comparing modelled time with their unique variables and variables used to undergo scheduled events could be updated according to changes in the environment. For example, at the time of allocation, a time of arrival (*time_arrived*) was randomly assigned to each patient. Patients checked current model time with their *time_arrived* variable and appeared at the unit once it was reached. Upon arrival a time for treatment to be delivered (*treatment_time*) was randomly allocated and a time for care completion (*time_complete*) was calculated by adding the treatment_time to a variable that indicated the time of placement in a clinical space in the model (*treatment_started*). If patients were delayed in accessing a clinical space, they updated their variable *delayed* for each every time step they waited.

6.2.3.1.2 Scheduled events in the environment

The model used a countdown system to schedule events in the environment because there were no software packages to facilitate DES coding in the ABM programme chosen to build the model. This was made easier by using model time-steps equal to one minute, but required variables identifying scheduled events (e.g., the beginning and end of peak referral time) to be updated continuously through the model to ensure than scheduled environmental events and scheduled patient events occurred in the same time landscape (i.e., scheduled events had to be programmed to occur at the same time every day using a series of complicated calculations in the code).

6.2.4 Design concepts

A full description of the design concepts is presented in the relevant section of Appendix C. Here, the key aspects are summarised.

Emergence: Outputs that described departmental efficiency such as occupancy levels, delays, and lengths of delays emerged as the outcomes of allocation decisions led to networks of queueing patients in competition for resources. This was enhanced by competition from patients seeking follow up care in the AEC area (modelled to attend from 0800-1600hrs daily) and organisational behaviours that sought to prevent overcrowding in downstream areas by creating barriers to transferring patients form the urgent care area.

Competition and Queues: Because AMU resources were modelled to be finite, networks of queueing patients formed. Queues were represented by patients waiting for resources upon arrival. These patients were in competition with each other for resources and could sense how long both they and other patients had been waiting. Patients could also sense when beds were available and would move to them. This was an artificial behaviour created to simplify the modelling process and remove the need to separately model staff working in the department. In reality, patients would only be move between areas at staff discretion. Other artificial moments of patient sensing were created to reproduce non-DM staff actions (e.g., delaying transfer into the hospital during ward rounds)

Stochasticity was necessary to introduce in several key points to mimic natural stochasticity in urgent care; the clinical needs of patients, the expertise, risk-taking profile of DMs, and the rate of referrals into the unit were the most crucial to represent. Values were taken from distributions that represented plausible ranges in each instance. All instances of stochasticity may be found in the 'Schedule' and 'Sub-model' sections of the ODD in Appendix C.

6.2.5 Sub-models

There are many sub-models within the SSM. Full descriptions are held in the 'Sub-models' section of Appendix C. The key sub-models are described here to provide the reader with a general overview of how decision-making occurred, what influenced it, and how organisational barriers to capacity creation were reproduced.

6.2.5.1 Referrals and arrivals

Patients were passive entities but were programmed to enact system behaviours (e.g., would move through the model according to an 'if/then' logic mimicking staff decisions). This assumed that a referral allocations and disposal outcomes were consistent with their preferences. Arrival patterns were determined by the rate of referrals and the time taken to travel from their location. Referrals into the system were created via a Poisson distribution at a rate (λ) that altered according to referral source, presence of a weekend day, presence of peak/off-peak activity, and duration of peak/off-peak activity. Two values reflecting mean daily demand were set at initiation for weekdays and weekends. Model calculations are summarised in Table 6:2. Values set at initialisation are presented in Table C:5 in Appendix C. Peak referral time was assumed to occur between 0900 – 1800hrs (modeller assumption).

Table 6:2 Calculation of rate for Poisson distribution of daily referrals

POPULATION	SCHEDULED EVENT	PROPORTION REFERRED	ARRIVAL RATE (λ)[a]
eds (emergency department)	*Peak*	*mean-demand * peak-demand * peak-split*	*eds/duration*
	Off-peak (until 0300hrs)	*mean-demand * peak-demand * off-peak-split*	*eds/duration*
	Off-peak (0300-0800hrs)	*mean-demand * peak-demand * off-peak-split*	*eds/ (duration * 2)*
noneds (community and out-patients)	*Peak*	*mean-demand * (1 - peak-demand) * (1 - peak-split)*	*noneds/ duration*
	Off-peak (until 0300hrs)	*mean-demand * (1 - peak-demand) * (1 - off-peak-split)*	*noneds/ duration*
	Off-peak (0300-0800hrs)	*mean-demand * (1 - peak-demand) * (1 - off-peak-split)*	*noneds/ (duration * 2)*

[a]modelled time for the peak off-peak period set at user interface (fixed throughout model run)

eds: emergency department referrals; *noneds*: referrals from sources other than the emergency department

Patients recorded their time of referral (time of creation in the SSM). They waited until a preferred DM was available for their allocation. Non-ED referrals preferred consultant DMs but would revert to trainee DM when consultants were off shift. Patients referred from the ED preferred nurse DMs only. Safety rules to prevent loss of a patient due to long referral waits existed. Once a DM was available, allocation would occur as described in Section 6.2.5.2. Patients held their AEC-suitability in a logical variable (*AEC_ok?)* and an initial logical disposition decision (*for_discharge*) would be made using the AEC prevalence calculated via Bayesian inference (Section 5.1.1.2.) as shown in Box 6:1. Patients were then assigned a model time to arrive on the unit as shown in Figure 6:4. A full description of sampling distributions for arrival times is available in Table C:6 in Appendix C.

Box 6:1

Patients' initial disposition variables (*for-discharge* true/false) were determined by the logic as shown in Eqn. 6:1 and the calculated posterior AEC prevalence (*post_prevalence*) described in

$$\begin{pmatrix} true = condition < post\_prevalence \\ false = condition > post\_prevalence \end{pmatrix}$$

Eqn. 6:1 *for-discharge* logic

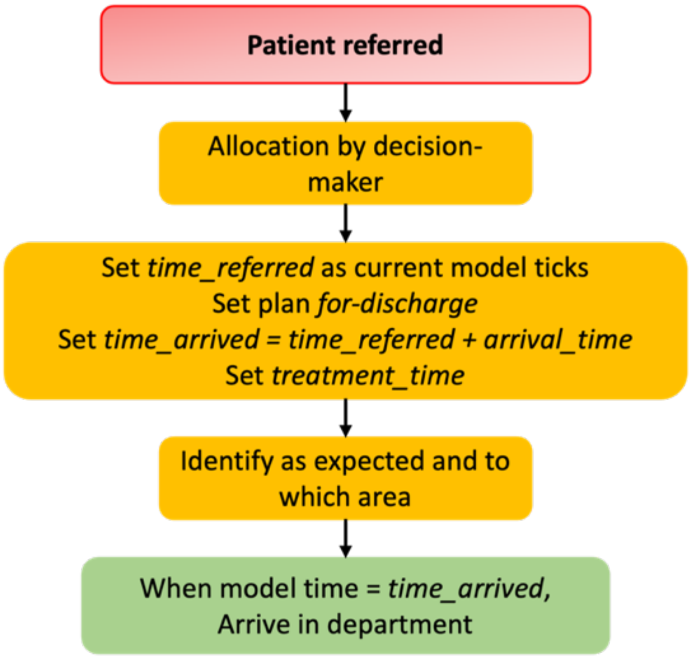


Figure 6:4 Patient activity at referral

Current and future model times were used to create scheduled events and reproduce patient movement in the environment. A unique *arrival_time* for each patient was sampled distributions according to source and allocation decision. Patient allocated to AEC were assumed to arrive earlier than bedded allocates. Patients from the ED were assumed to arrive earlier that non-ED sources.

Figure 6:5 provides an overview of the patient movement upon arrival. This summarises five separate procedures/sub-models ('*get-treatment*', '*relocate*', '*wait-for-*

resources', '*skip-queue*', and '*adjust-location*') described in Appendix C, Sub-models. Patient would sense resource availability in their allocated area, but would move to a waiting area when none was available and seek any space if waiting for too long. A system failure event occurred when all clinical and waiting spaces were occupied and would record every patient unable to enter the unit. System failure was seen as an extreme event indicating complete breakdown of the urgent care system. It also served to prevent the SSM from crashing in sensitivity analysis and predictive modelling.

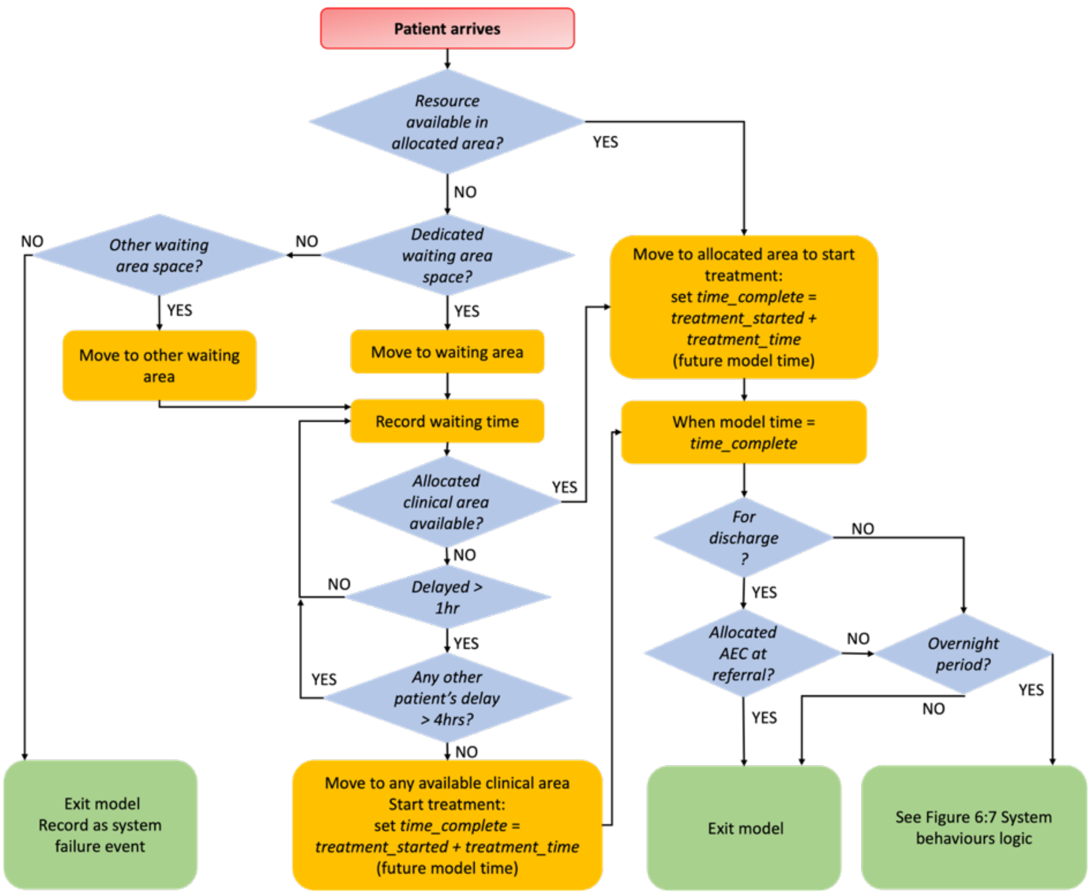


Figure 6:5 Summary of patient movement upon arrival

The figure shows how patients moved about the department upon arrival. Patients moved into allocated areas when space allowed. There were two separate waiting areas. Patients sensed their own delays and those of other patients. Bed-allocated patients who moved to AEC would seek to move to a bed when availability was sensed. System failure events occurred when no capacity to accommodate a new arrival existed. Each patient exiting due to system failure was recorded as a single failure event

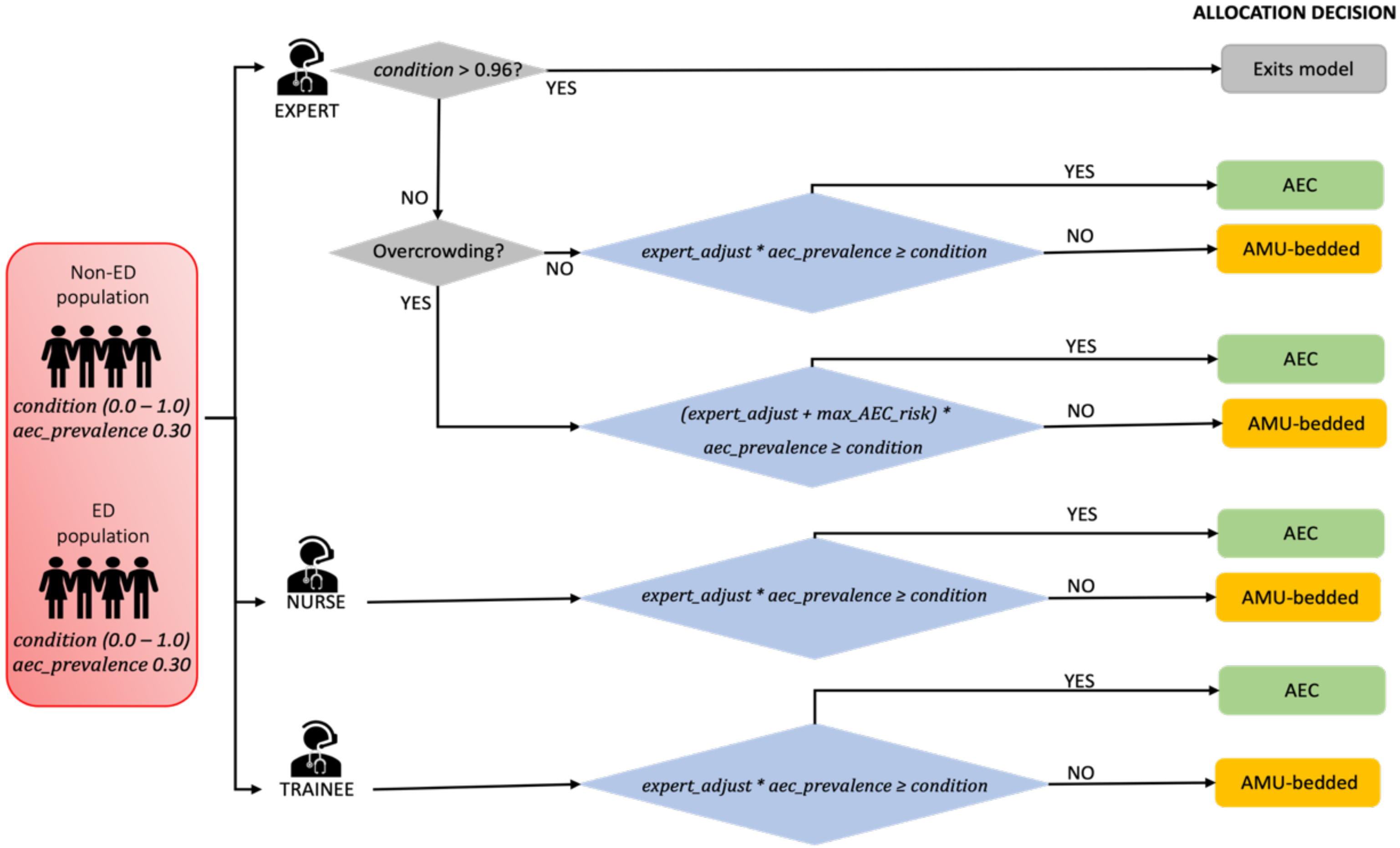
6.2.5.2 Allocation decision-making

Suitability for AEC was determined by DMs using four variables. Decision-makers combined their AEC recognition variable (*expert_adjust)* with the prior prevalence of AEC-suitability (Section 5.1.1.2) in the population (*aec_prevalence*), and the patient variable indicating clinical need (*condition*). As Figure 6:6 shows, allocation to AEC was determined by a logical expression using a calculated threshold. Decision-makers could increase this threshold by adding their *max_AEC_risk* to *expert_adjust* if overcrowding was present in the department or sensed by the number of expected arrivals. Table 6:3 describes the conditions for overcrowding to be sensed

Table 6:3 Conditions for overcrowding triggers

TRIGGER	DESCRIPTION	VALUE	SOURCE
Number of patients waiting for an AMU bed	Bedded occupancy >100% (overcrowding) triggers behaviour to prevent worsening overcrowding	≥3	Ethnography and modeller assumption
Expected bed allocations	Mimics desires of staff to proactively create capacity in anticipation of a large number of referrals arriving simultaneously	≥8	Ethnography and modeller assumption
Ratio of expected bedded allocations to current capacity	Mimics desires of staff to proactively create capacity current bed occupancy is high	>3:1	Ethnography and modeller assumption

Expert DMs would also trigger model exit for any patient with condition > 0.96. This reproduced the consultant-only behaviour of preventing attendance of patients judged as non-urgent. The non-urgent cut-off was a modeller assumption based on observations. Use of prior AEC prevalence reflected the DM opinion of AEC suitability rather than posterior prevalence calculated in the population. Posterior AEC prevalence was used for discharge decisions at a later stage in the model.



ED: Emergency department; AEC: Ambulatory emergency care; AMU: Acute medical unit

Figure 6:6 Allocation decision logic

The figure shows the decision logic for allocating patients to AEC or a bed upon referral. Patients would be allocated to a decision-maker (DM) according to source and time of referral. The DM would then use the value of their own expert_adjust variable and the aec_prevalence of the population the patient was referred from (ED or non-ED) along with the unique patient variable (condition) to allocate. Experts could identify patients suitable for non-attendance (exit model) and adjusted their threshold for AEC allocation if overcrowding was sensed

6.2.5.3 Care completion and model exit

Provided no delays were imposed upon patients, model exit occurred once a final disposition review occurred. A final disposition decision upon completion of care was performed to reflect the uncertainties inherent in urgent care, daily variation in resource availability, and the limited accuracy of early discharge predictions. Patients identified to move early for capacity creation did not undergo this process on the assumption that care processes were incomplete. A final disposition decision occurred via a reporter (*final_plan*) that randomly assigned each patient a value from 0 - 1.0 at time of completion and evaluated it against the probability of discharge/admission for each area as shown in Table 6:4. Discharge and admission probabilities from each area altered daily to reflect variation in the system's ability to facilitate discharge (e.g., diagnostic imaging availability, transport, reinstatement of community care support).

Table 6:4 Final disposal decision

PATIENT COLLECTIVE	REPORTERS	***for-discharge*** LOGIC	RATIONALE
AEC-ok? = true with *for-discharge* = true	*random_aec_adm* 0.1 – 0.4 (random uniform) *final_plan* 0.0 – 1.0 (random uniform)	$\begin{pmatrix} false = final\_plan \leq \ random\_aec\_adm \\ true = final\_plan > \ random\_aec\_adm \end{pmatrix}$	Assumes admission avoidance varies daily according to resources
AEC-ok? = false with *for-discharge* = false	*random_amu_dis* 0.075 – 0.2 (random uniform) *final_plan* 0.0 – 1.0 (random uniform)	$\begin{pmatrix} true = final\_plan \leq \ random\_amu\_dis \\ false = final\_plan > \ random\_aec\_adm \end{pmatrix}$	Assumes admission but opportunities for discharge

6.2.5.4 System behaviours influencing model exit

This section describes the sub-models that reproduced the impact of system behaviours upon model exit. System behaviours were reproduced by modelling autonomous decision-making patient behaviours. This programming realistically reproduced moments when decisions about patient movement were (as the modeller assumed) made by staff on patient-by-patient basis. This was also less complicated to model. Thus, the reader should assume that descriptions of patient behaviours these are proxies for departmental and external staff decisions about patient movement.

Patients were modelled to represent external influence via:

1. Early model exits of patients for admission if
    a) a pre-determined ratio of expected bed-allocates to available capacity was breached (proactive)
    b) Bedded occupancy exceeded overcrowding tolerance (reactive)
2. Delayed transfer if AMU beds were deemed sufficient (overridden by behaviour 1a)
3. Delayed transfer-exit from 0300-0800hrs unless behaviours 1a or 1b were triggered
4. Delayed discharge-exit from 2300-1000hrs for bedded area patients (no transport)
5. Delayed model-exit of patients during the morning senior/specialist ward round

The behaviour logic is presented in Figure 6:7 with variable and values used in the figure described in Table 6:5

Table 6:5 Variables involved in reproducing system behaviours

Variable	Description	Value	Annotation
proactive-capacity-creation-threshold	Trigger for early movement of patients to free bed resources in anticipation of new arrivals Altered to reflect hospital occupancy in the if demand in previous 24hrs high	≤65 arrivals in the last 24hrs: 10* >65 arrivals in the last 24hrs: 15*	Q_t
Sufficient AMU-beds	If the AMU area is sensed to have > a predetermined number of empty beds, the hospital system will delay transferring patients to prevent overwhelming downstream areas. This behaviour is ignored if the anticipated capacity threshold is breached	Daytime period 6 Overnight period 6	*sufficient-beds-days* *sufficient-beds-nights*
Queue of expected AMU-bedded patients	Absolute number of expected bed allocated patients. Along with bedded area occupancy and capacity threshold used to determine if early moves should be triggered	dynamic	Q_{amu}
Unoccupied bed resource	Number of beds currently available in the AMU. Used to determine if hospital transfers can be delayed preventing overcrowding in non-urgent areas	dynamic	U_{amu}
Bedded area occupancy	Proportion of beds currently occupied by patients. Includes the waiting area to allow values >1.0	dynamic	O_{amu}
time_complete	Model time assigned to each patient upon commencing treatment. Indicates the model-time when they are ready to exit	Model-time	T_c
Ward round delays to departure	Time for morning review of patients. Transfers and discharges delayed pending consultant review/staff availability to organise departure	Truncated normal distribution $\mu = 300\ sd = 180$ Min. 60mins*	D_w
	Delay to discharge if allocated to the bedded area and completed care overnight (transport and safety logistics)	Uniform normal distribution 60-420mins*	D_d
Transfer delay of bedded patients	Delay to transfer when sufficient number of AMU-bedded resources available. Behaviour to mitigate overcrowding in downstream hospital wards.	Add 2mins for every model minute until AMU-bedded resources insufficient*	D_r
	Delay to transfer when identified as an early-move to create AMU capacity (create of downstream beds due to boarding etc…)	≤65 arrivals in the last 24hrs: 60-120mins* >65 arrivals in the last 24hrs: 10-70mins*	D_{em}

*source of values modeller assumptions

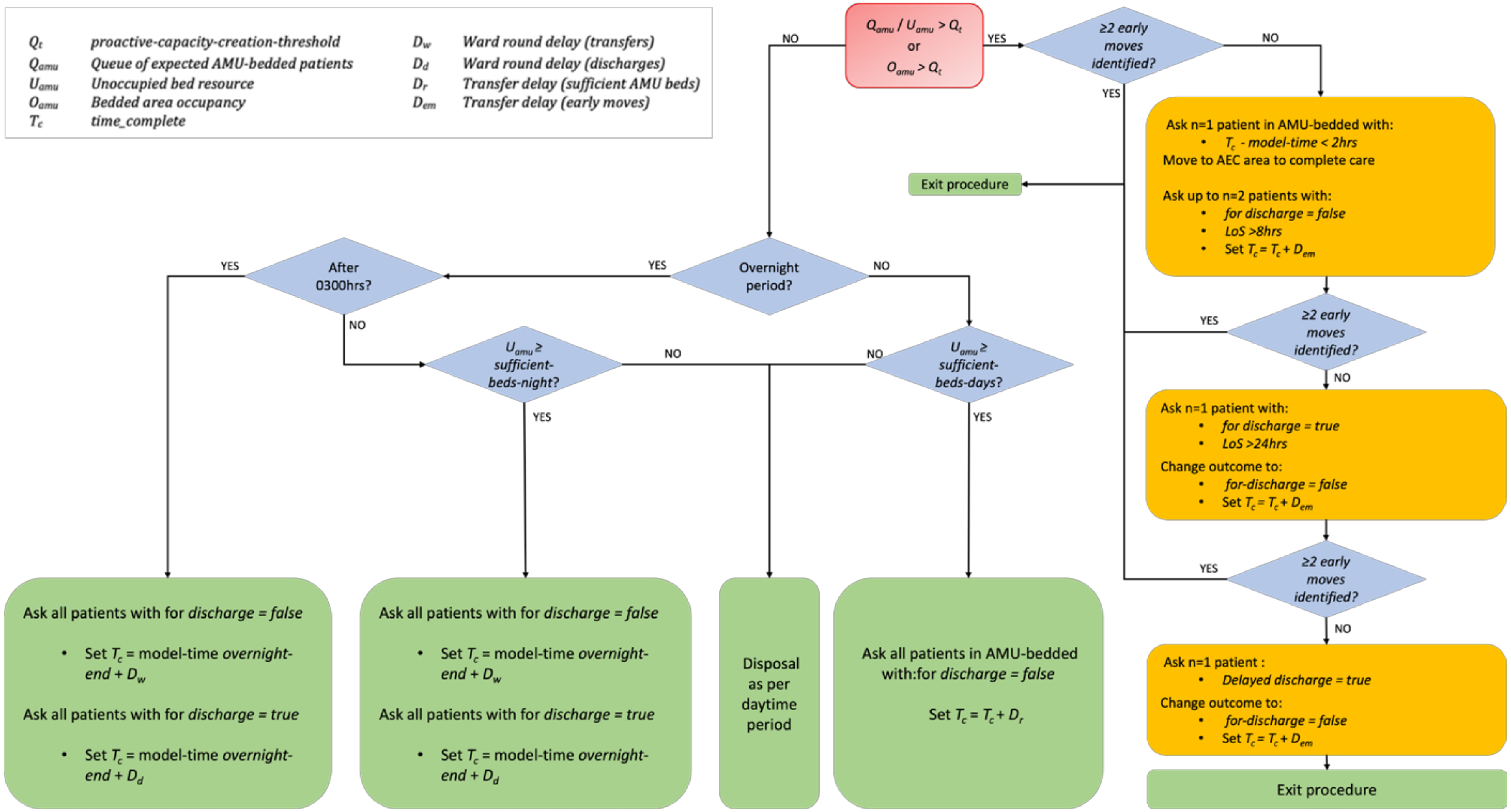


Figure 6:7 System behaviours logic

The red box highlights the conditions for capacity creation – threshold ratio of expected patients to available beds breached or overcrowding present.

Activity was evaluated at each model tick (1minute). Capacity threshold was checked at the beginning of each model tick.

Bedded area overcrowding check occurred at the end of each model tick. Delays were individually assigned to reproduce stochasticity

6.2.6 Patient reported outcomes

Sampling distributions for allocating a health index (HI) change were created using the mean and standard deviations of the HI data collected in the ethnography in (Section 5.1.2.2, Table 5:6). Health change values were only applied to discharged patients. This assumed that the prospective data collected was representative of health change in all patients discharged according to their area of care.

Patient experience was programmed as a binary phenomenon. Each individual patient was assumed to have a positive experience of care in the department (value=1) unless one or more of the following conditions was met:

1. Bedded area delay to accessing a bed >1hour
2. Length of stay (LoS) in AEC allocated populations >8hrs
3. Delay to starting care >4hrs in any patient

If any of the conditions listed were met, patient's recorded their individual experience value=0.

Patient experience values assumed that all AEC allocated patients were made aware of the potential for a LoS of up to 8hrs upon arrival and did not object to this. Eight hours was chosen to reflect the results of the initial patient experience survey and modeller assumptions of time taken to delivery care based on observed practice.

A cumulative score of patient experience as a proportion of all patients attending was collected in the departmental outputs at the end of model runs and presented as the proportion of patients who had left the AMU with a positive experience.

6.3 Data evaluation

Chapter Five provides an evaluation and critique of the data used to inform the SSM design and model inputs. Appendix B (Table B:5) presents the assumptions used in the data evaluation. Assumptions created on the basis of the data are presented in Appendix D.

6.4 Implementation verification

Implementation verification was carried out during model building and upon completion. This was an iterative process and continued until the model functioned as conceptualised with no coding errors. Verification including testing the sub-model functioning with extreme values to ensure that behaviours were consistent with those conceptualised and that emergent outputs were explainable.

6.5 Model output verification

This section describes the process of verifying that each element of the model functioned as designed to contribute to emergence of modelled outputs (Ormerod & Rosewell, 2006; Sargent, 2010). This was an iterative process of dynamic testing, pattern-orientate verification, and debugging performed as the model was being built and upon completion.

6.5.1 Visual inspection, interrogation, and pattern-matching

Output verification was performed as the model ran using the graphical user interface (GUI). This allowed the modeller to compare emergent activity in the simulation with the departmental activity observed during the ethnography and her knowledge of the case study site (e.g., demand, arrival, departure, occupancy patterns, and delays). A screenshot of the GUI is shown in Figure 6:8 to demonstrate how patterns were visually inspected. Model sensitivity and assumptions behaviours leading to modelled outputs were tested by altering parameter values and stressing the model with extreme parameter values to test predicted behaviours. For example, evaluating how the model functioned with unrealistically high demand which was hypothesised to rapidly lead to repeated system failure. Verification use descriptive statistics in modelled outputs and compared them with the October 2019 dataset. No tests of significance were performed.

In addition to pattern-orientated verification, random patients, and groups of patients with similar characteristics were followed through the model to study behaviours. Patient variables were interrogated at random stages of model runs to check for unrealistic patient parameter values and outputs compared with the October 2019 dataset and the modeller’s knowledge of urgent care activity (e.g., lengths of stay in excess of five days). Where found, the model was interrogated to understand how and why values had emerged. The model was recalibrated as necessary to ensure patient values fell within plausible ranges and expected ranges for extreme/rare external events (e.g., very long delays to transfer).

6.5.2 Stochasticity

The outcomes used to explore stochasticity were described in Section 4.7.4.1 (Table 4:8). All outputs met the minimal important difference (MID) within 100 model runs with the exception of length of delay in the bedded area. The preferred MID for this output was an IQR of 30mins - 100runs achieved 33mins. This was accepted as sufficient to minimise the computational burden of additional runs. The runs required to achieve the MID for length of delay meant that all other outputs came with very narrow confidence intervals (~0.002 for proportional outputs with a preferred MID of 0.05). The very high precision was borne in mind when analysing for differences in the sub-model and alternative staffing strategies outputs. Meaningful difference (0.05), rather than statistically significant difference, was determined more appropriate for hypothesis testing.

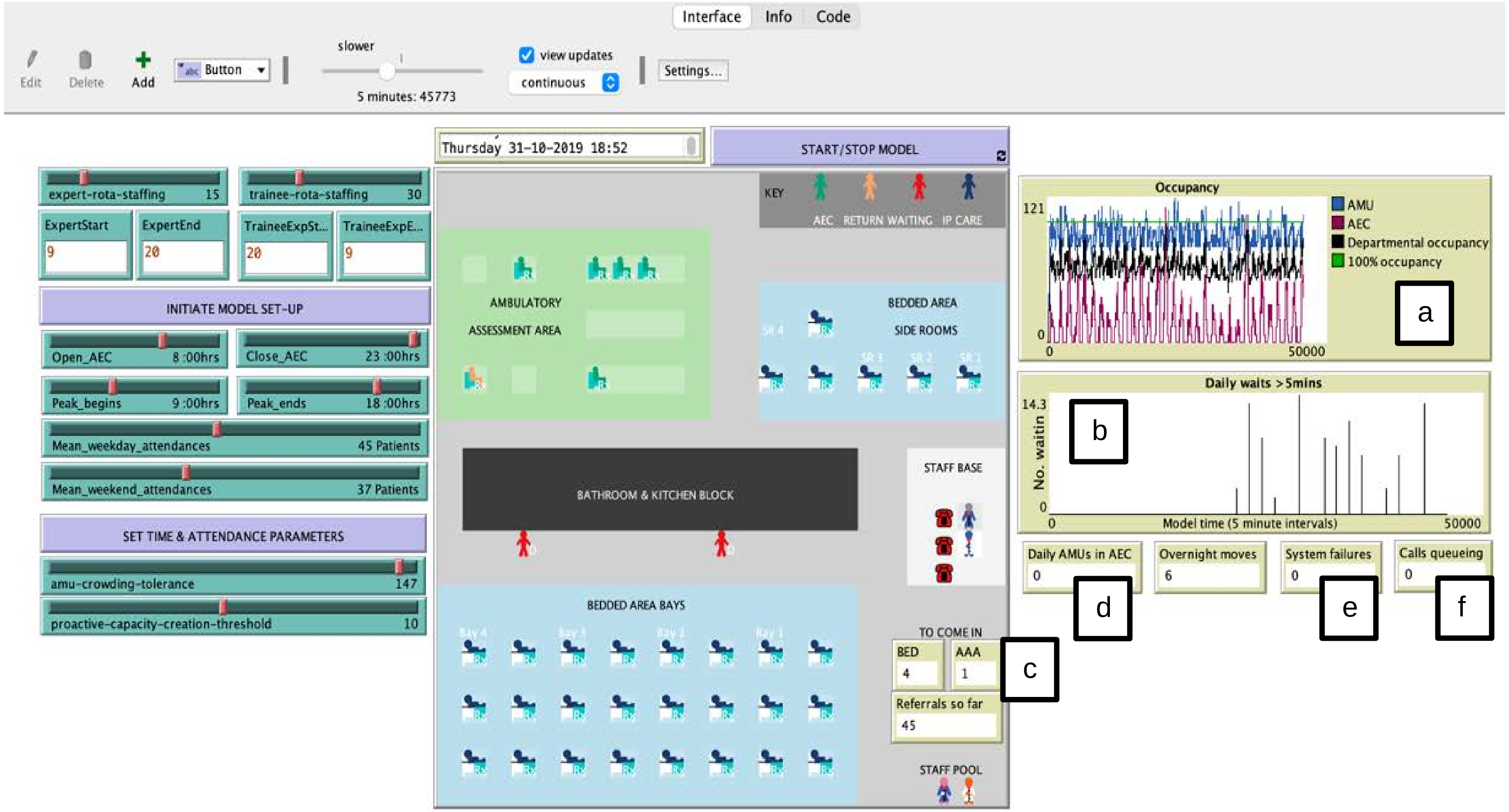


Figure 6:8 Graphical user interface (GUI) with live updates for departmental activity verification

Departmental occupancy levels (a) were recorded every model tick (1 min). Daily bed waits (b) were tallied at midnight. 'To come in' (c) provided verification of the trend of referrals and total number referred throughout the day (midnight to midnight). 'Daily AMU in AEC' (d) identified the number of bed allocated patients who moved to AEC to start care. 'System failure events' (e) occurred when all resources were exhausted as described above. 'Calls queueing' (f) was used to identify any referrals not addressed by staff indicating coding bugs. The GUI was also used to check patient movement through the unit by ensuring the shape and colour of patient agents matched the area and activity (key).

6.5.3 Alternative expert decision-maker sub-models

Alternative parameter distributions and rules were explored in the representation of decision-maker behaviours. This was performed to find the most useful reproduction of decision-making for the predictive modelling that minimised computational burden from overly complicated decision-maker rules. To do so, alternative sampling distributions informing the decision-maker parameter *expert_adjust* (the value used to detect AEC suitability) were created. Alternative programming options included running the different decision distribution samples with and without the expert decision-maker behaviour that increased allocations in the presence of overcrowding (the addition of the *max_AEC_risk* value). All other parameter values and behaviours were unchanged in the alternative sub-model testing. Expert rules to identify patients for non-attendance were maintained in all tested alternatives. Individual staff, created at the start of each model run, were programmed to maintain their unique propensity to allocate to AEC when on shift in all alternative sub-models explored. This reproduced the realities of a fixed pool of staff delivering care in the location across different shifts. The alternative sub-models and parameters are presented in Table 6:6.

Figure 6:9 presents the alternative parameter for expert and trainee described in Table 6:6 distribution in visual format to aid appreciation of the sampling differences. The deterministic Charge nurse allocations have been omitted from Figure 6:9 for ease of visualisation. Also excluded for ease of visualisation are the empirical distributions for the additional AEC allocations.

Table 6:6 Alternative parameter values for decision-maker sub-model

ALTERNATIVES	STAFF	PARAMETER	DISTRIBUTION/ VALUES	DESCRIPTION	RATIONALE
Option 1: NORM	Consultants	*expert_adjust*	Random Normal: μ1.2 *sd* 0.2 Truncated between 0.5 - 1.9	Individual value randomly sampled. Increase allocation in overcrowding	Moderate proportion of ambulatory allocations observed with individual variation in risk aversion. Truncated to reflect limits of ambulatory care and daily presence of some ambulatory suitability
		max_AEC_risk	Random Uniform: 0.05 – 0.15	Level of risk to increase non-usual allocations assumed nonpredictable	Modeller assumption
	Trainees	*expert_adjust*	Random Normal: μ0.0 *sd* 0.1 Truncated between: 0.2 – 0.5	Individual value randomly sampled.	Low proportion of patients allocated to ambulatory. Some trainees nearing consultant expertise. Truncated to reflect limits of ambulatory care and some ambulatory suitability recognised by trainees
		max_AEC_risk	0.0	Not observed to increase allocations	Modeller assumption
	Charges nurses	*expert_adjust*	Random Uniform: 0.0 – 0.1	Group value randomly sampled	Very low proportion of ambulatory allocations.
		max_AEC_risk	0.0	Not observed to increase allocations	Modeller assumption
Option 2: NORMNA	Parameters as above but consultant *max_AEC_risk* set to zero to prevent additional allocations				
Option 3: GAM	Consultants	*expert_adjust*	Random gamma: α8.0 β6.9 Truncated at 0.5	Individual value randomly sampled. Increased allocation in overcrowding	Potential that observed behaviours represent lower than usual proportion allocation. Truncated at the upper end by the limits of ambulatory feasibility, but includes staff who allocate very high-risk patients in overcrowding
		max_AEC_risk	Random uniform: 0.05 – 0.15	As before	As before
	Trainees	*expert_adjust*	Random Normal: μ0.0 *sd* 0.1 Truncated between: 0.2 – 0.5	As before	As before
		max_AEC_risk	0.0	As before	As before

ALTERNATIVES	STAFF	PARAMETER	DISTRIBUTION/ VALUES	DESCRIPTION	RATIONALE
	Charge nurses	*expert_adjust*	Random uniform: 0.0 – 0.1	As before	As before
		max_AEC_risk	0.0	As before	As before
Option 4: GAMNA	Parameters as above but consultant *max_AEC_risk* set to zero to prevent additional allocations				
Option 5: FIX	Consultants	*expert_adjust*	Deterministic value of 1.2	Group behaviour assumed	Computational simplicity and tests modeller hypothesis that individual variation in decision behaviours is large enough to have an impact on emergent outputs
		max_AEC_risk	Deterministic value of 0.75	Group behaviour assumed	As above
	Trainees	*expert_adjust*	Deterministic value of 0.24	As before	As before
		max_AEC_risk	0.0	As before	As before
	Charge nurses	*expert_adjust*	Deterministic value of 0.05	As before	As before
		max_AEC_risk	0.0	As before	As before
Option 6: FIXNA	Parameters as above but consultant *max_AEC_risk* set to zero to prevent additional allocations				

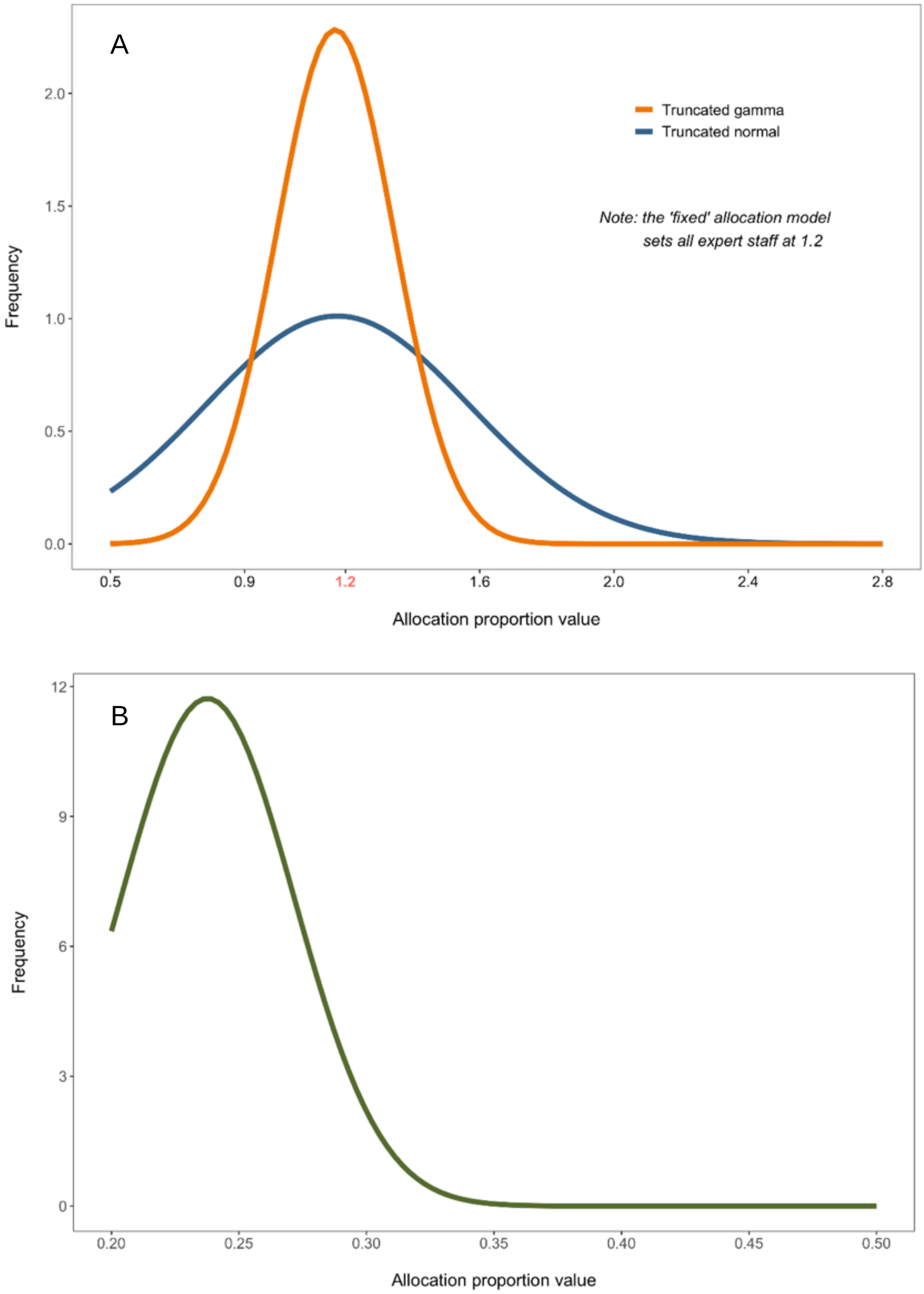


Figure 6:9 Sampling distributions for AVPs

Panel A shows the truncated normal distribution and the truncated gamma distributions tested to reproduce consultant allocations. All distributions produced mean expert allocation value of 1.2 (the value attributed to all experts in the fixed model). Panel B is the sampling distribution of trainee AVPs – note a small number will have AVPs that meet the lower expert AVPs. AVP for trainees in the fixed model was 0.2 and 0.05 for charge nurses.

6.6 Model analysis

Sensitivity analysis of the model is presented along with the finding and output corroboration in Chapter Seven (Section 7.2). Explanations for the emergent outcomes is provided in the discussion.

6.7 Summary

Chapter Six provided a detailed explanation of the systems simulation model created for the research question. It explained the conceptual model created to overcome the limitations of modelling the complex decision-events observed in expert clinicians, how the decision environment, and patient population that move through it would be modelled. It also provided the assumptions generated to achieve this. Several alternative parameter inputs and sub-models of decision-making were created to determine the most useful and efficient SSM to describe how departmental outcomes emerged via early allocation decision-making of experts on the case study site. The final model would be chosen for the third stage of the research - predictive modelling describing how departmental outcomes could alter with different decision-maker staff configurations.

Chapter Seven presents the final stage of the TRACE framework - validation of the explanatory model.

7 Results: Validation of the explanatory systems simulation model

This chapter provides the results of the explanatory component of the SSM. This validated its usefulness for predictive modelling. I demonstrated that the final SSM and chosen sub-model for decision-maker (DM) behaviours provided an acceptable representation of the state of the case site departmental activity as a function of the DM allocation behaviours. Recall that the research sought to reproduce the decision-maker behaviours and their outcomes on the case study site with sufficient representativeness to explore what would happen to the outputs if the staffing configurations changed. This considered trends of rising in demand on urgent care services across the UK and the unpredictable nature of resources available to provide care that avoid admission into hospital. The research had three main areas of enquiry:

1. Does the SSM reproduce the allocation decision behaviours at the level of individual patient allocation outcomes and departmental outcomes? (i.e., accuracy in determining and realising AEC suitability, utilisation of AEC facilities, patient disposal outcomes of admission or discharge)

2. Does the SSM successfully reproduce the activity of patients in the department? (i.e., the lengths of stay experienced and lengths of delays in the Bedded area)

3. Does the SSM successfully reproduce the decision environment in its influences on and its reactions to the DM behaviours (i.e., demand on the unit, arrival and departure patterns, and the local efficiency in freeing resources for new arrivals)

The results for the first two questions are presented in Section 7.1.1 via an exploration of alternative sub-model for DM behaviours. As the alternative sub-models exhibited largely equivocal performance, Section 7.1.2 presents the outputs pertaining to question three from the SSM with the chosen sub-model only. Section 7.2 presents the uncertainty in the structure and the model parameters that emerged via sensitivity analyses which should be considered when interpreting the predictive model results. The chapter ends with a discussion of the SSM performance overall – its strengths, and weaknesses, and their implications for the predictive modelling.

7.1 Model validation

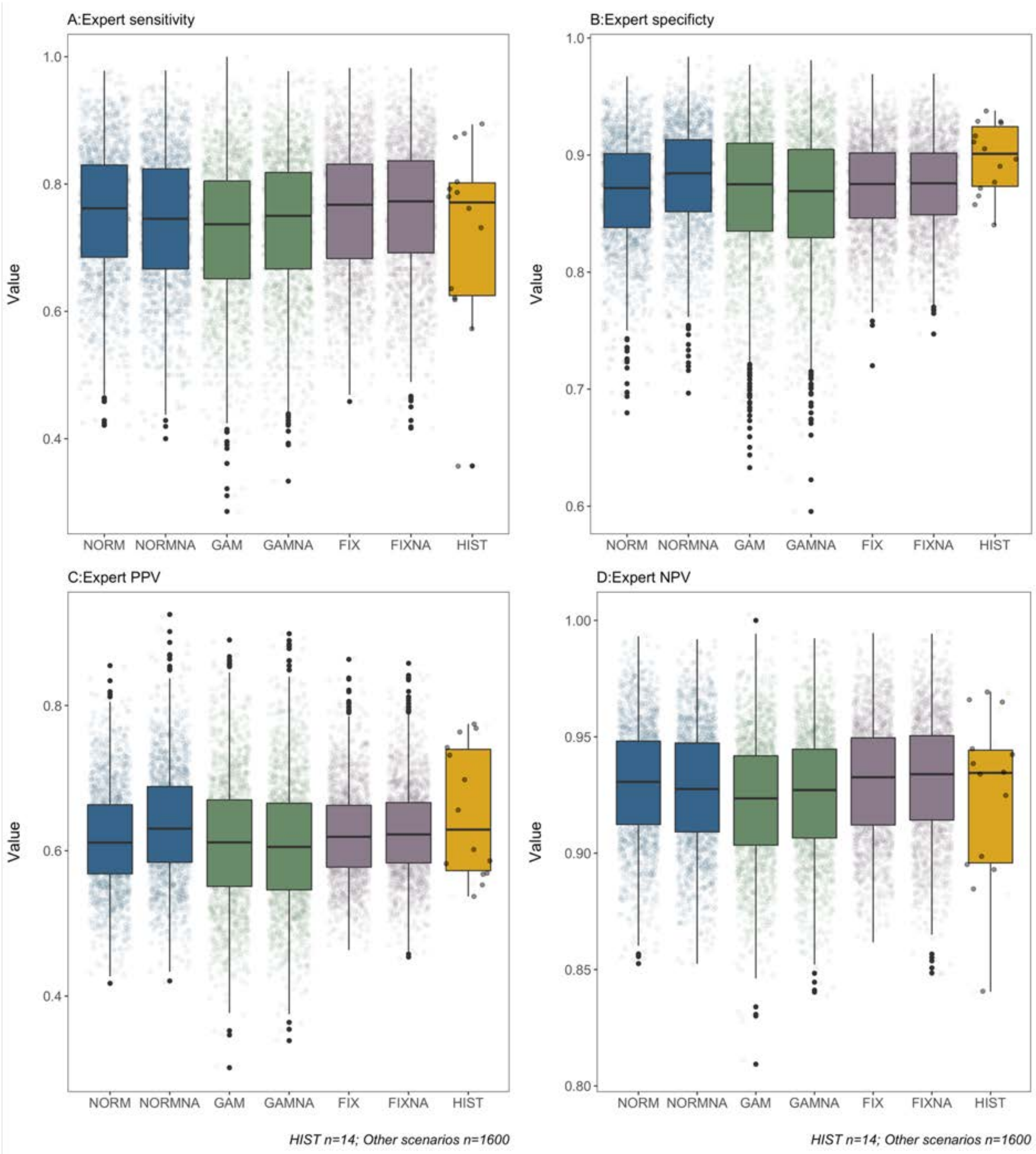
7.1.1 Decision-maker sub-models

This section compares the modelled outputs of the alternative decision-maker (DM) parameters/sub-models described in Section 6.5.3 with historical data from the case study site from November 2019 to end-February 2020. The annotations provided in Table 6:6 will be used to identify each modelling option throughout the section and in Figures. The section begins by analysing the sensitivity, specificity, and predictive values of the alternative DM sub-models before moving on to each sub-model's ability to usefully reproduce patterns of patient and departmental activity. Weekly outputs for sensitivity, specificity, and predictive values were necessary to minimise division by zero/of zero during calculations. [17] All other activity was analysed by daily outputs with the exception of delays experienced which were analysed s minutes delayed per patient minutes.

7.1.1.1 Reproducing decision-maker accuracy

The alternative sub-models (hereby called the sub-models) fulfilled the validation criteria – capture of the historical median within the interquartile (IQR) range of modelled outputs (Figure 7:1). Of note, the IQRs of the GAM and GAMNA sub-models mimicked the IQR of the historical data closely. Although this was not necessary for validation, it suggested drawing expert value for decision-making (*expert_adjust*) from a gamma distribution more closely mimicked the variation in outcomes, particularly moments of poor accurate identification of AEC suitability. Testing against the null hypothesis revealed showed no statistically significant difference between modelled outputs and historical data for all sub-models (Appendix E (Table E:3), confirming all six sub-model usefully reproduced accuracy of decision-making.

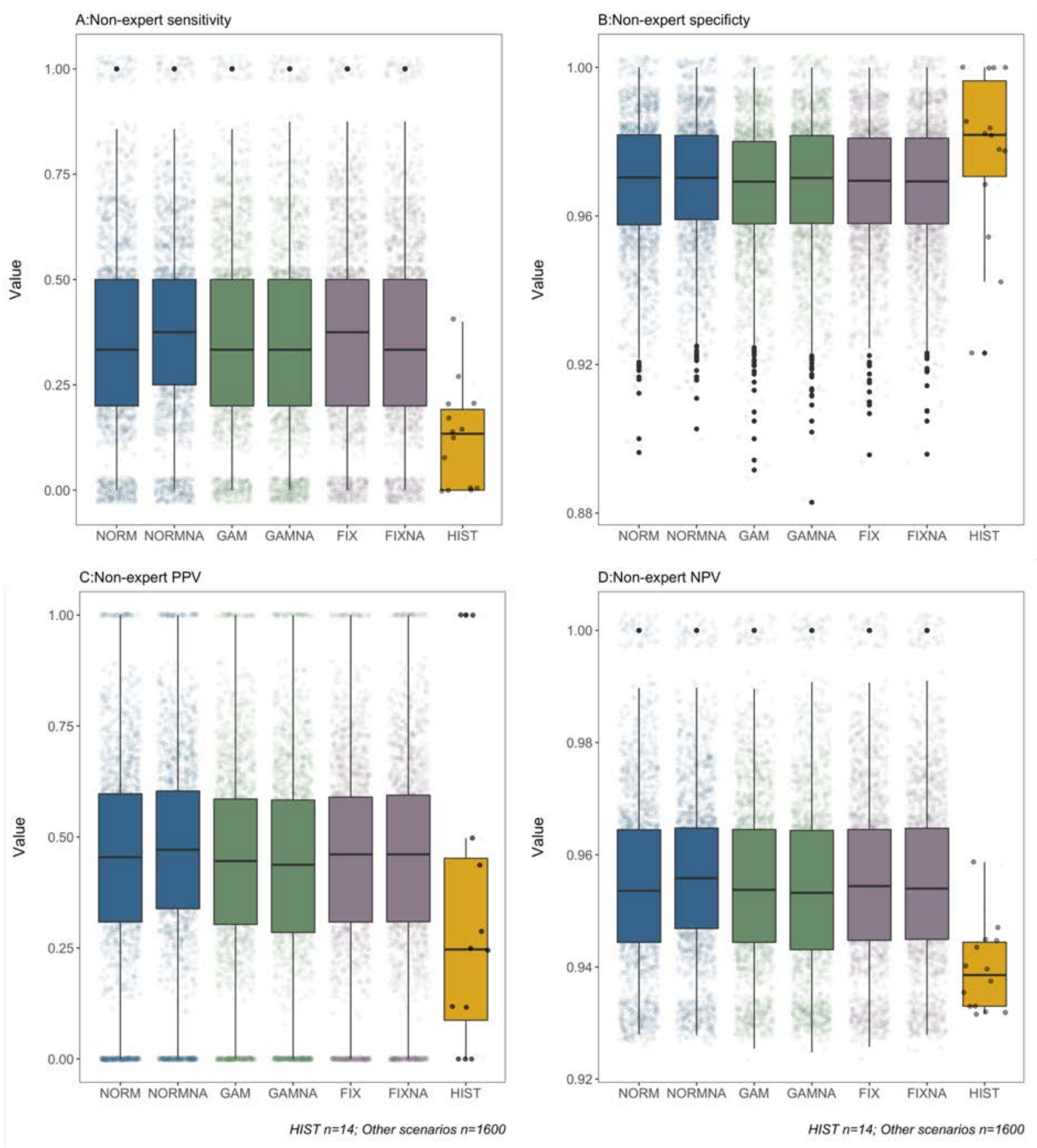
[17] Division by zero could occur if no events were observed in a day (e.g., no patients fulfilling AEC criteria). See Eqns. 4:1 to 4:4



PPV/NPV: Positive/Negative predictive values

Figure 7:1 Validation of alternative DM outputs: Weekly expert accuracy

Panels A to D provide a measure of each sub-model's (x-axes) ability to reproduce the accuracy of expert allocation decisions. The boxplots compare the interquartile ranges (IQRs) and the median values for each dataset (black line in the IQR box). Individual data points are also provided to compare the volume of data available in each dataset. Note the relatively small amount of historical data available for validation. All sub-models tested (NORM to FIXNA) capture the historical median (HIST) with their IQR. Note that the GAM and GAMNA sub-models most closely resemble the IQR of the historical data.



PPV/NPV: Positive/Negative predictive values

Figure 7:2 Validation of alternative DM outputs: Weekly non-expert accuracy

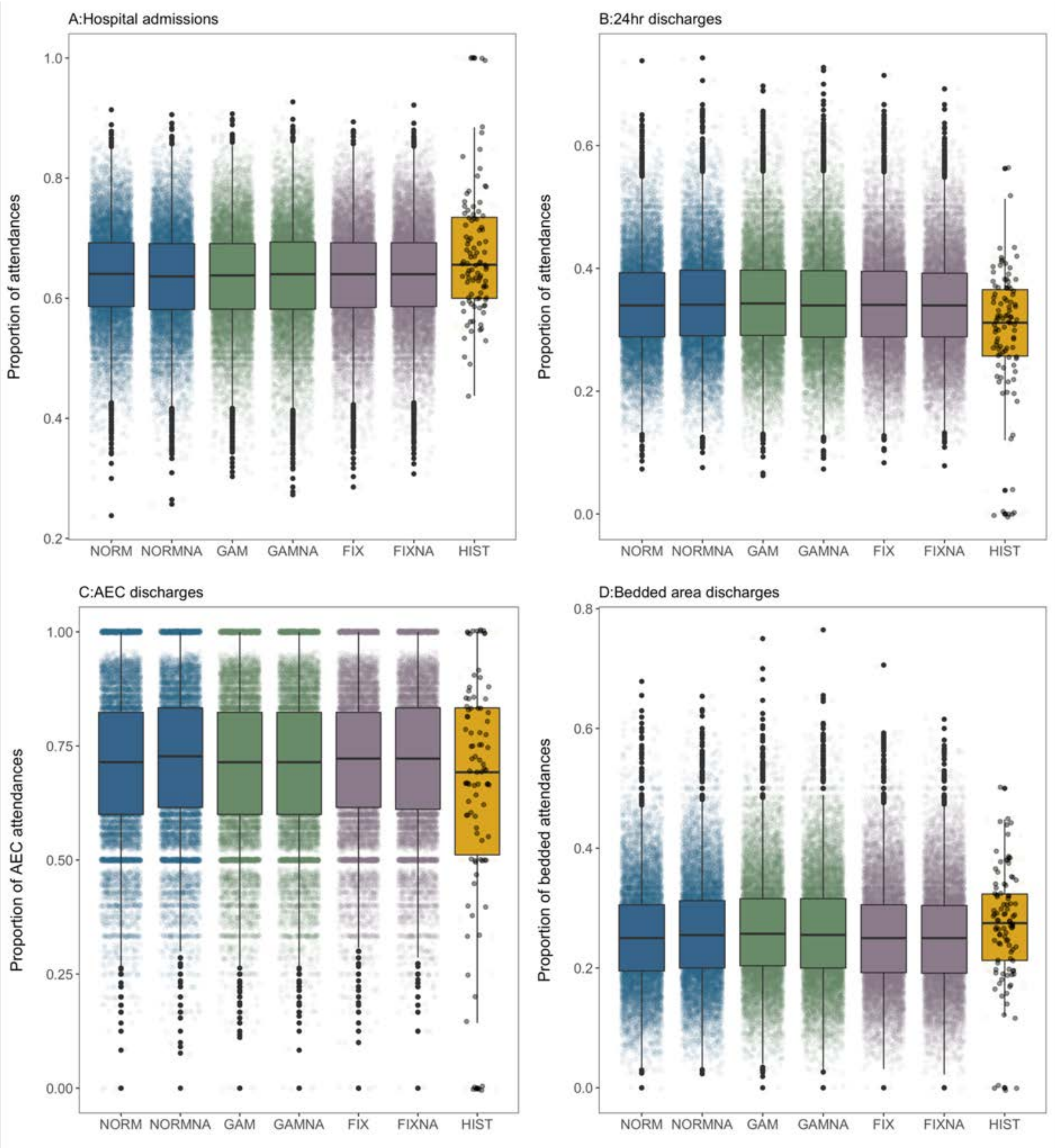
Panels A to D provide a measure of each sub-model's (x-axes) ability to reproduce the accuracy of expert allocation decisions. The boxplots compare the interquartile ranges (IQRs) and the median values for each dataset (black line in the IQR box). The median value in the historical data (HIST) was not contained amongst any of the sub-model IQRs (NORM to FIXNA). Note the large skew in the historical data (HIST).

Failure to capture the historical medians of non-expert decision outcomes within the modelled IQRs is worth commenting upon at this point. Modelled assumptions about non-expert behaviours in the overnight period (due to an absence of observational data) were likely to have been a significant influence, as was the decision to merge nursing and trainee decision-makers into a single group for analyses. An analysis of possible underlying explanations for the results in Figure 7:2 is presented in Section 7.3.2.

7.1.1.2 Reproducing departmental and patient level activity

All sub-models reproduced departmental activity to the desired levels for validation. As with the DM accuracy, validation required capture of the historical median with the modelled output IQRs. There was little difference in performance between the sub-models in this regard as Figures 7:3 to 7:4 demonstrate. However, there were significant differences in variation around the mean between the historical data and all sub-models with the exception of outputs reflecting hospital admissions (Figure 7:3A) and bedded area delays (Figure 7:4B). Results are provided in Appendix E, Table E:1

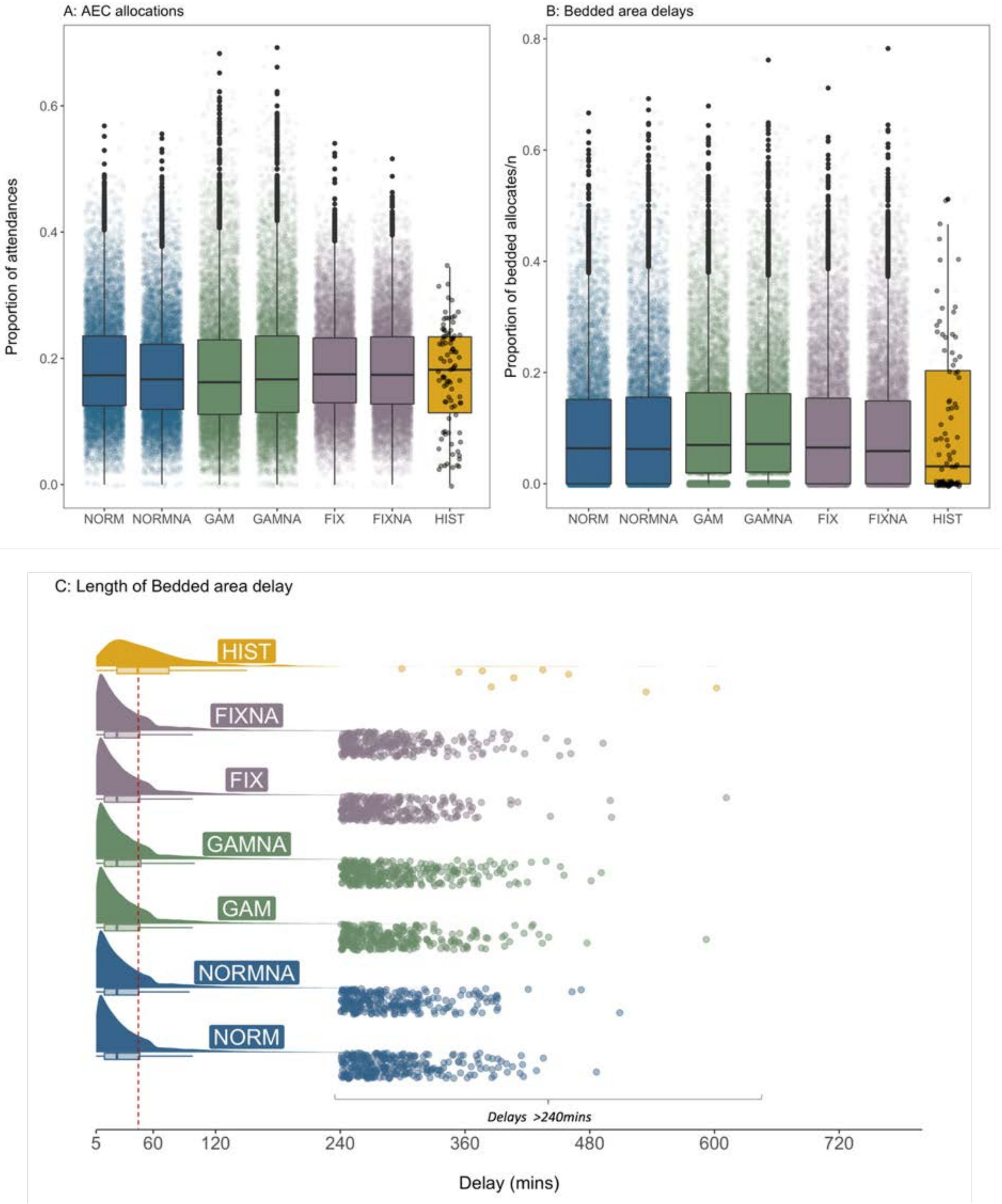
Modelled outputs of patient-level data met validation criteria for all outputs in all sub-models. Lengths of patient delays were underestimated by all sub-models, but Figure 7:4C reveals the median held within the IQRs in all cases. Lengths of stay for the four groups of patients (according to disposition outcomes and place of care) also met criteria for validation (Figure 7:5), but tests of variance revealed that the GAM and GAMNA performed – with no difference found in variance testing for LoS in two of the four patient groups (Appendix E, Table E:2).



AEC: Ambulatory emergency care *HIST n=90; SSMs n=11200 in all figures*

Figure 7:3 Validation of alternative DM outputs: Daily departmental outcomes

Panels A to D provide a measure of each sub-model's (x-axes) ability to reproduce departmental outcomes. The boxplots compare the interquartile ranges (IQRs) and the median values for each dataset (black line in the IQR box). Individual data points are also provided to compare the volume of data available in each dataset. Note that the IQRs of all sub-models (NORM to FIXNA) contain the median value from the case site dataset (HIST). The case site data showed some outlying days when no bedded area patients were discharged. This was not observed in the sub-model outputs



HIST n=90; SSMs n=11200 in all figures

Figure 7:4 Validation of alternative DM outputs: Daily departmental efficiency outcomes

Panels A and B provide a measure of each sub-model's (x-axes) ability to reproduce departmental outcomes. The boxplots compare the interquartile ranges (IQRs) and the median values for each dataset (black line in the IQR box). Individual data points are also provided to compare the volume of data available in each dataset. All models meet validation criteria for these outputs. Panel C is a raincloud plot combining a boxplot, data distribution curve, and individual data points. Data points have been restricted to only patients delayed >4hrs for ease of visualisation. Delays were underestimated in all sub-models, but the median value (45mins) was contained within all IQRs as shown by the dashed line.

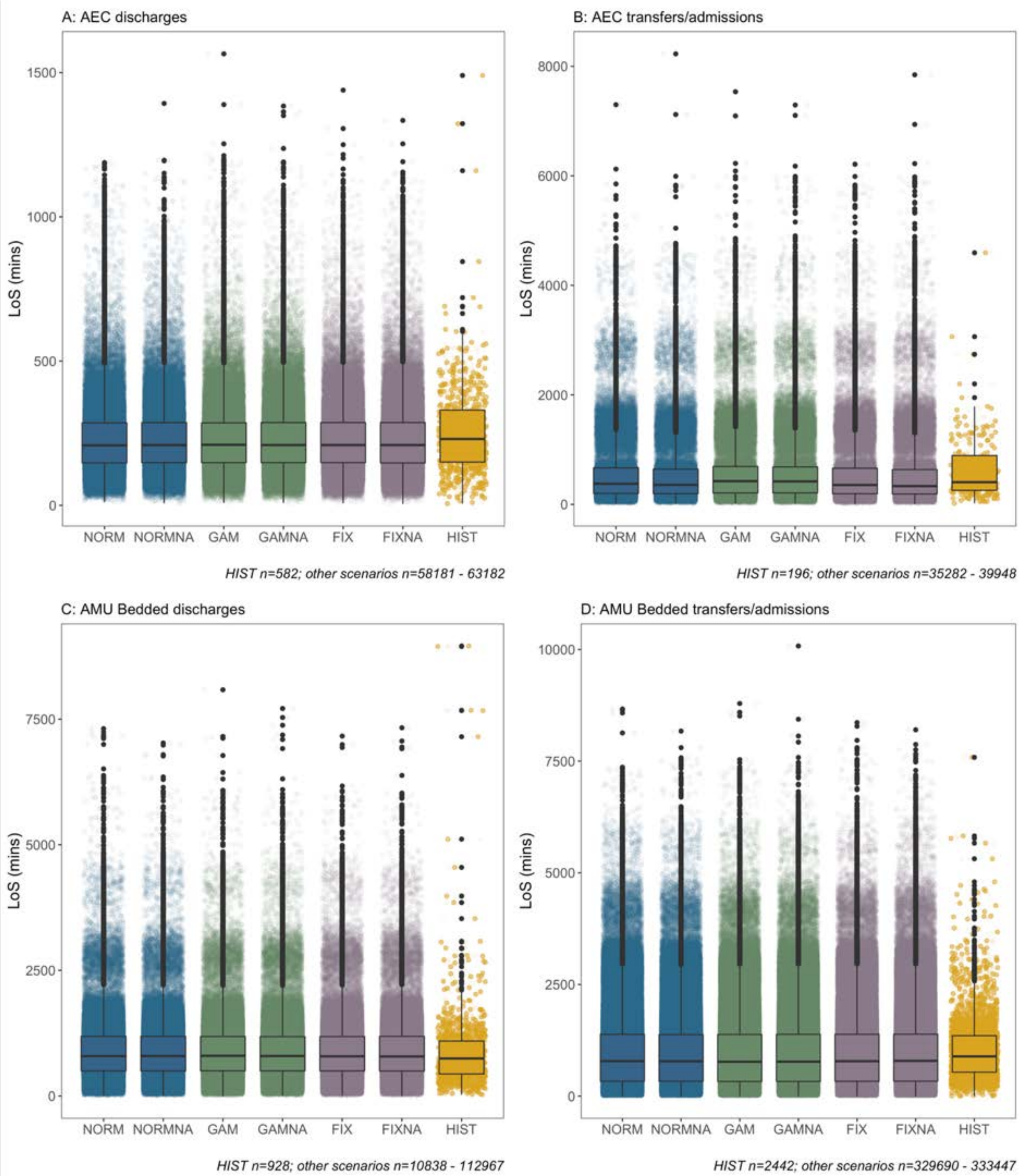


Figure 7:5 Validation of alternative DM outputs: Patient lengths of stay

Panels A to D provide a measure of each sub-model's (x-axes) ability to reproduce departmental outcomes. The boxplots compare the interquartile ranges (IQRs) and the median values for each dataset (black line in the IQR box). Individual data points are also provided to compare the volume of data available in each dataset. Dataset size varied between sub-models due to stochasticity of the referral rate. Each sub-model (NORM to FIXNA) met validation criteria with the historical median (HIST) contained within their IQR

7.1.1.3 Decision-maker sub-model choice

The GAMNA sub-model was chosen for the final SSM. This sub-model used a random gamma distribution without additional ambulatory emergency care (AEC) allocations by experts in overcrowding. With the exception of non-expert decision-making, all sub-models met validation criteria and would have been suitable to use in the final SSM for predictive purposes. However, the gamma distribution sub-models (GAM and GAMNA) closely mimicked most of the case study site data IQRs representing the accuracy of expert DMs. In addition, variance around the mean for non-expert positive predictive value was non-different to that of the case study site for the gamma distributions. This increased their usefulness when compared with the other sub-models. There was no difference in tests of variance between the gamma distributions for all outputs modelled, therefore GAMNA was chosen as removal of the additional allocation behaviour calculations was more computationally efficient. The remainder of this chapter presents the validation of the hybrid systems simulation model (SSM) using the GAMNA sub-model of decision-making. Henceforth, it will be referred to as the SSM.

7.1.2 The modelled environment

The SSM was designed to run over three-months of activity during autumn and winter excluding brief periods of unusual activity (e.g., festive public holidays) as there were not described as representative of usual activity and were short-lived. Winter months were chosen to reflect the gradual disappearance of seasonal variation in urgent care over the last 15 years (see Section 2.2.3). The SSM ran for 126 days with a warm-up period of 14 days during which time no model outputs were collected. A 14-day warm up period was chosen to allow the modelled department to go from a state of 0%

occupancy to a pattern of daily activity commensurate with the case site. This was determined upon visual inspection. Table 7: describes the activity reproduced over 100 model runs.

Table 7:1 Comparison of activity reproduced by the SSM and the case study site dataset

Output	Modelled environment	Historical dataset
Days of activity	126	90
Time horizon of activity	18 weeks	14 weeks
Patients attending	~7800 ~1500/month	4135 1378/month
Patients redirected without attendance	~10 per week	Not recorded

7.1.2.1 Demand and movement through the department

Daily demand was successfully reproduced in the SSM (Table 7:2). Outlying days of very high and low demand not seen in the historical dataset but realistically possible were also produced. ANOVA test for variation revealed no significant difference between SSM outputs and local data.

Table 7:2 Summary statistics for daily demand and analysis of variance

Data	Number	Mean	St. dev	95% C.I. lower	95% C.I. upper	Anova
CSM	11200	48.67	8.113	48.53	48.82	P 0.722
Historical	90	48.37	12.018	45.85	50.88	

The Kolmogorov-Smirnov tests in Figure 7:6 showed good pattern reproduction but statistically significant differences between the historical data and SSM outputs. This is not concerning for validation of an SSM for the research purposes but is explored in the discussion section of this chapter.

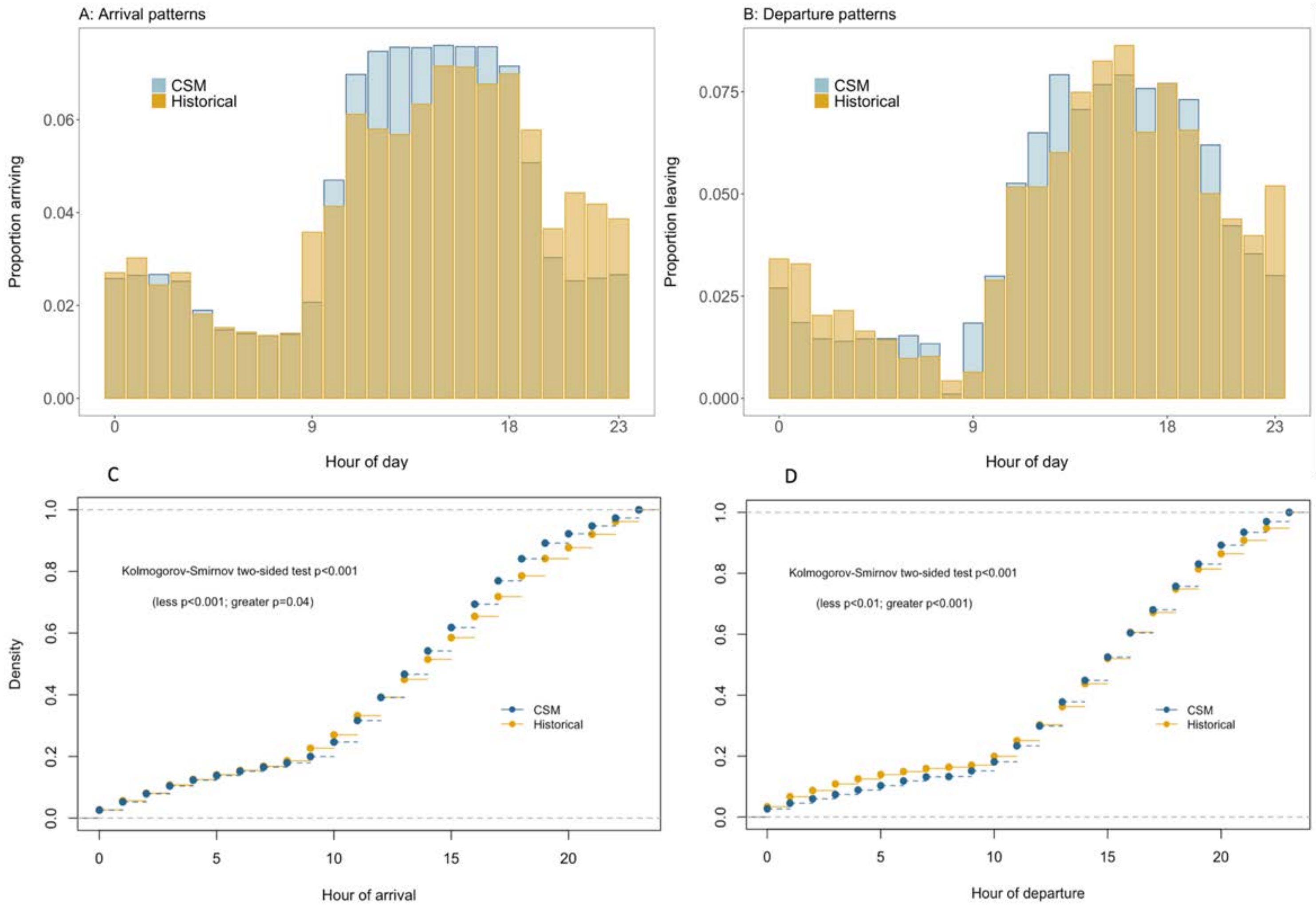


Figure 7:6 Validation of arrival and departure patterns across the department

The Kolmogorov-Smirnov two-sided test provides analysis of the variation between two datasets. Panel A shows the proportion of patients arriving at various time across a 24hr period and Panel B the proportions as they leave. The patterns are, subjectively, very similar, however, the KS test reveals that the dataset differ significantly in both directions, i.e., too many patients per hour or two few in the model compared with the case study site

7.2 Sensitivity analysis

Staff early allocation values (the parameter *expert_adjust*) had a weak influence upon modelled departmental outputs. AEC prevalence and daily discharges had the greatest influence. For the global sensitivity analysis, parameters observed to have a monotonic relationship to outputs were varied across a realistic sample space via Latin hypercube sampling (LHS). Partial ranking correlation coefficient statistic (PRCC) values and significance levels showed stability at 800 model runs. As Table 7:3 shows, the parameters that described external influences upon departmental activity (tolerance of crowding, ability to realise discharge) had a greater influence upon modelled outputs that the allocation decisions made prior to arrival in the model. This is consistent with the conceptual model and ethnographic observation of the real-world setting where staff decision-making was influenced by prevalence of AEC suitability in referred populations, but successful admission avoidance was dependent upon the department being able to realise discharges after evaluation.

A summary of the parameters and sample spaces explored is provided in Appendix E (Table E:4). Parameters with non-monotonic relationships were omitted from the GSA as they are not supported by the technique. Predictive values were omitted as they were directly calculated from sensitivity and specificity so may be assumed from the results provided by these. Analyses were performed on mean outputs at the end of model run to capture all patients in the model and prevent division by zero/division of zero when calculating sensitivities and specificities.

Table 7:3 Results of the global sensitivity analysis

Parameter[1]	24hr Discharges	AEC utilisation[2]	Admission	Bed waits	Overnight transfers	Patient experience	HRQoL[3]	Expert sensitvity	Non-expert sensitvity	Expert specificity	Non-expert specificity
expert_adjust (consultant)	-0.305	0.648	0.287	-0.169	0.537	-0.810	-0.307	0.385	0.111	-0.797	-0.376
expert_adjust (trainee)	NA	-0.109	NA	NA	NA	NA	0.079	-0.135	0.112	0.088	-0.220
expert_adjust (nurse)	NA	0.131	NA	NA	NA	NA	-0.082	0.094	0.249	-0.084	-0.317
noned_aec_prev	0.963	0.856	-0.961	NA	0.629	-0.559	0.888	0.597	0.304	-0.808	-0.763
ed_aec_prev	0.549	0.168	-0.542	NA	0.105	-0.104	0.395	NA	0.548	-0.074	-0.631
amu_crowding_tolerance	0.176	NA	-0.190	0.698	-0.733	-0.728	0.125	NA	NA	NA	NA
Proactive_capacity_creation_threshold	NA	NA	NA	0.431	NA	-0.251	NA	NA	NA	NA	NA
aec_admits	-0.840	NA	0.827	NA	-0.405	NA	-0.324	-0.309	-0.335	-0.627	-0.384
amu_discharge_plan	0.813	NA	-0.856	NA	0.280	NA	0.788	-0.445	-0.438	NA	NA
Mean_weekday_attendances	NA	NA	NA	0.405	0.120	-0.258	0.427	-0.088	NA	NA	NA

[1] as labelled in the model [2] Ambulatory emergency care [3] Health related quality of life

Negative sensitivity: increased colour saturation indicates stronger influence

Positive sensitivity: increased colour saturation indicates stronger influence

p<0.01 for all values indicating statistically signficant relationships; NA represents either no monotonic relationship or non-statistically significant monotonic relationship

The table provides the partial ranking correlation coefficient statistics for each of the parameters applied to the global sensitivity analysis (rows). The influence of a parameter (rows) upon each modelled output (corresponding columns) is given in relative magnitude and direction. Values (magnitude) may range from -1.0 – 1.0. Negative values indicate an inverse relationship. The table is colour-coded to allow easy identification of the most influential parameters in either direction. Strength of the influence of a parameter upon modelled outputs was determined via quartiles. The dominance of parameters informing the external influences upon urgent care activity - prevalence of AEC suitability, discharge/admission probabilities - is clear. Modelled outputs have weak-to-moderate sensitivity to the values used by decision-maker to allocate

7.3 Discussion: The explanatory systems simulation model

In this section, I discuss the results presented above. The final section summarises the SSM's usefulness in reproducing the case site AMU ESDM phenomenon for the purposes of predicting outcomes with alternative staffing scenarios before discussing the results for the key components of the SSM: decision-maker reproduction, environment reproduction, system behaviour reproduction. The two questions considered were:

1. *Did the SSM successfully represent the outcomes of urgent care when DM perform remote early allocation decisions?*

2. What were the models strengths and weaknesses to be considered when performing predictive modelling and interpreting results?

7.3.1 Summary of model validation

Excepting the accuracy of non-expert allocation decisions, the SSM was able to produce a pattern of outputs at multiple levels that satisfied the conditions for validation outlined in Section 4.7.4.3 (Table 4:9). As Section 4.7.4.3 explained, a pattern-orientated approach was the most appropriate method for validating outputs which were known to emerge from a dynamic and interactive human environment; this approach was commensurate with the use of agent-based modelling in the SSM (Grimm et al., 2005; Railsback & Grimm, 2019). The patterns chosen for validation represented outputs of sub-models within the SSM (arrival patterns, decision-maker predictive values, lengths of stay) as well as the predictive outputs (AEC utilisation, disposition outcomes, delays).

This facilitate validation of the internal structure of the model as well as its final results. There were no previous studies, additional data from case study site, or data from alternative sites to support validation beyond these measures. No data to validate the input distributions estimated by the modeller, such as travel time to hospital from referral, were available to enhance validation of the internal structure.

The SSM sufficiently represented the case study site as a function of allocation decision-making for the purposes of the research despite the weakness in reproducing non-expert DM accuracy. There were several arguments in support of this decision. Firstly, the successful validation of both the sub-models and modelled outputs provided in the previous sections overwhelmingly supported it usefulness in predictive modelling in all other elements. Secondly, the model for intended to provide a useful explanation for the state of the system and not an accurate representation of what were largely unknown processes of human decision-making and behaviours. In a domain where little knowledge resided, the SSM represented a theory of what may be happening in early allocation decision-making, how a system may respond to influence decisions, and the impact that individual decision-making may have at a departmental level. It was not intended to provide a definitive explanation of allocation decision-making and its outcomes. Finally, and related to the last point, the model was designed to reproduce the processes of allocation decision-making and the emergence of departmental level outcomes subject to external influences beyond the allocation decisions. The intention was to create an SSM that would function within a range of realistic contexts. Programming the model to reproduce an exact historical moment would have created a model with processes highly specific to that moment in time and not one capable of predicting how outcomes would differ with alternative circumstances. Nonetheless, the weaker performance in reproducing non-expert decision-making compared with experts warranted further consideration.

7.3.2 Non-expert decision-making

The SMM underperformed in its reproduction of non-expert decision-making accuracy. There were several possible explanations for differences in modelled versus real-world trainee decision-making which were not mutually exclusive:

1. Trainee decision-making may have altered overnight (not observed thus modelled using assumptions based on daytime behaviours).
    a. anticipated poor access to AEC resources and the absence of consultant supervision may have made trainees more reluctant to allocate to AEC overnight
    b. as medical staff were fewer OOH, there may have been a preference to place all patients in the same area for efficiency in work
2. Incorrect assumptions about the prevalence of highly performing trainees in the model based on the ethnographic study
3. Fewer higher-level trainees captured in the historical dataset than are present in real-life (meaning assumptions based on the ethnography were correct)
4. Fewer AEC-suitable patients presenting in the OOH period in the real setting than the model created. Patient self-selection – e.g., those with stable illness choosing to delay presentation – may had led to a smaller prevalence of AEC potential in the OOH periods in the historical dataset

The absence of observational data in the OOH period meant that assumptions about trainee decision-making had to be created. It is likely that, in reality, trainees made fewer AEC allocations than the SSM assumed. With no evidence to support altering the modelled behaviours OOH, trainees were assumed to perform as they were observed to during the day (AEC opening hours allowing). The differences observed in Figure 7:2 suggest trainees' behaviours changed overnight for reasons other than AEC opening hours, leading the model to overestimate their AEC-allocation tendencies overall.

A closer look at the modelled outputs also supports the suggestion that a wide variation of non-expert allocations in the validation dataset is another key factor in the performance of the SSM. Figure 7:2 revealed that modelled outputs demonstrated sufficient variation in non-expert decision-maker (DM) outcomes to capture the historical values within their output range. In addition, the historical positive predictive value (PPV) was highly skewed supporting the presence of high performers (expert-adjacent) in the dataset. This was assumed to represent a small number of higher-level trainee DMs in the historical data. If correct, this suggested that the modelled range, but not the distribution, of non-expert allocation decision outputs was realistic. This skew could also have arisen by misidentifying consultants as trainee DMs within the historical dataset (recall that the data analysis assumed the allocating DM according to shift patterns and patient arrival times - Section 4.7.4.4.1, Table 4:13). Against this last argument is the demonstration of consultant-level allocation decisions in higher-level trainees nearing completion of training. Trainee DMs may have been accurately identified in the dataset after all.

Validation of the modelled outputs was reliant on assumptions made in the analysis of the historical dataset about the allocating member of staff (Iooss & Saltelli, 2017). However, recalibrating the model to mimic the historical data risked underrepresenting trainees and their outcomes for three key reasons. Firstly, their decision-making during the usual working hours of 0900 – 2000hrs could have been different (as described above). Changing the modelled behaviours could have led to greater inaccuracies in prediction modelling had trainees been more confident in allocating to AEC during a time when supervision was present and resources supporting discharge were available[18]. Secondly, the real-world data could result from non-expert decision-making that is collectively more risk averse than the conceptual model assumed. The negative predictive values (Figure 7:2, Panel D) - accuracy in detecting patients for admission - were lower in the historical than the modelled data although differences were small compared with the PPV (<0.02 vs. >0.10). Considered along with the low median value for non-expert PPV, a higher than modelled NPV suggests that non-experts have a lower threshold for assuming a patient needs admitted than modelled. Thirdly, the small volume of data available to compare decision-making makes judging accuracy in real-life allocations of trainees challenging. More data would capture more trainees, but each could have a higher or a lower threshold for allocating to AEC depending upon stage of training. Of note, the hospital placed the same trainee doctor as decision-maker for three-to-four consecutive nights whereas nurse DMs and consultants DMs altered with every shift. Based on these reasons, the modeller determined that it was unwise to recalibration the trainee allocation parameter value (*expert_adjust*). Supporting this decision were the findings of the global sensitivity analysis - trainees' *expert_adjust*

[18] Concern about alternative daytime decision-making is not relevant to charge nurse behaviour in the model as they performed allocation decisions for ED populations across the whole day on the study site.

parameter had a weak influence upon modelled outputs. Recalibration risked greater inaccuracy without any real difference in overall research findings. Uncertainty in the modelled outputs of trainees would have to be considered in the predictive modelling.

7.3.3 Choice of the decision-maker sub-model and expert decision-making

All DM distribution scenarios met the validation criteria for reproducing expert decision-making accuracy but the sub-models employing a gamma distribution were superior. A finding of near equivalence was unsurprising as the mean *expert_adjust* across a single run was consistent amongst the scenarios (equal to ~1.2 and used as the deterministic value for the FIX and FIXNA sub-model). That said, providing stochasticity (via individual parameter values) was most successful in reproducing decision and departmental outcomes to a level of statistical significance in positive predictive values as well as the validation criteria.

Comparison of sub-model performance revealed that the programmed expert response to overcrowding (extra allocations) had little impact on the modelled outputs. Within the sub-models tested, there were two alternative distributions to sample from and one with a fixed value applied to all DMs in the same category. Each was tested with and without the additional allocation behaviour. Comparison within distribution choice (with and without additional allocations) showed non-difference in modelled outputs on both pattern-orientated comparison and upon tests of variance. This suggested that allocating large numbers of unsuitable patients to AEC was more prevalent in decision-making that consultant staff realised or described. In real life, allocation to AEC in high volumes could have reflected the observed tendency of some consultants to creatively test the out-patient capabilities of the system (Section 5.1.3.2). Alternatively, the desire to mitigate overcrowding and distribute workload across the whole department may have been more influential on their everyday practice than they realised or preferred to admit to. Placing unsuitable patients into the AEC could revealed hidden preferences to prioritise efficiency goals over individual patient's needs. Both explanations could easily co-exist. Regardless of the underlying reasons, the findings supported incorporating all observed behaviours into a single, individually assigned parameter and removing the expert DM overcrowding response would not impact upon the usefulness of findings. This eased the computational burden of calculating the need for increasing allocations to AEC.

Global sensitivity analysis informed the degree of influence that uncertainty in the *expert_adjust* parameter of experts had over the SSM outputs. Controlling for the prevalence of AEC suitability in non-ED populations and the variables that determine daily discharges (AEC admissions and AMU discharges), the influence of expert decisions upon departmental outputs was low. This reflected the observed the real-world setting and influences variation in admission avoidance capabilities observed in other settings (Irvine et al., 2022). Admission avoidance via AEC may be assumed to be more readily realised if patients attend a healthcare system that has the resources to meet those demands – for example access to computerised tomography (CT) scanning with 24hrs for a suspected pulmonary thromboembolism (PTE). If the proportion of the population with AEC potential reduces (e.g., a system with >24hrs delay for a CT reducing AEC suitability for suspected PTE or few AEC facilities), fewer patients will be allocated to AEC. If the proportion of patients capable of realising discharge that day reduces (a factor only partially dependent upon the location of care), then the allocation decision has less influence on the outcomes for AEC patients.

Patient experience was strongly, negatively influenced by consultants' *expert_adjust* parameter. This suggested that the higher AEC utilisation seen with consultants led to networks of queues forming as experience was modelled to be dependent upon time spent waiting or receiving care in AEC (consultant decisions had little influence on bedded area waits). The positive influence on patients transferred overnight (increased with higher AVPs) also supported the emergence of inefficiencies as overnight transfers largely emerged when occupancy levels were breached or when patients from AEC were admitted as facilities closed.

7.3.4 Reproduction of the decision environment

Arrival patterns were the direct result of model design with an element of stochasticity via sampling from the Poisson distribution at each point of the day and the patient travel time; departure patterns were emergent. The pattern reproduced were assumed to be valid reproductions for two reasons:

1. The historical data sample size was comparatively small (by a factor of >100) therefore limited in its capture of a full spectrum of activity
2. The intention was to reproduce the trends in arrival and departure behaviours observed rather than accurately reproduce patterns from a specific point in time

Events peculiar to days of the week – e.g., a slight increase in referrals on Mondays - were not specifically programmed beyond known weekend variations. This was assumed to lead to a more regular pattern of arrival activity in the SSM than would be observed over a short time horizon in the real-world setting.

7.3.5 Reproduction of system behaviours

Validation of the modelled outputs confirmed that the modelled rules around system behaviours were sufficient to represent those observed to have impact on departmental outcomes during the ethnography. These behaviours were reproduced by placing rules which could facilitate or delay patients leaving the department according to available resources. Although all the modelled outputs that system behaviours contributed satisfied the validation criteria, some were less representative than others - notably the proportion of patients forced to wait for a bed upon arrival. Related to the this was a tendency for the SSM to under the time each patient spent waiting. This may have resulted from the small volume of data available for validation which a larger sample size could resolve.

The conceptual model may have underestimated the extent of the barriers placed upon transferring patients SSM meaning proportion and lengths of delays in the predictive model may also be artificially low. Global sensitivity analysis revealed that the proportion of patients waiting was moderately sensitive to the level at which overcrowding in the bedded area was tolerated. This is understandable as higher levels of tolerance prohibited capacity creation in urgent care. Linked to the creation of capacity in the modelled was a delay time between identification of patient for transfer and leaving the department (model exit). However, overall lengths of stays for patients that emerged in the model were a good reproduction of observed lengths of stay in the historical data. Recalibrating the model to achieve closer approximation in delays was determined by the modeller to be unwise in view of this. However, underestimation in delays would have to considered when analysing the results of different staffing strategies.

Global sensitivity analysis also revealed that a higher tolerance of overcrowding had a weakly negative influence upon the number of admissions which is lower than was anticipated by the modeller. The direction of influence is to be expected as keeping patients in AMU for longer provides more time for direct discharge to be realised. The weakness of the influence suggests that the parameters with the greatest influence (AEC prevalence and discharge/admission parameters) have the greatest influence upon admissions. This is a realistic finding as resources available in a system (represented by the admission/discharge decision step) and the prevalence of AEC suitability the population it serves will determine the feasibility of direct discharge within the first 24hrs of attendance.

7.3.6 Discharge decisions

During model building, it became clear that basing the final disposal decision (discharge or admission) on the patient condition and AEC prevalence was insufficient to represent the stochasticity of urgent care outcomes. Although most AEC patients were discharged, observed variations in the availability of diagnostic resources, specialist staff support, and community resources to facilitate discharges were known to exist. These were difficult to quantify for model inputs and their true values could never be known at a granular level. To overcome this, I created two parameters in the SSM - the proportion of patients admitted from the AEC and proportion discharged from the AMU which altered daily and at random from a plausible range. These parameters has an expectedly large influence on departmental outcomes, but only a small influence on DM sensitivity and specificity because DM outcomes were also determined by time spent in the department. The impact of disposal parameters on patient HRQoL should be disregarded as HRQoL is dependent upon a discharge outcome.

7.3.7 Other considerations

The findings of the validation and sensitivity analysis raised some concerns about the usefulness of all the outputs chosen to reflect effectiveness in the final stage of the research, the predictive modelling. This largely related to those choice to model outputs as proportions rather than summative values and the reductionism necessary for creating a simulation model of the system. The healthcare leaders observed on the study site anecdotally referred to proportions/percentages of populations experiencing outcomes when discussing performance on the case study site (e.g., the percentage of discharges the previous day). The use of proportional values in modelled outputs was a deliberate choice as to create research findings with meaning to those with an interest in predictive modelling results. If was also necessary to compare outputs reflective of the stochasticity in activity. However, as proportional outcomes may reflect differences in the numerator and/or the denominator, interpretation of the results required all modelled outputs to be considered collectively. For example, the sensitivity of 24hr discharges to the consultant *expert_adjust* parameter but not to other DMs. Sensitivity analysis revealed that 24hr discharges would be lower when patients were allocated to AEC in high numbers by consultants because the model was programmed not to create barriers to transfer in those identified for admission in the AEC facility. Those awaiting transfer from the bedded area could face long delays meaning care could complete before transfer occurred and discharge realised. Those transferred from AEC could very well be discharged within 24hrs from their new ward, but the model did not include this.

A second consideration was the programming of activity in response to overcrowding. To ensure efficient model running, the transfer of patients from the AMU into the hospital assumed availability of resources for all transfers. To reproduce high hospital occupancy levels, delays were added. These delays may have been insufficient and overestimated the efficiency of the hospital system to transfer patients. This could have resulted in artificially numbers of patients delayed and/or a ceiling effect on the efficiency outputs that emerged. Programmed behaviours in response to overcrowding may also have overestimated the efficiency of AMU activity in general as neither the patient treatment times, nor the disposal plans were programmed to be directly affected. High occupancy levels have been shown to reduce effective admission avoidance in some locations and increase it in others (Blom et al., 2014; Gorski et al., 2017; Jung et al., 2021). Attempting to incorporate a behaviour that is not fully understood risked diminishing the credibility and usefulness of the SSM.

Finally, it is important to reiterate the inability to validate the patient-reported outcomes (PROM) and the hourly occupancy levels as no local data existed. These outputs were incorporated into the final stage of the research under the assumption that the successful reproduction of the decision and departmental outcomes were sufficient to support their use and reporting as useful in predictive modelling outputs. This aspect is discussed in more detail with the presentation of alternative staffing results in Chapter Eight.

7.3.8 Conclusions

The chapter presented the results of model validation and supported the usefulness of the SSM for predictive modelling purposes. It found that all validation criteria, but one, were successfully met. Recalibration of the model to address this was determined by the modeller to be unwise in view of the limited knowledge available to inform changes. The modeller accepted its tendency to overestimate the accuracy of allocation decisions as representative of how they would perform when the safety net of senior supervision and suitable access to resources was available. However, when comparing the findings of different staffing strategies caution would have to be applied. All departmental outputs modelled were found to be strongly influenced by parameters that represented the system's ability to provide care without admission. These were represented by the parameters involved in final discharge decision and the prevalence of AEC suitability in the populations presenting. This finding is consistent with the observed activity during ethnography and the researcher's extensive experience as an urgent care clinician.

The intention of the model was to usefully represent the system for experimental purposes. The next chapter presents the findings when the staffing strategy of allocation decision-making was altered from the one used on the study site, to strategies involving all expert, all non-experts, and combinations of staff.

8 Results: The predictive systems simulation model

This section provides the findings from the predictive modelling of different early decision-maker staffing scenarios. The purpose of the SSM was to reproduce departmental activity and outcomes that emerged as a direct result of the allocation decisions in different staffing scenarios. Outputs were chosen to reflect how staffing models may influence effectiveness. When interpreted together, the outputs chosen created a holistic picture of what effectiveness of care in the AMU means. The results are presented in four sections as described in Table 8:1 with a summary in Section 8.5. Discussion of the findings incorporating the results in Chapters Five and Seven and the extant literature are presented in Chapter Nine.

Table 8:1 Order of results presented

SECTION	MEASURE	DESCRIPTION	MODEL OUTPUT	MID
Section 8.1	Departmental effectiveness	Success in addressing urgent illness without need for transfer to-patient care	24hr discharges	MID: 0.05
			Utilisation of AEC	MID: 0.05
Section 8.2	Departmental efficiency	Ability to house new patients into their allocated area and immediately start care processes	Hours per week in crowding	MID: 560mins
			Hours per week in overcrowding	MID: 560mins
			Proportion of patients waiting	MID: 0.05
			Length of delay	MID: 30mins
			Incorrect placement	MID: 0.05
Section 8.3	System efficiency	Impact on resources in other hospital wards	In-patient admissions	MID: 0.05
			Overnight transfers	MID: 0.05
Section 8.4	Patient reported outcomes	The impact on patient-centred goals	QALY gain	MID: 0.07 per patient
			Proportion of patients with a positive experience	MID: 0.05

AEC: Ambulatory emergency care MID: Minimal important difference QALY: Quality adjusted life year

Sections 8:1 – 8:4 present a comparison of the SSM outputs observed in the seven alternative staffing strategies described in Section 4.7.6 and summarised in table 8:2 below. The Baseline strategy represents the current early allocation staffing model.

Table 8:2 Summary of alternative staffing strategies and annotation used in results

SCENARIO	DESCRIPTION
BASELINE	▪ Consultants take non-ED referrals 0900-2000hrs ▪ Trainees take non-ED referrals 2000-0900hrs ▪ Charge nurses take all ED referrals
CONSULTANTS	▪ Consultants take all referrals 24hrs per day
TRAINEES	▪ Trainees take all referrals 24hrs per day
NURSES	▪ Nursing staff take all referrals 24hrs per day
CONSULTANTS/ TRAINEES	▪ Consultants take all non-ED referrals 0900-2000hrs ▪ Trainees take ED referrals 0900-2000hrs ▪ Trainees take all referrals 2000hrs-0900hrs
CONSULTANTS/ NURSES	▪ Consultants take all non-ED referrals 0900-2000hrs ▪ Nursing staff take ED referrals 0900-2000hrs ▪ Nursing staff take all referrals 2000hrs-0900hrs
TRAINEES/ NURSES	▪ Trainees take all non-ED referrals ▪ Nursing staff take all ED referrals

Uncertainty analysis occurred via scenario testing and by combining the outputs of non-experts. To explore uncertainty in system behaviours reproduced, each strategy underwent 100 model runs in three different scenarios of overcrowding tolerance – 100% ,115%, and 130% (Section 4.7.6.2). To explore uncertainty in trainee decisions-making, the outputs of the best/worst performing non-expert strategies were combined to create a range of predicted outputs representing non-expert early allocation decisions. Comparison of modelled outputs was performed using Welsh Two Sample t-test to quantify differences between and within strategies at increasingly occupancy enforcement.

8.1 Departmental level outcomes

This section provides a comparison of the modelled outputs of utilisation of AEC services (as a proportion of patients attending) and 24hr discharges (as a proportion of patients completing care. As this section explains, representation as a proportion belies the complex nature of this emergent outcome and multiple forms of analyses are presented to enable understanding of how the results influence other departmental, patient-level, and system-level outputs.

8.1.1 AEC utilisation

Figure 8:2 demonstrates that AEC utilisation is greatest when consultants determine all remote allocations and lowest when only non-experts allocate. Statistically significant differences are observed between consultant staffing combinations (BL, CN, CT) but these are not meaningful as they do not meet minimum important difference (MID). Statistically significant but non-meaningful differences are also observed between the non-expert strategies of Trainee/Nurse (TN) and Trainee only (T).

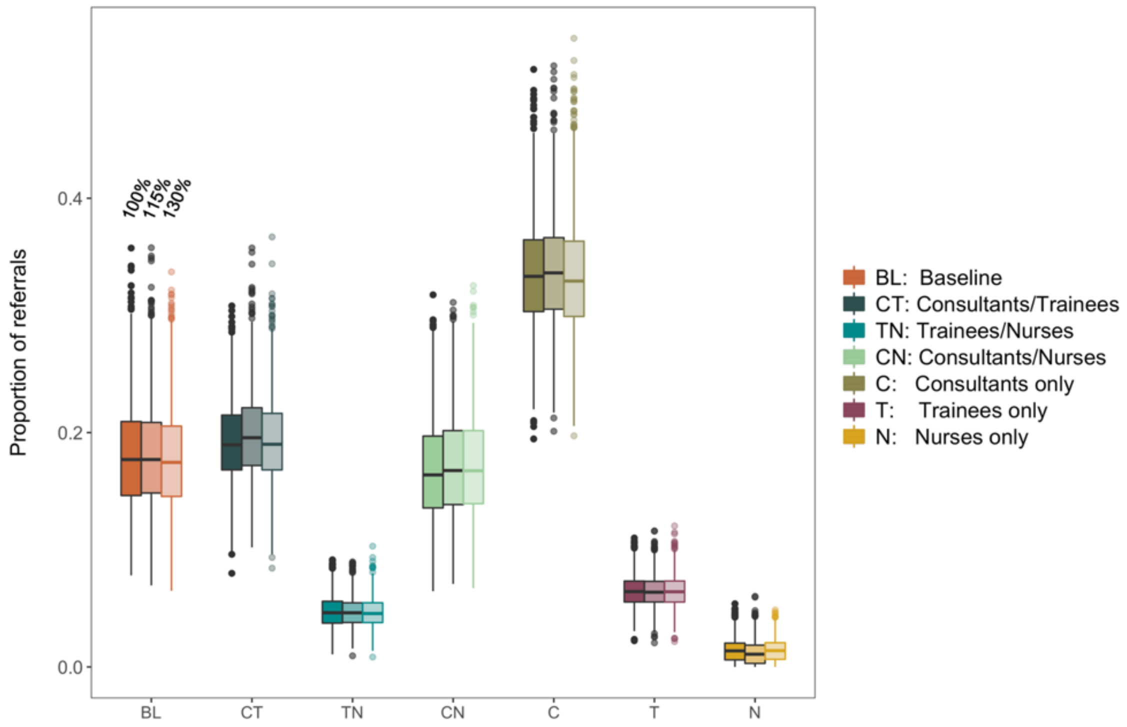


Figure 8:1 AEC utilisation for each scenario at increasingly tolerated occupancy levels

The proportion of patients allocated to AEC facilities via remote decision-making per week in each staffing strategy is summarised via boxplots at increasing levels of tolerated occupancy in the Bedded area. The ordering of boxplots according to forced occupancy is shown in the first strategy (BL). Marked differences between the strategies is apparent and understandable given the conceptual model. Recall that the results of the sensitivity analysis led to the removal of additional AEC allocations in response to overcrowding. Little variation beyond the programmed stochasticity was expected when increasing occupancy levels were enforced.

Expert strategies utilise AEC at greater than twice the MID (0.05) of non-expert strategies. Comparing the consultant combinations with the non-expert strategies (T, TN, N) a mean difference in AEC allocations ranging from: 0.104 – 0.154 for Baseline (99% C.I. 0.101,0.157), 0.102 – 0.152 for Consultant/Nurses (99% C.I. 0.099 – 0.155), 0.128 – 0.178 for Consultant/Trainees (99% C.I. 0.125 – 0.180). The consultant only strategy produced between 0.146 – 0.169 more AEC allocations that the consultant combinations (99% C.I. 0.142,0.175). The Trainee only strategy produced 0.05 (99% C.I. 0.049, 0.051) more AEC allocations than the Nurse only strategy. The greatest difference can be seen when comparing the outputs of the Consultant only (C) and Nurse only (N) strategies. The mean difference observed was 0.324 (99% C.I 0.320, 0.327). Differences were maintained at all occupancy levels. Tabulated summary of the mean values with their 99% confidence intervals is presented in Appendix F (Table F:1).

8.1.2 24hr discharges

As Figure 8:2 explains, there were differences in 24hr discharges between expert and non-expert strategies. This was greatest between the Consultant and Nurses only ones but not to a meaningful level (i.e., <0.05). At all levels of tolerated occupancy, non-expert strategies (T, N, TN) produced more 24hr discharges. When uncertainty in the modelled outputs of non-experts is included in analysis, there are no meaningful differences seen between the worst performing strategy (C) and non-experts: 0.044 - 0.056 at 100% forced occupancy (99% C.I. 0.042,0.058), 0.046 - 0.058 at 115% forced occupancy (99% C.I. 0.044, 0.060), and 0.044 - 0.056 at 130% (99% C.I. 0.043, 0.057).

Differences between the mean 24hrs discharges for CN, CT and BL strategies were not statistically significant at the 1% level at any enforced occupancy level. Differences in outputs between all other scenarios were statistically significant across all occupancy levels but did not meet the criteria for meaningful difference.

Differences were maintained at all enforced occupancy levels.

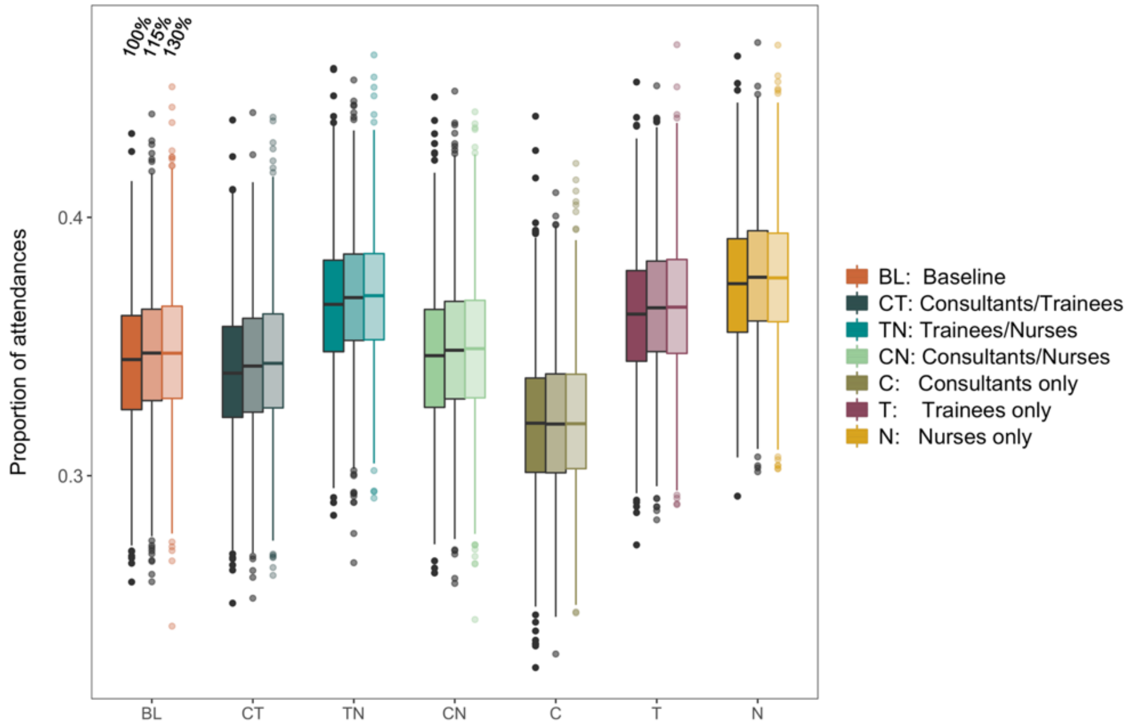


Figure 8:2 24hr discharges for each scenario at increasingly tolerated occupancy levels

The proportion of patients discharged within 24hrs in each staffing strategy is summarised at increasing levels of tolerated occupancy in the Bedded area before reactive capacity creation could occur. Each scenario has three boxplots (median, 2nd, and 4th quantiles, and range) corresponding to increasing forced occupancy levels in the Bedded area in the order shown in the first strategy (BL). Scenarios involving consultant DMs produced fewer discharges within 24hrs of arrival. This included the strategy that the study site used at the time of the study (BL).

8.2 Departmental efficiency

This section is separated into four sections with Section 8.2.4 further subdivided into separate discussions about the lengths of delays observed within and between strategies in the AEC and Bedded area populations.

8.2.1 Occupancy levels

Non-expert strategies lead to more time spent in crowded and overcrowded conditions per week than expert strategies. Figure 8:4 shows this trend for time spent in crowding (90-100% occupancy) whilst Figure 8:5 presents the modelled outputs for overcrowding (>100%). Absolute differences between strategies are provided in Appendix F, Tables F:3 and F:4. Consultant only is the only strategy to deliver median occupancy levels across a day consistently below 90% (Figure 8:6).

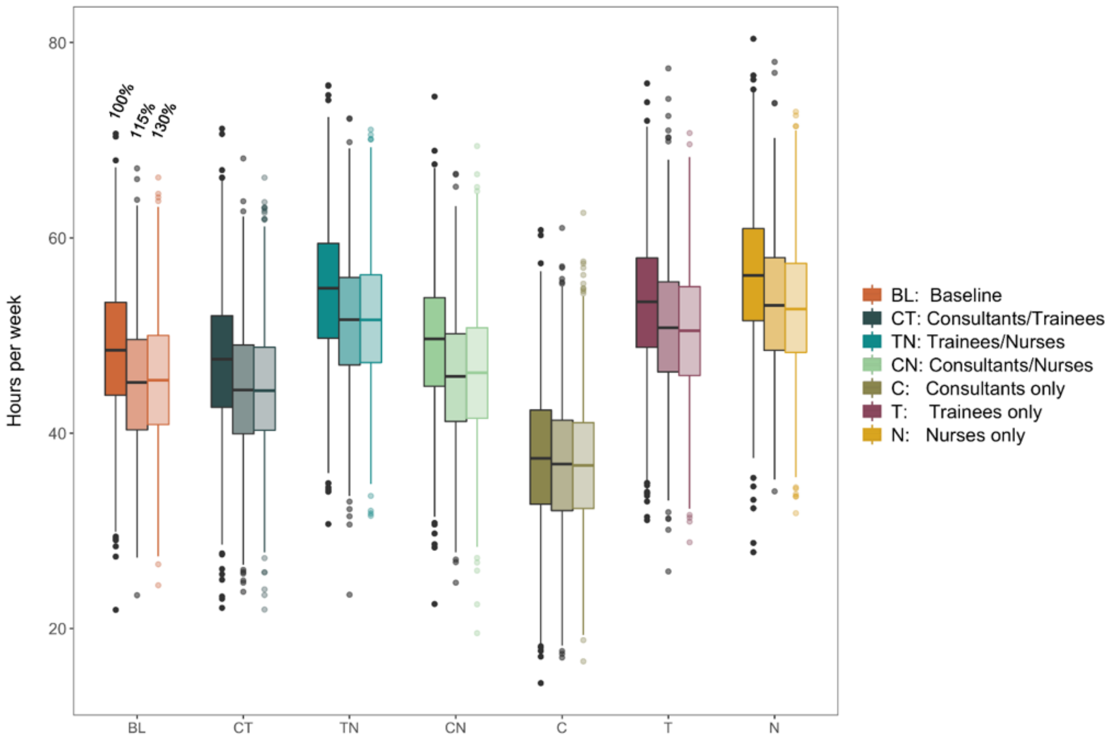


Figure 8:3 Hours spent in crowded conditions with increasing occupancy tolerance

The number of hours spent in crowded conditions per week in each staffing strategy is summarised in boxplots at increasing levels of tolerated occupancy (Bedded area) before reactive capacity creation could occur. Increasing forced occupancy ordering is shown for the first strategy (BL). Crowding was defined as Bedded are occupancy between 90-100%. Note that crowded conditions occur more frequently with a zero-overcrowding strategy (tolerated occupancy 100%) and hours spent in crowding similar at higher values of occupancy tolerance. Results observed should be consider alongside those shown in Figure 8:3.

Differences between strategy C and all other strategies on crowding are statistically significant and meaningful at 100% forced occupancy (>560mins/7hours). As forced occupancy increases, strategy C remains superior but meaningful differences are only observed in comparison with the non-expert strategies (T, N, TN). Tukey's Test for variance saw statistically significant (but non-meaningful) differences between all scenarios with the exception of CT-BL difference (non-significant at 115% tolerance) and CN-BL difference (non-significant at 130% tolerated occupancy).

The superiority of strategy C is reproduced when time spent in overcrowding is analysed (Figure 8:4). No meaningful differences are observed between any of the strategies at 100% forced occupancy levels. Differences between C and all other consultant models are large but remain below the MID of 560mins. As with the crowding results, the largest differences are seen when comparing strategies C to non-experts: additional time per week spent in overcrowded conditions lies between 812-1123mins and 849 – 1120mins at 115% and 130% enforced occupancy respectively.

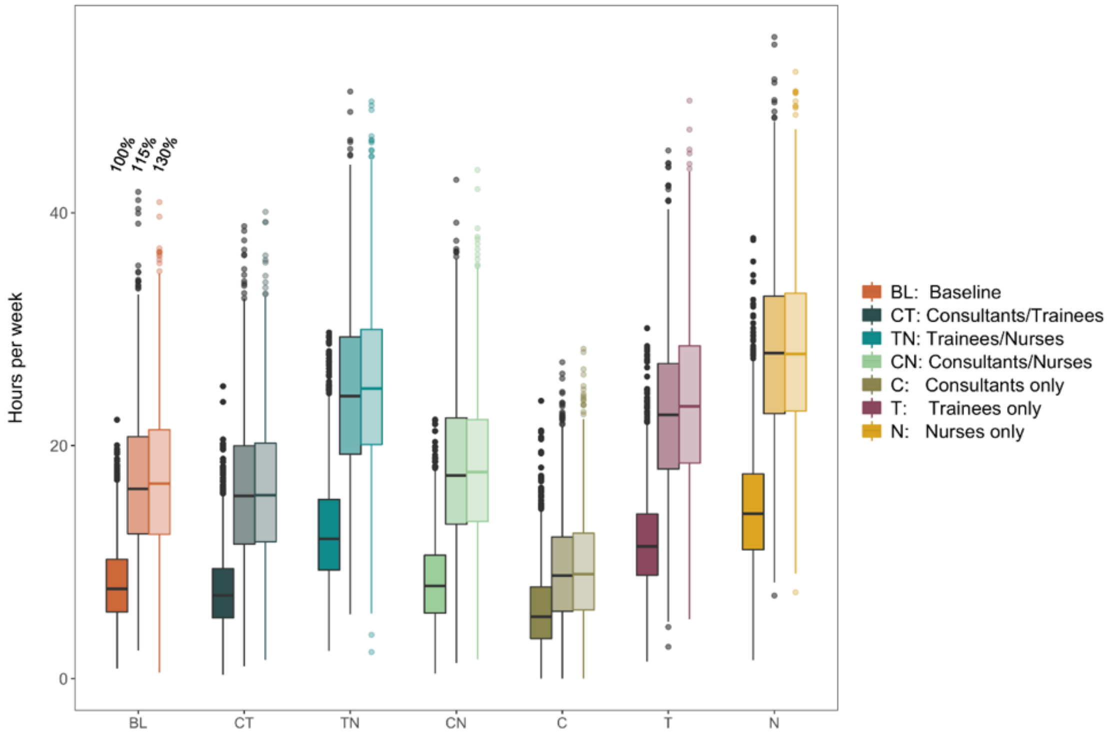


Figure 8:4 Hours spent in overcrowded conditions with increasing occupancy tolerance

The number of hours spent in overcrowded conditions per week in each staffing strategy is summarised in boxplots at increasing levels of tolerated occupancy in the Bedded area before reactive capacity creation could occur. Increasing forced occupancy levels ordering is shown for the first strategy (BL). Overcrowding was defined as Bedded area occupancy >100%. When higher levels of Bedded area occupancy are tolerated, the department spends more time in an overcrowded state. This is less pronounced in strategy C

At 115% and 130% occupancy, the expert combination strategies (BL, CT, CN) see less overcrowding per week than non-experts (T, N, TN), but the range of outputs includes non-meaningful values of <560mins. There are no meaningful differences when comparing expert strategies with each other (BL, CT, CN, C) nor when comparing between the non-expert strategies (T, N, TN).

Two system failure events occurred - i.e., two patients redirected to exit the SSM upon arrival due to the whole department position of maximal occupancy. Both events occurred on the first day of data collection in strategy C at 100% forced occupancy. This occurred very close to the beginning of the SSM run start as the area moves from being an empty unit to one being populated with new arrivals – the warm-up period. The significance of this will be discussed in Section 8.6.2.

Comparison of the median Bedded area occupancies across a 24hr period shows a median occupancy <100% in all strategies, at all forced occupancy levels (Figure 8:5). The consultant only strategy sees median occupancy consistently <90%.

8.2.2 Incorrect placement

Non-expert strategies saw more patients start care in a non-allocated area due to delays and high occupancy levels. Differences were statistically significant but not meaningful. A full summary of incorrect allocations is presented in Appendix F (Table F:5).

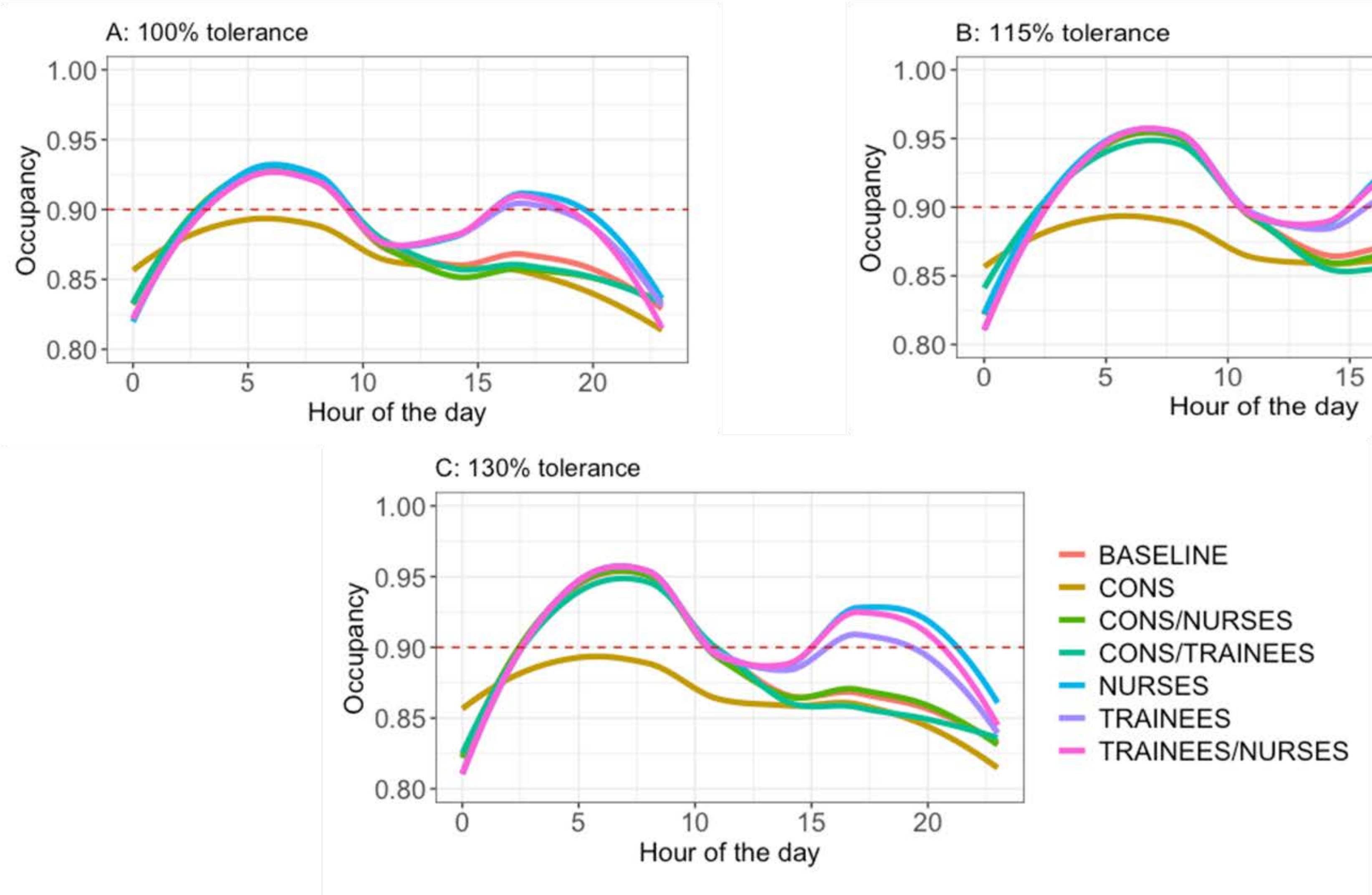


Figure 8:5 Median bedded area occupancy per hour of the day across 100 model runs

Panel A provides the median occupancy levels over a 24hr period at 100% enforced occupancy, Panel B at 115%, and Panel C at 130%. Strategy C is consistently below 90% occupancy (dashed line). At all enforced overcrowding, all non-expert strategies (N, T, TN) have a median occupancy nearing or exceeding 90% at two key points of the day – pre-morning ward and during the afternoon/evening new arrivals peak. Only strategy C is unaffected by variation in the tolerance of overcrowding.

8.2.3 Delays to starting care

Expert strategies see fewer patients delayed in accessing a bed upon arrival (Figure 8:7). Differences in the proportion of bed-allocated patients who experienced delay exceeds the MID of 0.05 and reaches statistical significance at the 1% level for all expert strategies (C, BL, CT, CN) when compared with non-expert strategies (T, N, TN).

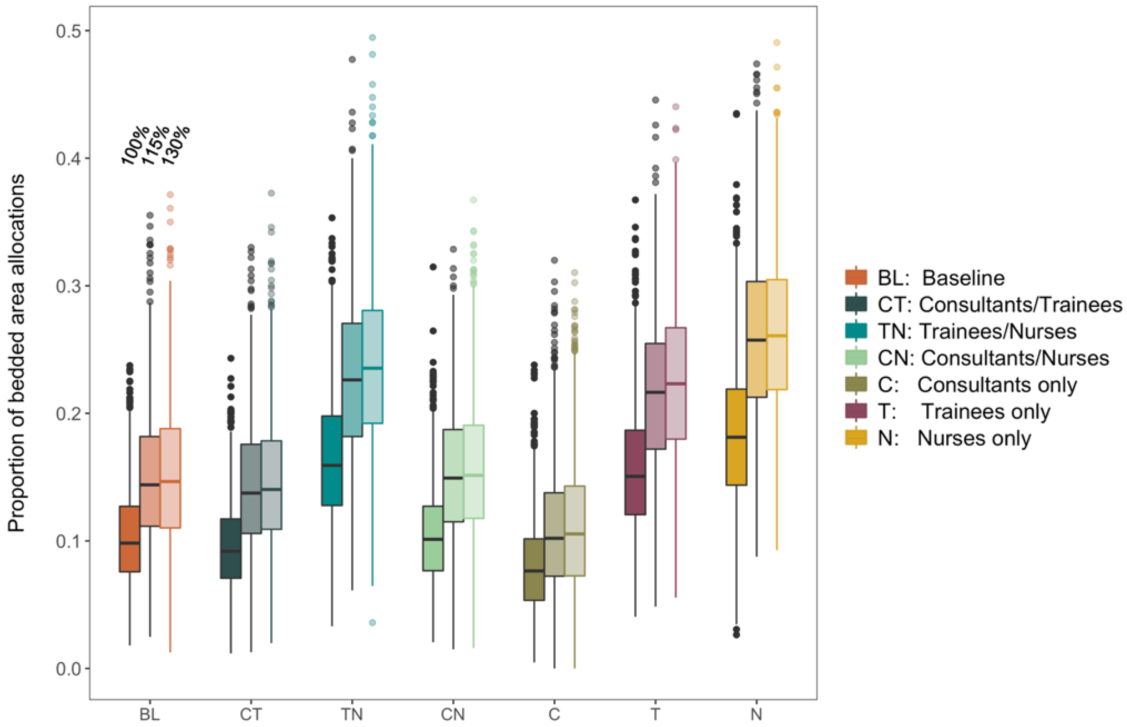


Figure 8:6 Patients waiting for a bed upon arrival at increasing levels of forced occupancy

The proportion of all Bedded area allocated patients delayed in accessing a bed upon arrival is summarised via boxplots for each strategy at increasing levels of forced occupancy (order shown in the first strategy - BL). Note the significant jump in proportion waiting when occupancy levels move from 100% to 115% in all strategies but marginal increases when occupancy tolerance moves from 115 - 130%. The greatest differences are seen between C and the non-expert strategies.

Differences between the non-expert and expert strategies may be as 0.063 or as high as 0.152 (more than three times the MID). Values are provided in Table 8:3. The greatest differences are observed when comparing C (Consultant only) with the non-expert strategies.

Table 8:3 Difference in proportion of patients delayed expert versus non-expert strategies

	Difference in delay with non-expert strategies (99% C.I.)		
Strategy	**100% forced occupancy**	**115% forced occupancy**	**130% forced occupancy**
Consultant	0.075 - 0.105 (0.071, 0.110)	0.109 - 0.152 (0.104, 0.157)	0.113 - 0.152 (0.108, 0.157)
Consultant-Trainee	0.06 - 0.09 (0.056, 0.094)	0.074 - 0.118 (0.069, 0.123)	0.079 - 0.118 (0.074, 0.123)
Consultant-Nurse	Non-meaningful	0.063 - 0.106 (0.058, 0.112)	0.069 - 0.107 (0.063, 0.113)
Baseline	Non-meaningful	0.068 - 0.111 (0.063, 0.117)	0.073 - 0.112 (0.067, 0.117)

C.I. – confidence interval

Note that the minimal important difference (meaningful difference) is determined as 0.05. Table provides the mean differences in proportion of Bedded area delays only

At all tolerated occupancy levels, the differences in proportion of delays between consultant strategies (BL, CT, CN, C) are significant at the 1% level but non-meaningful. Differences between all non-expert strategies (T, N, TN) are also statistically significant but non-meaningful. Of note, consultant strategies (BL, CT, CN, C) create a greater number of patients delayed in starting care in the AEC area than non-expert strategies. When analysed as a proportion of AEC-allocated patients, all strategies see <4% of patients delayed with no meaningful (>0.05) difference between strategies.

8.2.4 Lengths of delays experienced

All strategies see a change in length of delay (LoD) as higher levels of occupancy are tolerated. However, comparison between strategies reveals no meaningful differences in LoD for Bedded area patients. Higher levels of overcrowding tolerance see significant and meaningful differences in delays for AEC patients in full non-expert strategies compared with expert strategies.

Figure 8:8 compares the distribution of delays ≥5mins in both areas. All strategies see a rise in the median length of delay for Bedded area patients as forced occupancy rises; however, there are no meaningful differences between the strategies regardless of forced occupancy level. Moving from occupancy tolerance of 100% to 115%, sees increases in median wait times of between 35 – 37mins (99% C.I. 34, 38) in strategies that combine consultants with other staff (CN, CT, BL). Increasing occupancy from 100% to 130% produces rises in median delays of between 45-47mins (99% C.I. 44, 49) in all consultant strategies. There was no meaningful change to median delays in the non-expert only strategies moving from 100-115% tolerance, but a rise of 35mins when moving from 100-130% tolerance (99% C.I. 34, 36mins). A summary of median delays for each scenario is available in Appendix 7, Table F:7.

Statistically significant and meaningful differences in median length of delay for AEC patients emerge as occupancies of 115 and 130% are forced upon the department. Not all strategies see meaningful difference and superior performance (shorter delay) varies as shown in Table 8:4. A summary of the delays for each scenario is presented in Appendix F, Table F:8.

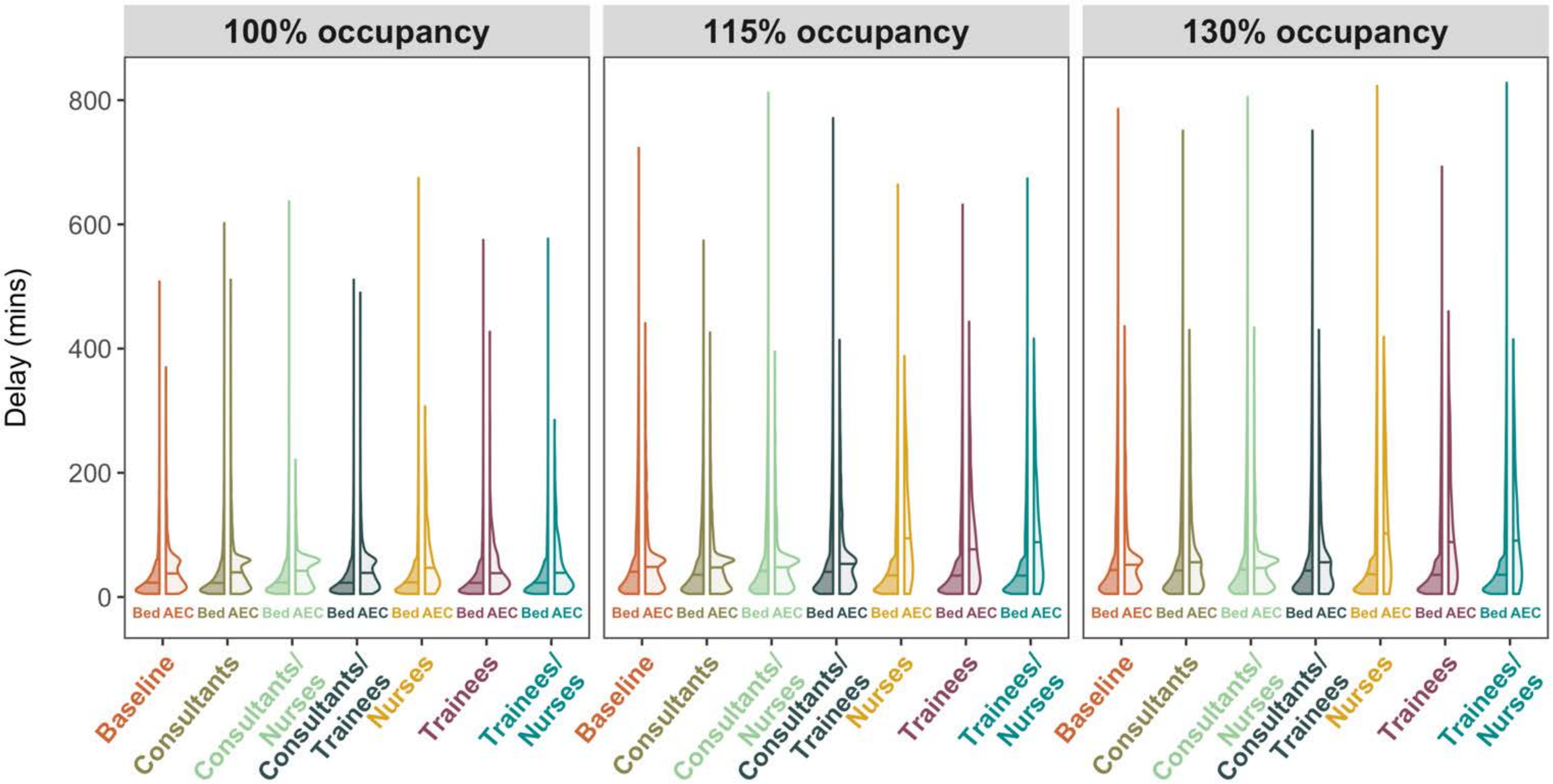


Figure 8:7 Delays experienced across increasing forced occupancy

Distribution of delays to accessing a clinical upon arrival by patients (≥5mins). Delays experienced by patients allocated to the Bedded area (Bed) compared with delays experienced by patients allocated to the ambulatory emergency care area (AEC). Distribution of delays are presented as half-violin plot with the median value indicated by the bold line. Note the very similar distribution of delays at 100% for all strategies and how this alters at increasing levels of forced occupancy particularly in AEC populations allocated by Nurse and Trainee strategies

Table 8:4 Comparison of between strategy delays for AEC care at different occupancy tolerances

Occupancy	Strategies with significant and meaningful differences in AEC delays				
	Strategies	Superior	Difference (mins)	99% C.I.	p-value*
115%	Consultants vs. Trainees/Nurses	Consultants	44	36 - 52	<0.001
	Consultants vs. Nurses	Consultants	48	33 - 63	<0.001
	Consultants/Nurses vs. Trainees/Nurses	Consultants/Nurses	47	38 - 57	<0.001
	Consultants/Nurses vs. Nurses	Consultants/Nurses	50	35 - 66	<0.001
	Baseline vs. Trainees/Nurses	Baseline	41	32 - 49	<0.001
	---------------	---------	---	---------	--------
130%	Consultants/Nurses vs. Nurses	Consultants/Nurses	61	45 - 77	<0.001
	Consultants/Nurses vs. Trainees	Consultants/Nurses	54	46 - 62	<0.001
	Consultants/Nurses vs. Trainees/Nurses	Consultants/Nurses	51	42 - 60	<0.001
	Baseline vs. Nurses	Baseline	47	30 - 63	<0.001
	Baseline vs. Trainees	Baseline	40	32 - 49	<0.001

* Welch Two Sample t-test

Note only strategies with difference >30mins are shown. All other comparisons showed non-meaningful difference. A shorter delay indicated superior performance

As forced occupancy rises, all strategies see an increase in the median length of delay for AEC patients, but only non-expert strategies see meaningful change: an increase of 41 – 52mins (99% C.I. 28, 64) and of 57 - 59mins (99% C.I. 38, 76) when moving from 100-115% and 100-130% respectively.

8.3 Whole system efficiency

8.3.1 Admissions to in-patient hospital beds

No meaningful differences are seen in the proportion of referred patients who are subsequently admitted into a hospital bed when comparing remote allocation staffing strategies (Figure 8:9). Hospital admissions marginally reduce as higher levels of Bedded area occupancy are forced.

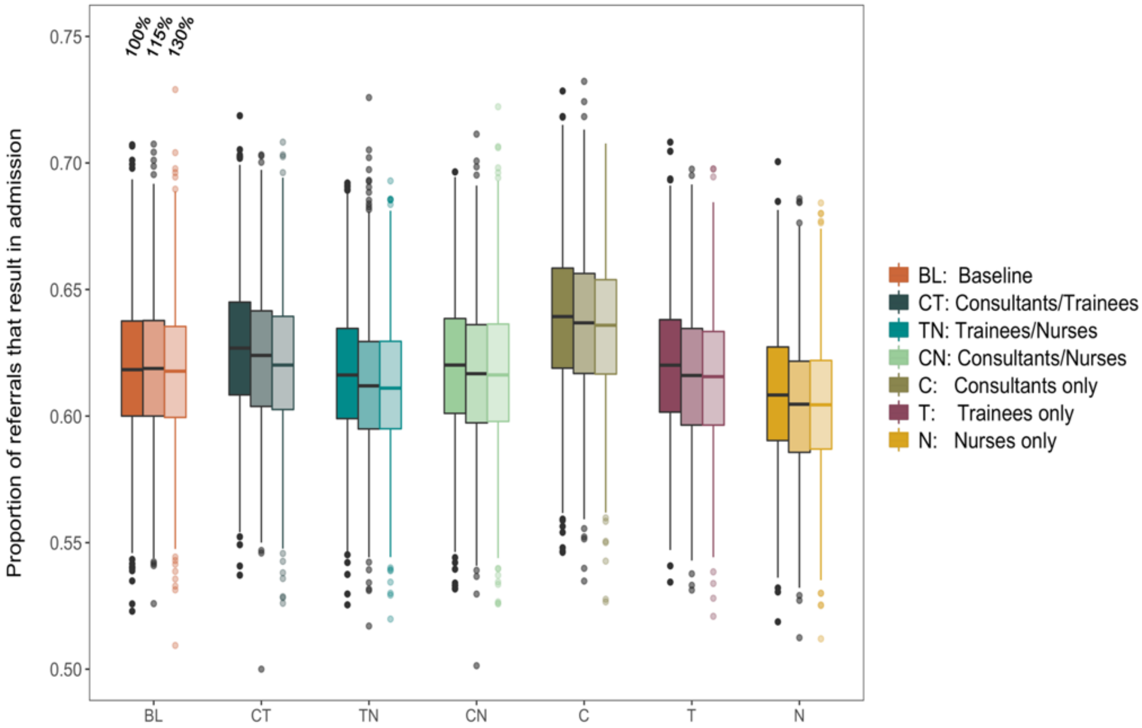


Figure 8:8 Hospital admissions in each scenario at increasing forced occupancy levels

The proportion of patients admitted (of all patients referred) into a downstream hospital bed per week in each staffing strategy is summarised via boxplots at increasing levels of tolerated occupancy. Ordering of forced occupancy levels are presented as shown in the first strategy (BL). Scenarios not involving consultant DMs produced fewer admissions that strategies that did involve consultants. Admissions tend to reduce as higher occupancy levels are forced

No meaningful differences (>0.05) in the proportion of referrals that convert to an admission are observed between staffing models. Non-expert strategies see fewer admissions; compared with the strategy that sees the greatest number of admissions (strategy C) differences lie between 0.019 – 0.030 fewer admissions (99% C.I. 0.016-0.027) at 100% occupancy enforcement, 0.021 – 0.033 fewer (99% C.I. 0.019, 0.035) at 115%, and 0.020 – 0.030 fewer (99% C.I. 0.017, 0.033).

8.3.2 Overnight transfers

Consultant inclusive strategies see a higher proportion of admitted patients transferring between 2300-0800hrs (overnight transfers). Differences between strategies are non-meaningful though statistically significant at the 1% level. Results are available in Appendix F (Table F:6).

8.4 Patient level outcomes

Patient-reported outcomes are separated into two sections – health-related quality of life (HRQoL) and patient experience.

8.4.1 Health related quality of life

There are statistically significant differences in the mean health gain observed between scenarios at the 1% level. However, applying the value of 0.07 as MID reveals no meaningful differences between scenarios (Table 8:5). This is consistent across all levels of enforced overcrowding.

Stochasticity in the model inputs and the programmed behaviours of staff lead to differences in the total number of patients attending and being discharged from the unit in each model run for each staffing strategy. Health gain is equivalent to quality adjusted life year (QALY). As QALYs generated by an intervention are analysed cumulatively when evaluating the effects of an intervention, model runs with more patients will see a larger generation of health that is only partially influenced by the departmental area where care was delivered.

Table 8:5 Health gain of discharged patients over 100 model runs as overcrowding enforced

100% forced occupancy					
strategy	N	mean	sd	99% CI Lower	99% CI Upper
Nurses	195633	0.110	0.131	0.109	0.111
Trainees/Nurses	191011	0.107	0.130	0.106	0.108
Trainees	188801	0.105	0.130	0.104	0.106
Consultants/Nurses	174681	0.099	0.128	0.098	0.100
Baseline	174692	0.097	0.128	0.096	0.098
Consultants/Trainees	170441	0.095	0.128	0.094	0.096
Consultants	155145	0.082	0.123	0.081	0.083

115% forced occupancy					
strategy	N	mean	sd	99% CI Lower	99% CI Upper
Nurses	198785	0.110	0.131	0.109	0.111
Trainees/Nurses	193450	0.107	0.130	0.106	0.108
Trainees	191221	0.106	0.130	0.105	0.107
Consultants/Nurses	176238	0.098	0.129	0.097	0.099
Baseline	175193	0.097	0.129	0.096	0.098
Consultants/Trainees	172766	0.095	0.128	0.094	0.096
Consultants	155963	0.081	0.124	0.080	0.082

130% forced occupancy					
strategy	N	mean	sd	99% CI Lower	99% CI Upper
Nurses	198291	0.110	0.132	0.109	0.111
Trainees/Nurses	193899	0.107	0.130	0.106	0.108
Trainees	191651	0.105	0.130	0.104	0.106
Consultants/Nurses	177004	0.098	0.129	0.097	0.099
Baseline	175613	0.097	0.128	0.096	0.098
Consultants	173727	0.095	0.128	0.094	0.096
Consultants/Trainees	173727	0.095	0.128	0.094	0.096

N: number of patients discharged over 100 model runs, sd: standard deviation, CI: confidence interval

Note: mean health gain is equivalent to mean quality adjusted life year generated.

Adjusting for total numbers via analysis of health change per 1000 patients discharged shows clear trends in the cumulative health production – non-expert staffing strategies tend to produce greater health (Figure 8:9). Tukey's test for variance confirms statistically significant differences (1% level) between all scenarios at all occupancy levels with the exception of BL-CN (no significant difference at 100% forced occupancy but significance at 115% and 130%). No MID was set per 1000 patients to determine meaningful difference. The influence of methodological choice on cumulative health measurement is discussed in Section 8.6.1.1.

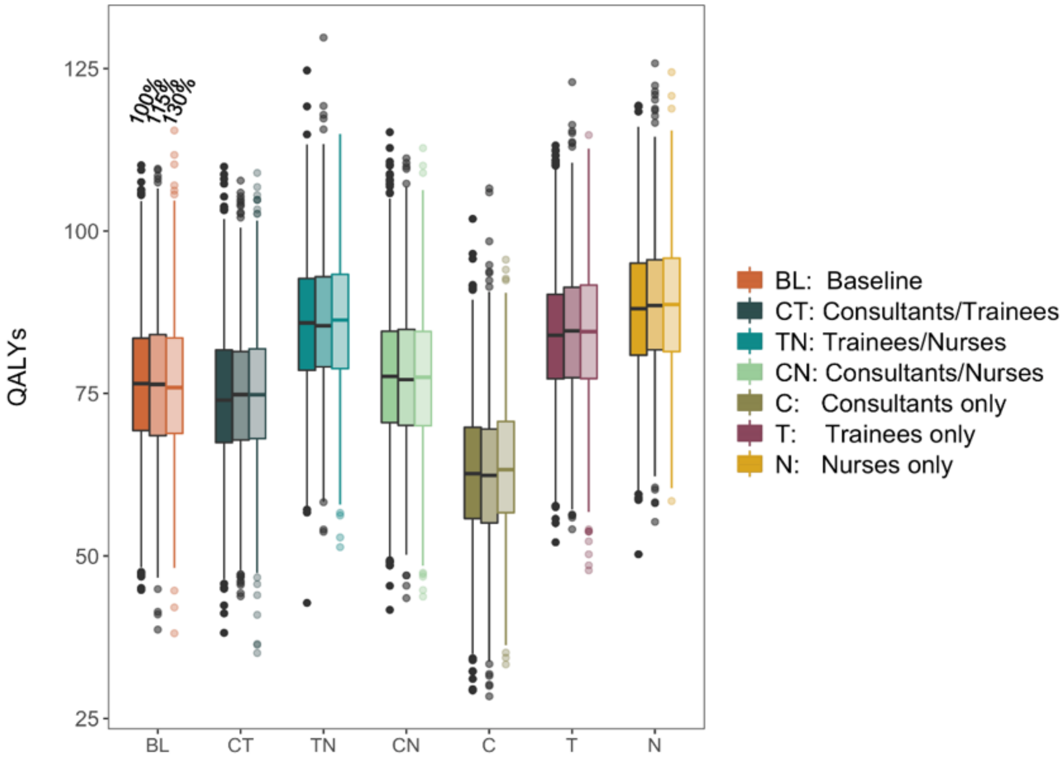


Figure 8:9 Quality adjusted life year (QALY) gain per 1000 patients discharged across forced occupancy levels

Each scenario has three boxplots corresponding to increasing forced occupancy levels in the Bedded area in the order shown in the first strategy (BL) – i.e., the occupancy level that triggered proactive movement of patients to create capacity for new arrivals on to the unit. The boxplots present the median QALY gain per week contained with the 50% most frequently observed data points around the median value (bold line in the boxplot). As the data are normally distributed the mean and median are equivalent. Note the higher median value with non-expert strategies, the overlap of interquartile ranges in the non-expert, and combined expert strategies, and the outlying health change with the Consultant only strategy

8.4.2 Patient experience

Greater than 90% of all patients attending the unit have a positive experience of care regardless of the staffing strategy and overcrowding tolerance applied (Figure 8:10). Experience is lowest in strategies with some or all consultant allocations, but no meaningful differences (≥0.05) are seen when comparing outputs between consultant-inclusive and non-expert only strategies. Patient experience significantly (but not meaningfully) decline in experience at increasingly higher levels of overcrowding tolerance in all strategies.

Recall that patient experience is programmed to emerge from a patient's length of stay (LoS) in the AEC and any delays to starting care. Delays are discussed in Sections 8.3 – 8.4. The median LoS of AEC patients is up to 50mins longer when consultants are involved in some or all remote allocation decisions. Consultant strategies also demonstrate a larger rightward skew of AEC LoS than non-expert strategies (Appendix F, Tables F:7 and F:8).

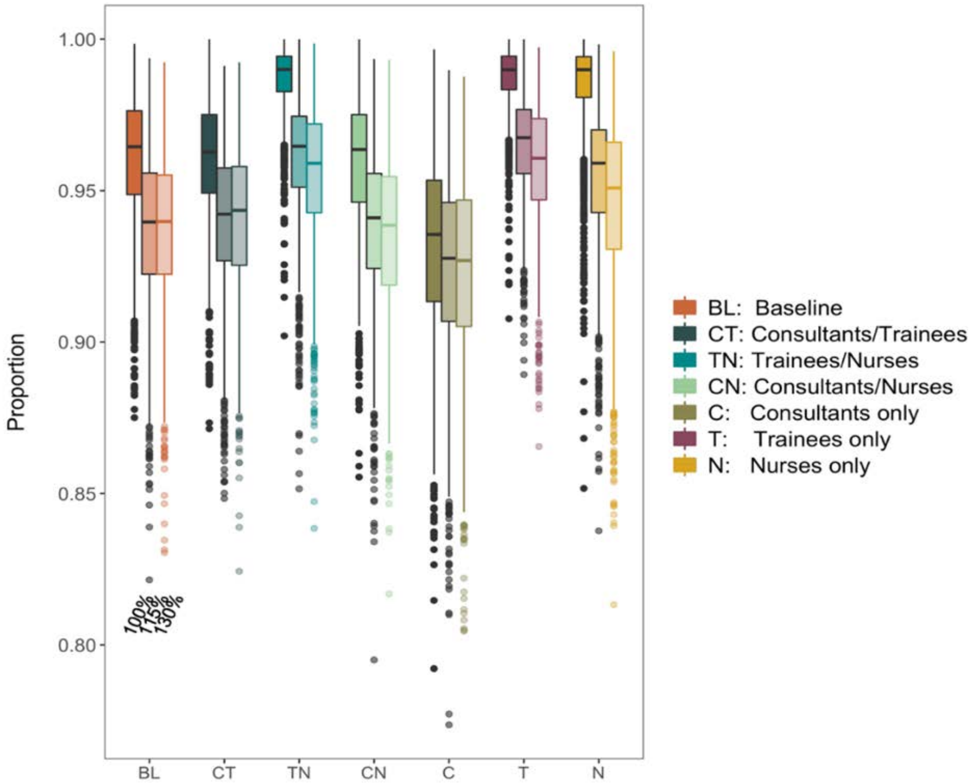


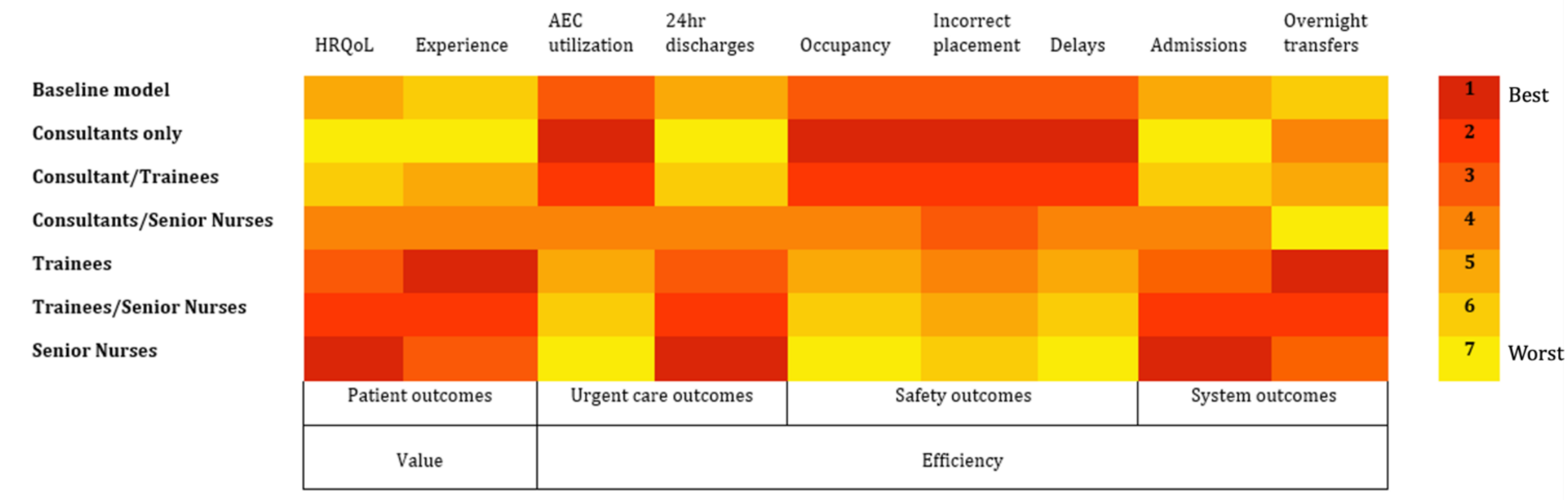
Figure 8:10 Proportion of patients with a positive experience of care at increasing occupancy

Each scenario has three boxplots corresponding to increasing forced occupancy levels in the Bedded area in the order shown in the first strategy (BL). Each box represents the 50% most frequently observed data points around the median value (bold line in the box. The boxplots show the experiences of care to be skewed towards good experience in >90% of patients in all strategies. When a zero tolerance of overcrowding is present (tolerated occupancy 100%) experience is poorest in the Consultant only strategy. As higher levels of overcrowding are tolerated, patient experience is reduced in all strategies.

8.5 Summary of findings

Staffing strategies which involved consultants in some, or all early allocation decisions saw greater utilisation of AEC facilities, less overcrowding, fewer delays to starting care, and smaller lengths of delay for patients who were forced to wait upon arrival. There were no meaningfully significant differences in the proportion of patients referred who were subsequently admitted to an in-patient bed between the alternative staffing strategies even when high departmental occupancy levels were tolerated. Although patient experience was lower in consultant strategies, differences were non-meaningful and a positive experience still emerged in >90% of attending patients. The modelled consultant behaviour to allocate patients to the AEC in large numbers was the key driver of this. Because AEC resources were not increased to reflect high demand, delays and longer lengths of stay emerged, both of which triggered dissatisfaction in the model. The health and well-being outcomes of early decision-making could not be usefully interpreted when the limitations of the data informing the model parameters were considered.

Modelled outputs present and array of results that represent effectiveness in urgent care of AIM patients. The effectiveness of each staffing strategy may be better appreciated via ranked comparison of their performance for each modelled output. Visualising the best and worst performing strategies across all modelled outputs allows the reader to see where strategies which perform well to achieve goals in one domain (e.g., safety) perform less well in others. As the heat map presented below conveys (Figure 8:11), no single staffing strategy is superior. The heat map presents the results at 100% overcrowding tolerance as this reflects what is arguably the safest of the three levels explored. Outputs are categorised into the three themes of effectiveness as defined in this research – safety, value, and efficiency. Strategies are ranked and colour-coded according to the performance in each modelled output. Best performance (identified as deep red) may be the highest value achieved for a desired goal (e.g., AEC utilization) or the lowest (e.g., hospital admissions). Red drains towards yellow as performance worsens. Modelled outputs representing safety are significantly better when experts allocate (shown in red), but some elements of departmental efficiency are compromised as is value to patients. When presented as seen in Figure 8:11, it becomes clear that the best performing strategy is dependent upon how safety, value, and efficiency are prioritised. It is important to note that only occupancy levels and delays saw meaningful differences between expert and non-experts.



AEC: Ambulatory emergency care, HRQoL: Health-related quality of life

Figure 8:11 Heat map comparing staffing scenario outputs

The heat map provides a way to rank how each staffing strategies performs across all modelled outputs. Performances (best modelled output) are ranked from 1 (best) – 7 (worse) relative to each other. The Baseline model is the one currently used on the study site - a combination of consultant, trainees, and senior nurses. Outputs relate to the three levels where effectiveness in urgent care is measured – the departmental, the patient, and the system levels. Safety is included as this also contributes to effectiveness. These categories represent the goals of the policies -value and efficiency in the healthcare system. Strategies are ranked according to performance when there is a zero tolerance for overcrowding – i.e., when the system supports the transfer of patients to other wards when occupancy of urgent care beds exceeds 100%. Where modelled outputs were equal, strategies were ranked equally. As can be seen, strategies than include experts outperform those without experts in outputs representing departmental efficiency and safety. Non-expert strategies outperform expert ones in modelled outputs that represent patient and system goals.

9 Discussion: The predictive model findings

The chapter discusses the findings presented in Chapter Eight to form an answer to the original research: '**How effective is early senior decision-making (ESDM) for acute internal medical populations compared with other staff decision-making?**'. The results from the ethnographic study (Chapter Five) and the exploratory model validation (Chapter Seven) are incorporated into the narrative to consider the research holistically. The chapter starts by summarising the findings, whether ESDM achieved the hypothesized outcomes, and the influence of expert decision-making upon model outputs. The findings are then discussed in relation to current literature under the following themes:

- Section 9.2: Safety
- Section 9.3: Efficiency
- Section 9.4: Patient outcomes

Section 9.5 is a discussion of what the findings tell us about the effectiveness of ESDM as an urgent care strategy followed and how they inform organisations considering adopting ESDM (Sections 9.6 and 9.7). The chapter concludes with recommendations for future research to improve knowledge of the subject (Section 9.8) and a discussion of the study limitations (Section 9.9). For the purposes of this discussion, the term early senior decision-maker (ESDM) refers to all allocation strategies that involved expert (consultant) clinicians specialised in the delivery of acute internal medicine (AIM). 'Non-expert strategies' refers to all strategies that excluded consultants.

9.1 Does early senior decision-making achieve the assumed goals of policymakers?

Early senior decision-making was modelled to enhance AEC utilisation as observed in the ethnographic study. This modelled behaviour did not lead to the hypothesized safety, efficiency, and effectiveness outcomes. Based on policymakers' assumptions, compared with non-expert allocating, ESDM was hypothesized to lead to: safer bed occupancy levels, fewer admissions, more 24hr discharges, fewer overnight transfers, fewer (and shorter) delays, improved patient experience, and an equivalent impact upon patient health. Experts were modelled to allocate significantly more patients to AEC facilities at the point of referral to reproduce the observed behaviours of admission avoidance in usual AEC patients, test intuitively created pathways, and mitigate overcrowding. This included allocating patients with a moderate probability for admission into the AEC facilities to commence care prior to in-patient transfer. This modelled behaviour reduced crowding, overcrowding, and delays to care, but did not see improvements in all metrics reflecting efficiency, health, or experience when compared with non-expert allocations.

As Table 9:1 reveals, fewer than half of the metrics were improved via ESDM - most were non-meaningfully different from non-expert outputs. The greater AEC allocation of experts reduced competition in bedded areas reducing overcrowding, and delays as shown in Figure 9:1. Figure 9:1 explains how these outcomes emerged via the large number of patients still receiving care as AEC facilities closed. Because AEC faced no barriers to transfer when a bed was required, admissions increased. Admissions were offset by experts by redirecting non-urgent patients (not included in Figure 9:1).

Table 9:1 Summary of research findings

	FINDINGS	CONCLUSION
Departmental occupancy	• No strategy is capable of eliminating crowded or overcrowded conditions from emerging even is a zero tolerance of overcrowding is adopted • Full expert strategies realise median urgent care bed occupancy levels across the day of between 80 -90% • When overcrowding is tolerated by the organisation, all strategies that include expert allocations see meaningfully fewer hours spent in overcrowded conditions per week than full non-expert strategies. Differences between expert-inclusive strategies are non-meaningful	• Crowding and overcrowding cannot be eliminated if the organisation tolerates urgent care bed occupancy levels of ≥100% • Utilising clinical experts to make early allocation decisions during standard working hours will realise meaningfully fewer instances of crowding and overcrowding but not meaningfully improved by increasing expert involvement to provide 24hr allocation decision-making
Delays to starting care	• Early allocation decisions performed exclusively be non-experts see between 6 - 15% more patients delayed in accessing a bed upon arrival than expert strategies as overcrowding is tolerated by the organisation. • Differences with a zero tolerance of overcrowding are only seen between full expert and full non-expert strategies when uncertainty in non-expert decisions is included • No staffing strategy eliminates delays to patients accessing a bed upon arrival and no meaningful differences in the lengths of those delays emerges when strategies are compared	• Delays to accessing bedded resources cannot be eliminated if occupancy levels ≥100% are tolerated • Delays may be lessened by expert early allocations during usual working hours. • Little meaningful benefit is seen this is increased to consultants making all allocation decisions
Incorrect placement	• No meaningful difference between strategies	• Incorrect placement of patients unaffected by choice of early allocation decision-maker
AEC Utilisation	• Expert strategies see a >10% more of referred populations allocated to AEC than fully non-expert strategies with the potential for >32% more patients allocated at referral if a full expert strategy is used • More patients experience delays to starting care in AEC as expert involvement in allocations increases, but increases are non-meaningful	• Expert strategies see greater utilisation of AEC resources without meaningful impact upon delays in AEC populations

	FINDINGS	CONCLUSION
24hr discharges	• No meaningful difference between strategies	• 24hr discharges unaffected by the choice of early allocation decision-maker
Overnight transfers	• No meaningful difference between strategies	• Proportion of patients transferred overnight unaffected by choice of early allocation decision-maker
Admissions	• No meaningful difference between strategies	• Proportion of patients admitted from urgent care unaffected by the choice of early allocation decision-maker
Patient experience	• No meaningful difference between strategies	• Experiences of care are unaffected by the choice of early allocation decision-maker
Health impact	• Equivalency in health impact per patient discharged across all staffing strategies • Cumulative health generated decreased as expert involvement in decisions increases	• Limitations of data make this a challenging finding to interpret • More research in the health outcomes of patients discharged from urgent care required to understand how early allocation decision-making impact upon health

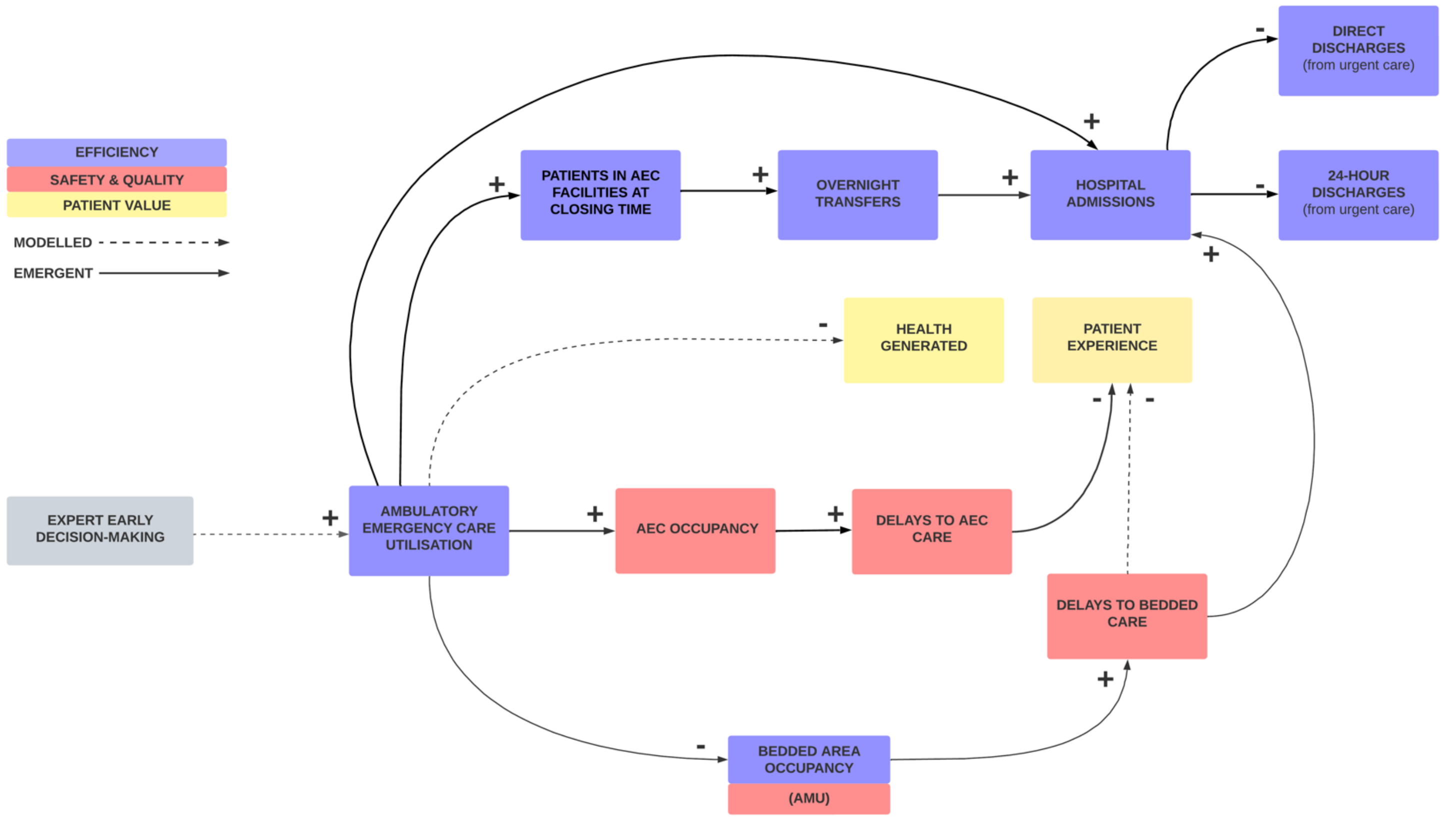


Figure 9:1 Influence of expert decision-making on model outputs

The diagram explains how the modelled outputs emerged as a function of expert decision-making. Outputs are coded to reflect their theme. Arrow format indicates whether influences were emergent or a programmed linear output. Polarity indicates the influence of an increase in the phenomenon at the start of the arrow had upon the output at the head. Increased expert decision-making reduced AMU occupancy and reduced hospital admissions via reduced AMU delays. However, increased AEC utilisation increased hospital admissions as more patients were present in AEC at closing time and required transfer for a bed to complete care. There were no barriers to hospital admission from the AEC clinic as patients were in need of a physical bed-space, whereas AMU patients awaiting admission already occupied one.

9.2 Safety

Harm arising from urgent care overcrowding is a concern for most UK and international urgent care systems(Bernstein et al., 2009; McCarthy et al., 2009; Morley et al., 2018; Moskop et al., 2019). Overcrowding is a known cause of inefficiency and patient harm (Bernstein et al., 2009; Chen et al., 2020; Higginson, 2012; Hoot & Aronsky, 2008; S. Jones et al., 2022; Morley et al., 2018). Delays to initial clinical evaluation and to commencing treatment are known to have a direct impact on patients' health. For example, clot removal in acute myocardial infarction, or stroke, or antibiotics in severe sepsis(Brodie et al., 1998; Mazighi et al., 2013; Seymour et al., 2017). All require rapid recognition of need and access to resources to optimise the effectiveness of treatment. A patient with a contagious pathogen (e.g., infectious gastroenteritis) will pose a risk to other patients and staff if they are placed a communal area without infection control measures in place. Early allocations strategies that facilitate recognition of needs at referral will therefore minimise immediate and long-term health loss.

Causal relationships between remote decision-making and harm are challenging to establish for AIM populations. Evidence from ED settings show reduced mortality with early consultant decision-making upon arrival to hospital (Davis et al., 2014). Consultant involvement in patient care within a few hours of arrival to an AMU has also been associated with reduced mortality (McNeill et al., 2009). No available studies explicitly explore the relationship between decision-making and overcrowding but patients delayed in ED settings do see an increased risk of mortality (S. Jones et al., 2022). Post-COVID, overcrowding has shown to be correlated with excess deaths by independent think tank analyses (Iacobucci, 2021; MacDonald, 2023). Interventions capable of reducing harmful occupancy levels are, therefore, likely to reduce mortality and morbidity provided they don't create health loss in populations diverted on to out-patient pathways. Research thus far is reassuring. Reschen et al. (2020) saw no change in mortality amongst AIM populations following the introduction of an AEC facility that incorporated ESDM, and there is no evidence of health loss some of the conditions commonly managed via AEC (Chapman et al., 2009; Dunn & Coller, 1999; Olivot et al., 2011; Reschen et al., 2019).

The findings of this research support policy assumptions that ESDM for AIM populations is likely to produce an overall reduction in patient harm. Moments of overcrowding were fewer with ESDM compared with non-experts strategies, but were not eliminated. Overcrowding was worse by several magnitudes when allocation strategies wholly or partial included non-experts. For example, moving from the case site's current strategy of hybrid ESDM to a full non-expert strategy saw the median time spent in overcrowding increase by 223 - 662mins (3.7 – 11hrs) per week; moving from the baseline strategy to full expert staffing reduced it by 128 - 458mins (2.2 – 7.6hrs). The ranges reflect both the uncertainty in the modelled outputs of non-experts and the impact of increased tolerance of overcrowding. The greatest difference in overcrowding was observed when comparing ESDM wholly by experts (full ESDM) and allocation wholly by non-experts – overcrowding occurred for an additional 351-1120mins (5.9 – 18.7hrs) per week.

Further evidence to support reductions in patient harm via ESDM was evident in outputs related to delays. The SSM reported more patients in the bedded area experiencing delays as non-expert involvement increased. Differences were greatest between the full ESDM and the full non-expert strategies. This ranged from 7.5 – 10.5% (99% C.I. 7.1 – 11.0) more bedded area patients delayed when a zero tolerance of overcrowding was present to an additional 11.3 – 15.2% (99% C.I. 10.8 – 15.7) at 130% overcrowding tolerance. Lengths of delays (LoDs) were non-meaningfully different between strategies across all enforced occupancy levels. This is likely to have resulted from the modelled efficiency in creating capacity once the overcrowding threshold had been breached. In real-world settings, capacity creation may show more stochasticity than was modelled and lengths of delays could well be longer.

Although LoDs for patients in the bedded area were equivalent, LoD could be meaningfully longer for AEC populations with non-experts decisions. Although differences between strategies were non-meaningful when there was a zero tolerance of overcrowding, tolerance of 115% occupancy show the median LoD with non-expert strategies increase by between 41 – 50mins (99% C.I. 32,66) depending upon staffing mixes. This rose to 40 – 61mins (99% C.I. 30,77) when 130% occupancy was enforced. As with overcrowding, comparison between the full ESDM and full non-expert strategies saw the greatest differences.

9.3 Efficiency

A key goal of ESDM is efficiency in the delivery of urgent care; descriptions of how this could be recognised were extrapolated from the policy goals and extant literature on efficiency. As explained in Section 3.4.3.1.4, AEC utilisation alone, is inadequate to inform on efficiency of urgent care in isolation, but policymakers recommend its use as a proxy for this. The stated policy goals - removal of non-value adding steps, reduced ambulance handover delays, better flow, and reduction of unnecessary intra-hospital transfers – describe an efficiency that is technical rather than allocative[19] (NHS England, 2019; Shiell et al., 2002; Urgent and Unscheduled Care Directorate, 2022). Thus, metrics describing time taken to deliver care and identification of moments of care that are not clinically appropriate/necessary can be used to complement AEC utilisation as measures of efficiency. With regards to efficiency in bed resource utilisation, previous systems simulation modelling has recommended departmental occupancy levels of ≤85% to release whole system efficiency (Bagust et al., 1999) with more recent research suggesting it should be as low as 52% in some settings (A. C. Pratt & Wood, 2021).

Reducing delays, and non-value-adding steps, and keeping occupancy levels below 85% represent technical efficiencies that may be realised in AIM populations. In ED settings, decisions upon or shortly after arrival to an ED by a senior doctor have been shown to reduce delays from between 8 – 26mins and reduce lengths of stay by 30mins (Abdulwahid et al., 2016; Han et al., 2010; Holroyd et al., 2007). In AMU settings, care delayed by up to four-hours is deemed acceptable although not preferable (Society for Acute Medicine, 2020). These findings fall short of the technical efficiency sought by early decisions defined in this research as improvement by 30mins or more. Studies were of ED and not AIM expert decision-making but suggest technical efficiency in early decisions by experts. Reducing overall lengths of stay by 30min is also of doubtful significance in a setting like an acute medical unit that explicitly provides care for up to

[19] Where technical efficiency refers to maximisation of outputs with the fewest inputs and allocative efficiency concerns the distribution of resources to achieve the greatest health gain overall

48hrs (Acute Medicine Task Force, 2007). Again, decisions made by experts in AIM may yield more favourable outcomes for AIM populations. With regards to non-value-adding steps, although data are few, placing moderately unwell AIM populations in a setting not focused on their health needs has been shown to create local and system inefficiencies in some settings (Franklin et al., 1988; Sykora et al., 2020).

This work finds ESDM to realise greater technical efficiency that early decisions made exclusively by non-experts, but no strategy could successfully eliminate inefficiencies as defined by delays and in-patient occupancy levels. The 24hr ESDM strategy saw the highest AEC utilisation (>0.33 of referred patients), yet differences in the proportions of in-patient delayed between this and the alternative ESDM strategies did not exceed 0.05. In fact, no meaningful difference in patients delayed was found when comparing AEC utilisation as low as 0.167 with utilisation >0.33 suggesting factors beyond the AEC suitability (e.g., insufficient bed resources for population needs) contribute to delays (RCEM, 2022). Meaningful differences in patients delayed for in-patient care emerged between ESDM and full non-expert strategies as occupancy levels ≥115% were tolerated much as they did for AEC patients despite ESDM increasing the competition for resources in this area.

Other outputs representing local inefficiencies were worse with non-expert strategies, but meaningful difference cannot be concluded across all findings. The very large differences in the time spent in crowded and overcrowded conditions that emerged with non-expert allocations represent an efficiency as well as a safety concern and were meaningful (see Section 9.2). Other non-value-adding steps emerged as non-expert strategies saw a larger proportion of patients incorrectly starting care in AEC before transferring back to the bedded area when resources became available. This suggests that moving patients around the unit to start care when overcrowding was present for prolonged periods perpetuated departmental inefficiencies. Of note, this only emerged when overcrowding was tolerated. In addition, uncertainty in the modelled outputs of non-expert decisions, means that differences in incorrectly place patients between ESMD and non-experts cannot be reported as meaningful. If the model has overestimated trainee allocation performance then differences may well be meaningful. Local inefficiency is also represented by the increased LoD for AEC patients in non-expert strategies at 130% overcrowding tolerance.

The modelled findings suggest that many of the local efficiency benefits of an ESDM strategy are context dependent and risk whole system inefficiencies. Local efficiency gains of ESDM were only realised when the AMU was forced to tolerate occupancy levels of 115% or more. This suggests that a strict urgent care bed occupancy rule would be as efficient as ESDM if set low enough (Bagust et al., 1999; A. C. Pratt & Wood, 2021). In addition, if we assume hospital admissions and overnight transfers are as a measure of system efficiency there is a risk that ESDM contributes to inefficiencies when performed for all referrals. AEC patients faced no barriers to transfer in the model, thus patients who would have undergone ward round review (and potential discharge) transferred before this was possible. These patients may still have been discharged from their new ward within 24hr thus potentially representing a non-value-added step. However, their rapid transfer facilitated efficiency in the urgent care area. The differences in admissions observed between all strategies did not meet meaningful significance so risks of system inefficiencies appear low but present, nonetheless. Finally, a 24-hour ESDM strategy increased the number of patients transferred into the hospital overnight when system resources were few, again to non-meaningful levels but still potentially contributing to inefficiency if overnight transfer is regarded as a non-value-added step.

9.4 Value to patients

Currently evidence finds that the health value realised by increasing AEC utilisation via ESDM compared with admission varies but is not reduced (Lasserson et al., 2018; Olivot et al., 2011; Reschen et al., 2020; Seaton et al., 1999; Zondag et al., 2013). This evidence is limited to a few sub-groups of AIM populations. Amongst healthcare leaders and policymakers in the UK, the definition of value extends beyond improvements in health alone (NHS England, 2019; NHSS Director General, 2020). In the UK, this is reflected by the prioritisation of efficiency and performance metrics. Measurement of health is not explicitly advised by urgent care policymakers. Tools to measure health impact in AIM populations receiving care without admission are underdevelopment (Mols et al., 2021). Until they are available, the most we can surmise is that increasing AEC utilisation is unlikely to lead to health decline in some settings and in some patient groups.

Value in urgent care extends beyond improvement in physical illness but our measurement and understanding of this is limited. Patients' perceptions of urgent care value include communication, access, and environments of care (Glogowska et al., 2019; Huang et al., 2018; McGinnis et al., 2010; Mohammed et al., 2016; Spechbach et al., 2019). Delays experienced in non-admitted ED patients is found to create greater dissatisfaction than in-patient delays (Huang et al., 2018), and ED overcrowding negatively affects patients' experiences (Pines et al., 2008; Tekwani et al., 2013). Of note financial costs to patients (e.g. travel or carer costs) are rarely discussed in the UK healthcare policies and values beyond health-related quality of life have not routinely featured in evaluation frameworks (Drummond et al., 2015, Chapter Four, pages 112 - 116).

Non-meaningful differences in patient experience were found when comparing strategies and all saw <10% of patients with a negative experience of care. Slightly better performance with non-experts appears to have emerged as fewer patients were allocated to AEC by non-experts. This meant that fewer patients would be in a position to experience a delay in starting AEC treatment and/or dissatisfaction with lengths of stay. The explicit programming of experience in the SSM made assumptions about value based on the ethnography and extant literature, but may have been incorrect. The calculations in the model to determine experience assumed negative experiences in AEC were as significant as those that occurred when overcrowding emerged. If overcrowding carries a greater significance to patients than assumed by the modeller, a more favourable outcome for ESDM could occur. This would be unlikely to have an impact on final outputs given the very low instances of poor experience overall. It should also be noted that poor experience of AEC could be triggered by one of two criteria whereas poor experience in bedded area only occurred with overcrowding. This may have biased results against strategies with high AEC allocations.

Health outputs are challenging to attribute to the allocation strategy applied. Health was directly informed by a small volume of data collected during the ethnography as no other sources were found. The reader is referred back to Section 5.2.2.1 for a critique of its representativeness. That the quality adjusted life years (QALYs) per person were not meaningfully different between strategies, but became so when summed across patients discharged is likely to be a feature of the model programming. The SSM intentionally created more hospital attendances and more patients discharged from the bedded area with non-experts than ESDM. Health outcomes of the referrals that did not attend were not included. Health loss as a consequence of overcrowding was also omitted from the model due to the limited available data to inform parameters. This could reduce the health gains seen with non-expert strategies.

9.5 The effectiveness of early senior decision-making

The research question asked if an expert delivered early senior decision-making (ESDM) for patients referred with an acute internal medical (AIM) health decline was more effective that non-expert early decision-making. The question was posed because new UK health policy explicitly recommends ESDM as preferred practice with implicit recommendations for experts or staff nearing expertise to perform the role. In this research, expert ESDM for AIM populations was defined as remote decision-making by consultants specialising in AIM, with non-experts being defined as all other staff. Effectiveness was defined as: improved time to accessing urgent care resources, reduction in hospital in-patient admissions, improvement in self-reported health of discharged patients, a positive experience of care in most patients, reductions in overcrowding, and reductions in delays. The latter two outputs represented both efficiency and safety in care. The concept of value-based healthcare was eschewed in favour of a range of outcomes known to contribute to patient health and well-being.

This included efforts to measure health and experience directly. Effectiveness was measured by reproducing the early allocation decisions in consultant, trainee, and senior nursing staff of a representative acute medical unit (AMU) via systems simulation modelling (SSM). Modelled outputs representing measures of effectiveness were explored at increasing levels of enforced departmental overcrowding to reflect recent pressure in the UK healthcare systems.

This research found no evidence to conclude that ESDM is more effective than non-expert early allocation decision-making for AIM populations in UK settings, but services experiencing persistent overcrowding is likely to realise efficiency and safety benefits if ESDM is adopted during periods of peak referral activity. When occupancy levels in excess of 100% were enforced, significant local efficiency and patient safety gains emerged as experts performed early allocation decisions during periods of peak activity (0900 – 2000hrs). When levels were successfully maintained below 100%, no meaningful benefit was seen beyond reduction in crowding. This suggests that efficiency benefits of ESDM are greatest in settings where efficient flow between the AMU and in-patient hospital beds is supressed – a not an uncommon phenomenon in UK urgent care services (NHS England, 2022a). The gains observed were limited and assumed a hospital system able to meet the demands of admission avoidance in greater numbers than a non-expert strategy would generate. These demands amounted to a responsiveness in urgent care and specialist staff to evaluate patients, the availability of urgent out-patient investigations for commonly encountered conditions all days of the week, and a transport network capable of supporting travel to and from hospital when multiple attendances are required.

Money required to run a 24hrs ESDM strategy are likely to realise more value if spent elsewhere in the system. A tendency towards system inefficiencies emerged as the extent of ESDM increased to all referred populations in the model. Overnight transfers and hospital admissions increased, although not to a meaningful degree. These were assumed to create inefficiencies in other parts of the hospital (e.g., boarding). It is also important to note that the improved crowding with 24hr ESDM failed to achieve the recommended median occupancy levels for a unit of the case study site size (67 - 75% according to work by Pratt and Wood (2021). The 24hr strategy was accompanied by a decline patients' experiences of care and the suggestion of a lesser impact upon health as AEC utilisation exceed local prevalence of AEC suitability. The negative consequence of ESDM may be addressed in other ways that represent additional costs, e.g., improved communication to set patients expectations and investment in interventions that reduce lengths of stay elsewhere in the system and facilitate urgent care transfer. However, monies spent may realise greater value if investment is focused upon services that support occupancy levels that remove the need for ESDM altogether (<100%). A 24-hour ESDM service is unlikely to represent allocative efficiency particularly as the consequences for patient health remain poorly understood. This cannot be concluded based on the work done in this research. Better knowledge of the health outcomes of admission avoidance should be a priority for future research.

Increased AEC allocations via any ESDM strategy has the potential to create inefficiencies in parts of the system not modelled. The increased AEC allocation of experts assumed that existing services external to the system were able to provide diagnostic and treatment support to facilitate discharge. For example, prioritising urgent care patients for radiology services, expecting external specialist reviews throughout the day. This fulfils criteria for negentropy in a complex adaptive system – the drawing of energy from another part of a system in order to mitigate entropy/failure (Fajardo-Ortiz et al., 2015). Greater knowledge of the impact that enhanced AEC utilisation has on a whole system should be explored before and organisation considers incorporating ESDM into standard operational policy. A systems dynamics model could take the findings of this research and combine them with the stocks and flows of other departments to deliver accuracy on how increased expertise in allocation decisions impacts a hospital system as a whole.

Assumptions of safer care with ESDM are reasonable but not as comprehensive as policymakers may have assumed. Fewer delays to starting care emerged with ESDM, but an observed non-difference in the lengths of delays between ESDM and non-experts suggests harm reduction from reducing overcrowding is only partial (S. Jones et al., 2022). That said, non-expert strategies saw more episode of non-value-added care as a reaction to in-patient overcrowding – moderately unwell patients transferred to AEC to begin care. An unmeasured element of harm and inefficiency may be assumed to occur in these patients as a result (Franklin et al., 1988). This behaviour may be unique to the case study site setting. Hospitals with inadequate AEC resources or facilities that are not co-located may not demonstrate this behaviour. In such settings, delays and overcrowding may be even worse with non-expert strategies than this study found. The ceiling of benefits to ESDM will still be observed.

9.6 Implications for the local case study site

Moving from the current mixed model to a full ESDM strategy on the case study site is unlikely to realise whole system efficiencies. There were few differences between the modelled outputs of the alternative expert-inclusive strategies. Occupancy levels were smoother across the day with 24-hour ESDM compared with the baseline strategy which resulted in meaningfully less time spent in crowded conditions. This will realise some benefit to departmental staff working conditions, but does not deliver occupancy levels equating to whole system efficiency for a department of its size (72-75% according to Pratt & Wood (2021)). The potential for inefficiencies in other parts of the system from increased overnight transfers, increased demand for AEC will also contribute to inefficiency. The resources available for AEC would have to increase if dissatisfaction from delays to care in AEC were to be addressed. In addition to the costs of additional consultant to deliver a 24-hour model, this is unlikely to realise value to the system overall, but this is impossible to know for sure without a system dynamic model of whole system impact and cost-effectiveness analysis.

9.7 Generalisability to other settings

The research provides useful knowledge for other sites delivering urgent care to AIM populations. The size and scope of the case study site hospital and department have similarities with other urban hospitals and district general hospital across the UK (Society for Acute Medicine, 2022). Few acute medical units in the UK currently experience consistently optimal occupancy levels or are likely to do so over the coming years (Atkin, Knight, et al., 2022; P. Smith et al., 2014). The research findings suggest they will realise local efficiency and safety gains if they frequently experience overcrowding. Generalisability of the findings will also depend upon whether or that location has a dedicated AEC (or similar) facility for admission avoidance managed by specialists in AIM. How it is resourced to deliver care – i.e., the physical space available, the availability of rapid diagnostics, and the presence of a senior clinician is also important. Patients referred to an ill-equipped area will generate inefficiencies in AEC areas as was seen when a full ESDM model was applied to the SSM. Where investment in AEC is insufficient or facilities are inappropriately used, enhanced allocation via ESDM will be futile (Mahase, 2021). Remote settings may find little comparable elements if their location limits admission avoidance feasibility due to unreliable transportation links (e.g., ferries).

9.8 Recommendations

9.8.1 Patient value in urgent care out-patient services

Further research into the health and harms generated via out-patient care for acute internal medical populations is warranted. A question that this research failed to answer with satisfaction was the impact of introducing ESDM upon health. A non-significant reduction in health per discharged patient was observed with ESDM. However, the cumulative difference in health between expert and non-expert strategies was large. The data used to the inform the systems simulation model was limited and no extant literature capturing the wide variety of clinical needs seen in AIM populations was available to contribute to the model. Delayed diagnoses, unsafe decisions about non-admission made within a few hours of care, or delayed recognition of poor response to treatment are valid concerns to raised when urgent care is delivered without direct observation (Gigante, 2023; Roopra et al., 2014). This research identified challenges to improving knowledge of these risks and demonstrated the ease of using the EuroQol 5D5L tool in urgent care settings. Anticipated tools specific to acute medical patients may also be available in time for use (Mols et al., 2021). Combined with available knowledge on harms of overcrowding, comparison of total health generation via the SSM created for this research would be possible. As knowledge in this domain is sparse, prospective data collection is recommended over simulation modelling to generate data at this stage.

Societal value would be a useful addition to complement health outcomes in future research. There are likely to be factors beyond the temporal underlying the dissatisfaction described in the ethnography and reproduced in the SSM. For example, time from work or carer duties. Such societal costs may be alleviated by out-patient care delivered provided patients are fully informed of what to expect. Alternatively, as the costs of travelling back and forth to hospital for care, and or receiving care from family/friends will be borne by the public, enhanced AEC utilisation may produce societal harm. This is an area that is poorly explored in research so far. Quality improvement work in other settings has revealed unrealistic expectations of the scope of AEC in patients due to poor information about services (Abdulazeez & Tran, 2020). Poverty of knowledge about AEC casts doubt on policymakers assumptions that patients prefer out-patient care (NHS England, 2019). Prospective data collection affords the opportunity to improve knowledge of how societal costs and measure preferences. This could also be used to update the SSM with the addition of new patient parameters that reflect non-health value beyond time where indicated

9.8.2 Cost-effectiveness evaluation

For the true value of the ESDM strategy to be understood its impact on patient outcomes in urgent care, societal costs, and costs to the wider hospital system should be considered. The health policies' recommendations for expert ESDM in urgent care promote an ideology of urgent care without hospital admission. As this work and other research has shown, we have incomplete knowledge of the costs and consequences of AEC compared with in-patient care (Lasserson et al., 2018). Thus, we have limited knowledge of the costs and consequences for patients whose care will be determined via ESDM. This research predicts whole system inefficiencies when ESDM is performed for all referred populations and identifies a need for more resources that facilitate admission avoidance in all iterations of ESDM. These resources are not available in all settings (Irvine et al., 2022; Mahase, 2021). The costs of running an AEC service are not explicitly described in extant literature.

The costs of AEC – enhanced via ESDM - are assumed to be fewer than those of in-patient care because overnight hospital stay is not required. This does not consider the costs of additional expert staffing, nor the ceiling of benefits observed in this research. It also does not consider the resources used to ensure AEC functions as planned. The Asplin model of ED crowding identifies three stages where urgent care flow must be addressed – input, throughput, and output (Asplin et al., 2003). The ESDM strategy addresses input and has some effect on throughput (delivery of care when commenced in AEC); however, output (exit from the system) remains predominantly under the control of the agents external to urgent care. This was observed in the sensitivity analysis of the SSM where AEC prevalence and daily discharges had a greater influence on modelled outputs than decision-maker allocations. In fact, the modelled efficiency of the AEC services created a non-meaningful increase in admissions because AEC patients were programmed to face no barriers to transfer if admission was required.

Improving access to resources that facilitate flow from all urgent care areas may realise equivalent or better outcomes to staffing an ESDM strategy. If bedded area admissions were modelled to be transferred as efficiently as AEC patients, episodes of overcrowding would reduce. This would lessen the harm and efficiency gains of ESDM. The costs of an ESDM strategy were not explicitly measured in this research, but it is useful to note that a full-time consultant salary in the UK exceeds £90 000 per year [20]. The costs of staffing an additional tier of staff for ESDM could easily exceed £500 000 per year on a single site[21]. Additional staff would be needed if the strategy were to be successful. Performing ESDM in addition to other duties risks poor decision-making and poor performance in all tasks undertaken (Pignatiello et al., 2020; Shanteau, 1992); this removes the benefits of intuitive decision-making sought from ESDM. Such costs would be in addition to the resources needed to meet the demands of enhanced AEC utilisation. Equivalent or greater value may be realised if decision support tools were enhanced to support non-experts and funding directed towards improving diagnostic, treatment, and/or specialist access in urgent care upon arrival.

[20] A full-time consultant physician's wage in the UK ranges from £91 474 to £121 548 per annum. Not inclusive of merit awards or additional duty rates. https://www.bma.org.uk/ [Accessed 08/01/2023]

[21] The costs of just five additional experts to support ongoing clinical care and deliver some ESDM on the minimum consultant wage, plus additional staffing costs (pension contributions, professional development fees) would see this easily exceed half a million pounds per year. This would rise with yearly incremental salary rises

9.8.3 Harnessing expertise in non-human systems

A decision-support tool that mimics the intuitive creativity of consultants could yield efficiency gains equivalent to ESDM. Creating this in an artificially intelligent system that applies rational calculation of contextually appropriate consequences to the decisions made would help mitigate the emergence of whole system inefficiency. This research found that clinicians with expertise in AIM intuitively combine their clinical knowledge and experiential learning to identify patients in whom they perceive a potential for admission avoidance. This has been observed in other AIM settings (Reschen et al., 2019). Their approach is holistic. It incorporates intermediate consequences for their local service provision along with patient-centred goals, but does not consistently include the consequences for external services. When modelled, this style of decision-making realised non-waste in urgent care resources but tendencies towards inefficiencies emerged. This is because admission avoidance is not always their goal nor is it consistently feasible. Experts test the limits of admission avoidance, but in doing so they fail to consider the consequences of increasing AEC utilisation upon the whole system. This research also found that they are not immune to instinctive decision-making and biases (Tversky & Kahneman, 1974).

Combining intuitive expertise with artificially intelligence (AI) software could be the key to mitigating whole system inefficiencies in expert allocation decision. There is a rising interest in the application of machine and deep learning to aid clinical decision-making (Rajkomar et al., 2019). Systems that combine clinical data with statistical probabilities have been developed to augment clinical practice in a variety of domains. For example in detecting patients at risk of critical decline (Escobar et al., 2016), alerting them to potentially cancerous polyps during endoscopy (P. Wang et al., 2019); deep learning has been shown to augment expertise in cancer diagnoses (Ardila et al., 2019; Haenssle et al., 2018). This research found expert decision-making to rely heavily on useful heuristics and pattern-matching. Pattern-matching informed by clinical experts and evidence-based medicine could be programmed into software that links to patient records and local availability of resources. Moments of logical analysis could then be incorporated for elements such as physiological parameters, patient preference, and current resources. Results outputs deliver real-time estimates for patients about time taken to receive care, and probabilities of hospital admission whilst providing information for proactive departmental and hospital capacity management.

An decision support tool that incorporates machine learning is not without risks, but would be far superior to current tools use. As Section 3.2.2 explained, currently available decision tools are risk averse and often too broad in their scope to consider patient circumstances or local context. Risk of bias is not fully eliminated in AI systems (Howard & Borenstein, 2018), and data inputs need to be meaningful when diagnostic support is sought. However, the allocation decision of ESDM is predominantly operational. The clinical aspect of the decision is in determining safety in delayed or non-attendance and not determining a diagnosis or comprehensive treatment plan. Use of an AI system could augment a non-expert in referral decisions about safety and feasibility of care via an out-patient pathway, and reduce unwarranted variation in AEC utilisation. It would have implications beyond AIM and beyond the UK as international healthcare systems seek to learn from the UK model of urgent care in admission avoidance systems (Goh et al., 2018; Keane et al., 2022; M N T Kremers et al., 2020).

9.8.4 Wider adoption of ethnography and simulation modelling to advise healthcare policy planning

Health policies advising on service design and delivery would benefit from exploring recommended interventions ex-ante via ethnographically-informed SSMs. Healthcare delivery research is challenged by a lack of research targeted at policymakers' needs (Orton et al., 2011). This is exacerbated in contexts that see policymaker priorities, and the funding to address them, subject to changes in political structures and national leadership philosophies (Morrato et al., 2007). The quality improvement projects and expert opinion presented as evidence supporting ESDM recommendations offered little in way of reliability or validity to support wide-spread adoption (Taylor et al., 2014).

Ethnography is an advantageous method to inform systems simulation models for health policy evaluation. Because SSMs are inherently reductive in their approach to reproducing events, modellers need to ensure representative accuracy in the mathematical functions that reproduce the behaviours of entities. As this research shows, ethnographic accounts with contextual relevance have the capacity provide modellers with a depth of data that may move an SSM from theoretical to realistic reproduction capabilities. Agent-based modelling is particularly suitable as similarities exist in the frameworks that ABM modellers and ethnographers apply (Dirksen et al., 2022). For example, Sattenspiel et al. (2019) applied contemporaneous media and journal accounts to inform an ABM of an isolated community during an infectious pandemic that provided new insight into disease transmission in small communities. Krejci et al. (2016) created an ABM with ethnographically-obtained data about consumers and producers in food systems revealing the importance of social factors over financial concerns in food markets; Bobashev et al. (2019) demonstrated variation in HIV transmission a consequence of source, preparation, and injection method of heroin via an ethnographically informed ABM.

This research is evidence that an ethnographic study of real-world settings applied to systems simulation modelling provides a safe platform to explore the 'what ifs' of policy recommendations in service design. Combining analytic auto-ethnography with traditional observational ethnography, meant that identification of truth-like statements about decision-making, influences, and behaviours that are likely to exist in other settings was possible. New knowledge of decision-events in clinical experts was created. This led to the creation of a realistic model with generalisable elements suitable to evaluate the health policy recommendations. The method choice proved vital for representing behaviours that appeared incommensurate with the stated ideologies of the organisation and staff observed - for example, allowing overcrowding to exist in the AMU but not the ED or hospital wards. It provided a means to create rules for model outputs with relevance to societal outcomes (time spent in AEC), support the exclusion of elements that were not altered by ESDM. It allowed identification of why a single SSM methods would be insufficient to represent ESDM in action.

9.9 Limitations

There are limits to the extent that the research findings may be said to represent truthlike statements about predicted outcomes of applying an early senior decision-maker model in acute internal medicine. These are covered in this final section.

9.9.1 Data limitations

Both the COVID-19 pandemic and the poor availability of extant literature about urgent care delivery meant that data used to inform and validate the model were small. Predictive modelling requires knowledge of historical trends and data to guide model building but not dictate it. Useful knowledge of potential futures emerges on the assumption that patterns informing the model are representative. Data to inform the variables involved in rules around discharge were small or poorly available and should be considered when interpreting modelled findings.

The daily discharge rates used as model inputs exerted a strong influence on model outputs. Assumptions about the likely degree of stochasticity in discharge rates may be incorrect but greater accuracy in their creation was not possible. The known variables influencing discharges in real world urgent care settings were too numerous to include without creating an overly complicated model. As the intended purpose of the model was to isolate the impact of the allocation decision-maker, it was reasonable to assume a fluctuating discharge rate that varied daily within an observed range - observed during ethnography and in the verification dataset. It was assumed that resources to facilitate discharge would be consistently available and not be affected by periods of very high or very low occupancy levels.

Daily discharge capabilities and prevalence of AEC-suitability in the population are connected as a system's capability to successfully manage patients without admission will be relative to the prevalence of ambulatory sensitive conditions in a population and the resources available to realise discharge. As incidence of AEC-suitability is assumed to equate to prevalence (Section 4.7.4.4.4), consistency in available services will lead to a stable prevalence. If there is poor access or inconsistent availability of resources that facilitate admission avoidance in a location, then prevalence and the proportion of patients requiring admission will vary. For example, a suspected pulmonary embolism may be safely managed via AEC but if a patient presents outside of usual service hours and the department responsible for diagnostic scanning classifies all non-admitted patients as non-urgent, then the patient may need admitted. In this research, the AEC prevalence remained fixed across all staffing strategies explored. The daily discharge rate was modelled to have daily stochasticity to reflect realistic variations in patients' needs and resources such as a broken scanner or staffing absence. These are reasonable assumptions for modelling a location where AEC pathways are established and resources consistently available.

9.9.2 Validating systems simulation model of a social space

The modeller assumptions about behaviours and how to represent them will have influenced findings (Pidd, 2004). The reductive nature of SSMs is a limitation in all research that adopts the technique, but this is particularly challenging when modelling dynamic social settings such as healthcare locations. The simplification of staff behaviours and patient activity down to mathematical rules and logic belied the complexity of a healthcare space and the intentions/actions of actors within it.

Data available to validate the SSM in this thesis was small. There is a risk that it poorly represented usual activity and outcomes. The SSM may have only succeeded in reproducing the moment in time captured by those specific months of activity and not the long-term outcomes of the system. Obtaining more data to validate the model post-COVID proved challenging as the changes in process introduced to manage strict infection control measure took more than 18months to be withdrawn on the case site. Access to data after usual practice was restored was not possible during the research period. The predictive modelled outputs assume that the processes of evaluation and care in place post-COVID are as described in Chapter Five. This assumption is supported by dialogue with the consultant team working on the case site.

The process of validation was particularly challenging given the hybrid nature of the model. Although other researchers have highlighted these limitations, an ideal framework that surpasses the TRACE one employed in this research is yet to emerge. A quantitative approach to analysis of some modelled outputs was possible as the discrete event simulation components were amenable to tests of statistical significance and quantifiable patterns emerged. However, some readers may find the predominantly pattern orientated approach and the uncertainty generated a difficult barrier to overcome when appraising the credibility of predictive outputs.

10 Conclusion

This thesis presents a body of research that sought to understand the value early senior decision-making (ESDM) in urgent care. Specifically, it sought knowledge of whether expert delivered ESDM for patients referred with an acute internal medical (AIM) health decline was more effective that non-expert early decision-making. The research was inspired by United Kingdom national health policy recommendations to reduce hospital admissions for patients with urgent health decline via remote, senior (read expert) clinical decision-making. The research concludes that urgent care areas that routinely experience occupancy of in-patient area in excess of 100% will benefit from introduction of expertise in the decision-making process for patients referred during peak hours of activity, but will tend towards whole system inefficiencies if the extent of ESDM exceeds a hospital systems capacity to facilitate admission avoidance. In the short term, hospitals experiencing urgent care overcrowding may consider increasing the involvement of experts in early decision-making. In the long-term a strategy that exploits expert knowledge in decision support tools holds promise for realising most of the efficiency benefits without whole system inefficiency emergence.

This research was a necessary step to improving knowledge of early senior decision-making before costly, and potentially harmful, changes were made to care delivery. Cost-effectiveness of an ESDM strategy was not possible to determine due to limited health outcome data. However, the ceiling of benefits realised in this research support the need for original research comparing the health outcomes of admission avoidance versus in-patient care inclusive of the harms of overcrowding in urgent care settings outside of the ED. This is necessary before wide spread adoption can be considered as costs are likely to be considerable and at the expense of other hospital services that may support efficiency in locations inclusive of, but not exclusive to, urgent care.

10.1 Contributions

This section outlines the theoretical, methodological, and practical knowledge contributions this research makes to the domains of urgent care delivery and expert clinical decision-making. It begins by discussing the contributions under these three themes listed before concluding with a table listing all contributions and the challenges faced in creating them.

10.1.1 Theoretical

This research has led to the development of a new conceptual model for urgent care decision-making in clinical experts tasked with allocation decision-making. This conceptual model holds potential for generalisability to other aspects of urgent care decision-making and expert decision-making in other domains of clinical practice. Available knowledge of how clinical decision-making occurs in expert clinicians is limited by a lack of field studies. A recent focus on Heuristics and Bias theory tends to focus on poor decision-making and is supported by studies that infrequently include expert clinicians amongst participants. The theory of conjecture formation and refutation was combined with theory of expert intuitive decision-making to describe the predominance of heuristics in the expert brain that are controlled for acceptability using conscious analysis. This research made a novel connection between theories of intuitive decision-making and naturalistic decision-making in non-clinical experts and applied them to a model of early clinical decision-making in urgent care.

Parallels between these findings and those of clinicians in controlled studies suggest the generalisability of the conceptual model in understanding how clinical experts made rapid decisions with a moderate to high degree of accuracy compared with non-experts in other clinical arenas. This research presents novel and useful evidence for academics in the fields of clinical decision-making and medical education.

10.2 Methodological

The chosen methodology of a hybrid agent-based model and discrete event simulation model contributes to the growing body of work on the use of hybrid systems simulation models for research in healthcare and other social spaces. As does the use of ethnography to inform systems simulation modelling. This benefits researchers in the fields of operational research, management science, and healthcare systems research. It also adds to the body of knowledge on the application of analytic autoethnography and ethnography in poorly accessible research domains – i.e., expert clinicians in urgent care. Finally, it contributes to knowledge of methodology in healthcare policy evaluation.

The use of hybrid systems simulation models in research is growing. This research delivers a clear example of where hybrid modelling can assist in explaining how complex social phenomena may occur whilst simultaneously deliver predictions for healthcare leaders when time and resources for extended data collection are limited. As discussed in Section 3.4, the output restrictions associated with a single modelling technique can make research of social realms challenging. Linear models belie the complexity of interactions and offer little explanatory power but can offer powerful predictions. Non-linear models may suffer from limited usefulness if outputs cannot be validated. Combing a linear and non-linear model provided mean to introduce complexity but enhance with predictive power. Recognition of the value that combining models brings is increasing, but there remain few examples compared with studies using single techniques. This may go some way to explaining why validation of hybrid model outputs is challenging (Taylor et al., 2014).

Research of healthcare delivery is small compared with clinical research and research into urgent care delivery outside of ED settings is poorly represented still. This research delivers evidence of the successful application of management science knowledge and technology to the practical problems of clinical and operational decision-making in daily practice. It has created a model and generated finding with generalisable implications for sites beyond the one used in the study in a hospital. Knowledge of the tools capable of usefully exploring service delivery is largely held by practitioners of computer sciences, operational research, and management science. However, it is clinical healthcare leaders who create the novel interventions for healthcare delivery and introduce them. Much work in operational research has had limited impact on clinical services because of this knowledge disconnect – few studies that present the usefulness of systems simulation modelling are published in clinical journals and clinical staff rarely read outside of their own domain of practice. Clinicians have little awareness of how SSM practices may enhance their service research and planning; nor how it may minimise the ethical and logistical barriers to research in urgent care. Few non-clinical researchers will have such intimate access to clinical settings and healthcare culture.

Few clinicians will have the time or capabilities to develop expertise in system simulation modelling. By adopting the dual role of clinical expert and modeller, the researcher has contributed by connecting the two domains and showing what closer collaboration in research may achieve and how clinician-led research of service design and delivery may be advanced beyond quality improvement practices.

10.3 Urgent care delivery

The key contribution of this research is evidence that early decision-making by clinical experts realises some short-term benefits for urgent care efficiency but fails to meet policymakers' expectations of reducing admissions. It is highly likely to realise an increase in costs of care due to inefficiencies it introduces and the costs of additional staff. With the current performance metrics, an expert ESDM will appear highly successful on paper, but this will not necessarily equate to reduced costs of care and equivalency in health and well-being. Costs and health may even be worsened. This is valuable knowledge for healthcare leaders planning the design of services and seeking to introduce innovative way to deliver care in the face of increasing urgent care demand and dwindling resources. Readers of the health policies may be under the assumptions that recommendations for expert ESDM are evidence-based. This work provides empirical evidence of its effectiveness to counter local case site reports and anecdotal evidence from experts who recommend it.

This research also contributes to service delivery knowledge by identifying a role for artificial intelligence to support allocation decisions. The modelled outputs show that expertise in allocation decisions has merit in achieve safety in care and staff workloads.

Algorithmic decision support tools are used in many aspects of healthcare delivery and the currently available risk averse models for allocating patients to non-admission pathways could be enhanced to better mimic expert decision-making. This could facilitate non-clinicians to allocate referred patients at a significantly lower cost whilst achieving the immediate gains of reduced overcrowding and reduced delays. An A.I. supported system is also likely to realise less variability in AEC populations creating less inefficiency in AEC that human expert systems.

Table 10:1 Contributions of the research to address identified gaps in the knowledge of early senior decision-making in urgent care

Knowledge sought	Types of knowledge	Gaps in knowledge	Potential sources of knowledge	Method to address gaps	Challenges faced	Contribution
How may the effectiveness of early urgent care allocations be determined?	Health produced Patient experiences of care Measures of hospital system efficiency	Patient-reported outcomes of health and well-being in urgent care populations Patient experience of urgent care via in-patient and out-patient pathways The impact of AEC utilisation on hospital admissions	Prospective data collection of health before and after receiving urgent care Experiences of patients receiving care in AEC and in-patient urgent care facilities Admission and discharge data from an urgent care system that uses AEC facilities to prevent hospital admission	Data collected used as model inputs to predict health generated per 1000 patients discharged Data collected used to inform a conceptual model to predict and understand the emergence of negative patient experience as patients interact with urgent care services Prediction of urgent care discharges and transfer to in-patient care over time as staff make early allocation decisions	• Small sample sizes and poor follow-up rates due to participant drop out • Heterogeneity of patient need in urgent health decline • No validated tools for capturing patient experience • Limitations of structured surveys to understand a subjective and nuanced phenomenon • Reluctance of patients to appear critical of staff and services • No knowledge of patient flow beyond the AMU • Limited knowledge of appropriateness of admissions and discharges • No measure of how efficiency affected beyond admissions (e.g., length of stay overall)	• Evidence of the reliability and usefulness of generic HRQoL tools for health measurement in urgent care • Evidence of a potential difference in health between in-patient and out-patient urgent care • Knowledge of the expectations of patients attending acute medical units • Evidence to contest policy assumptions about patients' preferences for out-patient urgent care • Evidence of the poor experiences of care in out-patient facilities to balance existing evidence • Evidence of non-meaningful difference on in-patient occupancy to questions assumptions about fewer admissions with early expert decision-making • Evidence of improved in-patient occupancy rates with early expert decision-making

Knowledge sought	Types of knowledge	Gaps in knowledge	Potential sources of knowledge	Method to address gaps	Challenges faced	Contribution
How may the effectiveness of early urgent care allocations be determined?	Measurement of departmental Efficiency Costs of early allocation staffing models Costs of delivering urgent care via AEC and in-patient care	No measurement for urgent care occupancy levels exist Types of staff and hours of labour required to deliver early allocation decision-making Demand on hospital resources to facilitate admission avoidance via AEC	Emergence of environment activity and occupancy when early allocation decisions are reproduced in a systems simulation model Cost effectiveness analysis of different staffing models Local system costs of diagnostic, treatment, and staffing resources used to deliver urgent care in AEC and in-patient facilities	Prediction of departmental occupancy levels over time as staff make early allocation decisions Provision of a range of predictive outputs to apply to an economic evaluation of different staffing models Prediction of daily attendances to AEC services with different staffing models	• Occupancy levels emergent in the model and not possible to validate beyond observed patterns • Unable to capture measure differences efficiency in patient care/processes at different occupancy levels • Data to inform health related quality of life measures difficult to apply to urgent care areas in isolation as other different teams involved in care such as the emergency department) • Costs of delivering AEC versus in-patient care unknown • Variations in resources access across the country make this difficult to calculate for all settings Costs of delivering AEC versus in-patient care unknown	• Evidence of reductions in but not elimination of overcrowding with early expert decision-making • Evidence of where reduced delays to in-patient care with early decision-making may be realised • Evidence of unanticipated inefficiencies introduced into AEC areas with early expert decision-making • Knowledge of the challenges to determining patient-reported health and well-being outcome • Evidence of occupancy levels per hour to apply to an economic evaluation model • Evidence of in-patient lengths of stay and hospital admissions to apply to an economic evaluation model Evidence of patient demand on AEC services that may be applied to an economic evaluation model

Knowledge sought	Types of knowledge	Gaps in knowledge	Potential sources of knowledge	Method to address gaps	Challenges faced	Contribution
How might early urgent care allocations and their outcomes be reproduced in a systems simulation model?	How allocation decisions are made	Internal rules and decision processes of clinicians when determining admission avoidance suitability Environmental influences that affect early allocation decisions How internal rules and the external environment combine to create the decision-making process	Participatory observational study of allocation decision-making in staff in real-time Participatory observational study of allocation decision-making in staff in real-time Analytic autoethnography and thematic analysis of expert early allocation decisions for urgent adult medical patients	Conceptual model of expert and non-expert decision-making in early allocation decisions. Simplification of allocation decision-making for systems simulation modelling	• Subjective nature of decision-making and unmeasurable elements of decision processes limit theory to what may be abducted • One possible explanation for how allocation decisions occur • Unable to validate generalisability without studies in other clinician experts • Limited access to data about trainee decision-making at different stages of career • Unable to evaluate how senior nursing staff allocate non-ED referrals Small volume of data available to validate due to the COVID-19 pandemic	• Novel concept for early urgent care decision-making in experts • Advancement of theory on expert clinical decision-making: (The role of intuitive expert decision-making in urgent care and the role of heuristics in rapid, high-stakes expert decision-making) • Evidence of the experiential learning of expert decision-making in clinical trainees • Evidence of the generalisability expert of decision-making in clinician experts (Naturalistic decision-making theory; Heuristic and Bias Theory; Conjecture formation and refutation) • Evidence of the use of heuristics in expert decision-making of clinicians Evidence of the environmental influences upon decision-making in urgent care settings

Knowledge sought	Types of knowledge	Gaps in knowledge	Potential sources of knowledge	Method to address gaps	Challenges faced	Contribution
How might early urgent care allocations and their outcomes be reproduced in a systems simulation model?	How allocation outcomes emerge The influence of the decision-making environment	The effect of the care environment on patient movement post-allocation Predictable external events Prevalence of AEC in Emergency department and non-emergency department populations referred	Observational study of patient movement through the hospital system. Observational study of culture and practice amongst clinical and non-clinical staff in the decision environment Historical data of admission avoidance via urgent care and expert opinion Observational study of activity in the department	Emergence of patient flow and disposal outcomes in the systems simulation model Reproduction of patterns of patient movement through the system as a result of organisational rules and culture Reproduction of departmental, system, and patient outcomes by incorporating regular external events Updated estimation of AEC prevalence in local populations via Bayesian inference	• Organisational culture followed trends and was not based on strict or objective rules that could be easily coded • Observed practice during the second COVID-19 lockdown may not be consistent with post-lockdown behaviours and rules • Small volume of data available to validate due to the COVID-19 pandemic • Observed practice during the second COVID-19 lockdown may not be consistent with post-lockdown or future events • Small volume of data available to inform calculations	• Knowledge of how the urgent care environment change in real-time and the influence of actors at the microscopic levels on the mesoscopic level of the urgent care environment in acute medicine • The influence of organisational culture on clinical decision-making in urgent care • The influence of sense of self as a clinical professional on decision-making • Novel application of predictive values to determine success in early allocation decision-making using • Novel application of Bayesian inference to determine local AEC prevalence for a hospital • The successful reproduction of urgent care stochasticity, clinical, and system behaviours in a systems simulation model

Knowledge sought	Types of knowledge	Gaps in knowledge	Potential sources of knowledge	Method to address gaps	Challenges faced	Contribution
How might early urgent care allocations and their outcomes be reproduced in a systems simulation model?	The influence of the decision-making environment	Random external events	Observational study of activity in the department	Creation of a hybrid systems simulation model with stochasticity to incorporate random events described or witnessed during ethnography	• Expert opinion based on local clinicians estimates and not evidence-based beyond anecdote • Observed practice during the second COVID-19 lockdown may not be consistent with post-lockdown or future events	• The novel application of a hybrid agent-based model and discrete event simulations modelling to reproduce a complex clinical environment
How may urgent care outcomes be compared?	Determining meaningful difference in outcomes Prioritising outcomes	How meaningful difference in potentially competing outcomes for urgent care are determined	Systems simulation model outputs representing an envelope of outcomes with meaning patients, policy-makers, providers, and staff	Cross reference of model outputs with health policy goals and issues of known public interest	• Policy makers are not explicit in targets for patient-centred goals • Meaningful difference in outcomes had to be assumed via local expert opinion as no clear guidance • Costs and consequences of overcrowding more difficult to measure than admission avoidance or health related quality of life	• The use of multiple outcomes to represent various stakeholder goals in determining effectiveness • Evidence of the conflict between patient-centred care and efficiency goals when introducing service innovation

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Appendix A: Patient-reported data surveys

The tool used for the initial patient experience survey is presented in Table A:1

Table A: 1 Patient experience survey upon recruitment

Question	Possible responses
Who referred you here?	GP/ED/ Paramedic/ Out-patient clinic
Did the referrer explain the type of area you were coming to (e.g., clinic setting/traditional hospital ward)?	Yes/No
Did the referrer provide a description of what to expect during your attendance (e.g., types of tests, processes of assessment)?	Yes/No
Did the referrer provide an estimated length of time for your visit?	Yes/No
Did the referrer explain that you may require admission into hospital?	Yes/No
Did the assessing AMU team provide a description of what to expect during your attendance?	Yes/No
Did the assessing AMU team provide an estimated length of time for your visit?	Yes/No
Did the assessing AMU team explain that you may require admission into hospital?	Yes/No
Do you have an estimation about how long you expect to be here for?	Time-based continuous variable

Adapted In-patient experience survey (Siebers et al., 2010)

Q1 How did you get referred to the Acute Medical Unit? Please select the option that best fits with your experience

- I went to the Emergency Department with a health concern who sent me to the unit
- I went to my GP with a health concern who then sent me into the unit
- I called for an Ambulance, and they took me directly to the unit without seeing my GP or going to the Emergency Department
- I was contacted by my GP or specialist doctors/nurse who asked me to come up to the unit
- I was sent to the unit from another hospital ward or clinic
- Other

Q2 When the doctor/nurse told you that you would be coming to the Acute Medical Unit, were you informed about what would happen when you arrived?

- YES COMPLETELY
- YES, A BIT OR PARTIALLY
- NO
- CAN'T REMEMBER

What information (if any) was missing? Please write your answer in the space below

Q3 When you arrived in the Acute Medical Unit, were you kept informed about how long you would have to wait to be seen by a doctor?

- YES COMPLETELY
- YES, A BIT BUT NOT ALL THE INFORMATION THAT I WOULD HAVE LIKED
- NO
- I WAS SEEN AS SOON AS I ARRIVED

- I CAN'T REMEMBER

Q4 When you arrived in the Acute Medical Unit where did you go to first? Please choose the option that best describes your experience

- THE AMBULATORY ASSESSMENT AREA (THE AREA THAT WORKS LIKE A CLINIC)
- A BED IN THE MAIN WARD AREA
- I WENT TO THE BED AREA FIRST BUT THEN WENT TO THE AMBULATORY ASSESSMENT (CLINIC) AREA WITHOUT HAVING TO STAY OVERNIGHT
- I WENT TO THE AMBULATORY ASSESSMENT (CLINIC) AREA FIRST BUT THEN WAS MOVED TO A BED TO STAY OVERNIGHT OR FOR TO GET TREATMENT NOT AVAILABLE IN THE CLINIC AREA

Q5 DID YOU HAVE TO WAIT IN THE GENERAL WARD AREA ON A TROLLEY OR CHAIR UNTIL A BED BECAME AVAILABLE?

- YES (PLEASE GO TO Q.6 NEXT)
- NO (PLEASE GO TO Q.7 NEXT)

Q6 DID THAT HAVE ANY EFFECT ON YOUR EXPERIENCE OF COMING INTO THE UNIT? PLEASE TYPE YOUR ANSWER BELOW

Q7 Once you were on the Acute Medical Unit, were you kept informed about how long you would have to wait to be seen by a nurse or doctor

- YES COMPLETELY
- YES, A BIT OR PARTIALLY
- NO
- CAN'T REMEMBER

Q9 Once seen by a doctor, were you kept informed about what was happening?

- YES COMPLETELY
- YES, A BIT OR PARTIALLY

- O NO
- O CAN'T REMEMBER

Q10 Did you feel safe when you were in the Acute Medical Unit?

- O YES COMPLETELY
- O YES, A BIT OR PARTIALLY
- O NO
- O CAN'T REMEMBER

Q11 What about your experience made you feel partially safe or unsafe?

Q12

How much do you agree or disagree with each of the following statements?

Please tick one box on each line. If a statement is not applicable, please leave that line blank

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
The area or room I stayed in was clean	O	O	O	O	O	O	O
The bathrooms and toilets were clean	O	O	O	O	O	O	O
I was bothered by noise from other patients	O	O	O	O	O	O	O
I was bothered by noise from hospital staff	O	O	O	O	O	O	O
I was happy with the food and/or meals I received	O	O	O	O	O	O	O
I was happy with the drinks I received	O	O	O	O	O	O	O
I received care and assistance when I needed it	O	O	O	O	O	O	O
There were times when I felt threatened by other patients or visitors	O	O	O	O	O	O	O

Q13 While you were in the Acute Medical Unit, did you feel you were able to spend enough time with the people that matter to you - for example family and friends?

- O YES COMPLETELY
- O YES, A BIT OR PARTIALLY
- O NO
- O CAN'T REMEMBER
- O NOT APPLICABLE

Q14 Overall, how would you rate the Acute Medical Unit (bed and clinic a area as applicable) environment?

- O Excellent
- O Good
- O Fair
- O Poor
- O Very poor

Q15 How much do you agree or disagree with each of the following statements?

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
I had enough privacy when being examined or treated	O	O	O	O	O	O	O
I got enough help with washing and dressing when I needed it	O	O	O	O	O	O	O
I got enough help with eating and drinking when I needed it	O	O	O	O	O	O	O
I got enough help with going to the bathroom or toilet when I needed it	O	O	O	O	O	O	O

Q16 Were you involved as much as you wanted to be in decisions about your care and treatment?

- Yes definitely
- Yes, to some extent
- No and I would have liked to have been
- No but I didn't want to be involved

Q17 Were the people that mattered to you, such as family and friends, involved in decisions about your care and treatment as much as you wanted?

- Yes, definitely
- Yes, to some extent
- No and I would have liked them to be more involved
- No but they didn't need to be involved

Q18 Overall, how would you rate your care and treatment during your stay in hospital?

- Excellent
- Good
- Fair
- Poor
- Very poor

Q19 Thinking about the hospital staff you came into contact with, how much do you agree or disagree with each of the following statements?

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
Staff spent enough time with me	o	o	o	o	o	o	o
Staff listened to me if I had any questions or concerns	o	o	o	o	o	o	o
Staff discussed my condition and treatment with me in a way I could understand	o	o	o	o	o	o	o
Staff gave me the opportunity to involve the people that matter to me	o	o	o	o	o	o	o
Staff talked in front of me as if I wasn't there	o	o	o	o	o	o	o
Staff helped me to feel in control of my treatment/care	o	o	o	o	o	o	o

Q20 Roughly, how many times did hospital staff ask you for your personal details, including your medical history?

- o A few times
- o A lot of times and this didn't bother me
- o A lot of times and this bothered me
- o I was never asked
- o Don't know / can't remember

Q21 Did you feel that staff treated you with compassion and understanding during your stay?

- o Yes, always
- o Yes, sometimes
- o No

- Don't know / can't remember

Q22 Did you think that the staff worked well together in organising your care?

- Yes, definitely
- Yes, to some extent
- No
- Don't know / can't remember

Q23 Overall, how would you rate the hospital staff you came into contact with?

- Excellent
- Good
- Fair
- Poor
- Very poor

Q24 Were you and / or your carer involved in planning for your discharge from hospital?

- Yes, completely
- Yes, to some extent
- No
- I did not want myself / my carer to be involved

Q25 Did the hospital staff give you, your carer or someone else close to you all the information needed to help care for you at home?

- Yes, definitely
- Yes, to some extent
- No

- I did not need care at home

Q26 Were the arrangements for any follow up appointments explained to you in a way that you understood?

- Yes, definitely
- Yes, to some extent
- No
- I did not require any follow up appointments

Q27 When you were ready to leave hospital, were you delayed for any reason?

- Yes (PLEASE GO TO Q.28 NEXT)
- No (PLEASE GO TO Q.30 NEXT)
- Can't remember or don't know

Q28 Roughly, how long were you delayed for?

- Up to 1 hour
- Between 1 and 2 hours
- Between 2 and 4 hours
- Longer than 4 hours
- Don’t know / can’t remember

Q29 Why were you delayed? Please tick all that apply.

- [ ] Waiting for medicines
- [ ] Waiting to see the doctor
- [ ] Waiting for hospital transport
- [ ] Waiting for private transport

- ☐ Waiting for my discharge letter
- ☐ Waiting for a care package to go home
- ☐ Waiting for equipment / adaptation for my home
- ☐ Waiting for a care home place
- ☐ Something else

Q30 If your condition meant you were eligible for hospital transport to take you home, were you happy with how this was arranged?

- O Yes
- O No
- O I was not eligible for hospital transport
- O Don't know / can't remember

Q31 Overall, how would you rate the arrangements made for your leaving hospital?

- O Excellent
- O Good
- O Fair
- O Poor
- O Very poor

Q32 Did you speak to staff about the standard of your care and treatment or the services provided at any time?

- O Yes
- O No
- O Can't remember or don't know

Q33 If you were unhappy or dissatisfied with care, treatment or services, were you able to find out how to provide feedback or complain?

- Yes
- No
- I was not unhappy or dissatisfied

Q34 If 10 is the best care you could have experienced and 0 the worst care, overall, how would you rate your experience in the Acute Medical Unit?

CIRCLE THE NUMBER THAT BEST FITS YOUR EXPERIENCE

0 1 2 3 4 5 6 7 8 9 10

Q35 Was there anything particularly good about your hospital care?

Q36 What could have made your stay better?

Q37 Is there anything else you would like to tell us about your experience in hospital?

Q38 Which best describes your gender?

- Female
- Male
- Non-binary
- Agender
- Gender fluid
- Prefer not to say
- Other

Q39 Which age group do you belong to?

- 16-25 years
- 26-35 years

- 36-45 years
- 46-55 years
- 56-65 years
- 66-75 years
- 76-85 years
- 85-95 years
- >95 years

Q40 How would you describe your ethnic origin?

- WHITE -English, Welsh, Scottish, Northern Irish, or British
- WHITE Irish
- WHITE Gypsy or Irish Traveller
- MIXED or Multiple White and Black Caribbean
- MIXED or Multiple White and Black African
- MIXED or Multiple White and Asian
- MIXED or Multiple Any other Mixed or Multiple ethnic background
- ASIAN or Asian British Indian
- ARAB
- ANY other ethnic group
- ASIAN or Asian British Pakistani
- ASIAN or Asian British Bangladeshi
- ASIAN or Asian British Chinese
- ASIAN or Asian British Chinese
- ASIAN or Asian British Any other Asian background
- BLACK, African, Caribbean, or Black British African
- BLACK, African, Caribbean or Black British Caribbean
- BLACK, African, Caribbean or Black British Caribbean
- BLACK, African, Caribbean or Black British Any other Black, African, or Caribbean background

EQ-5D-5L Health Questionnaire - English version for the UK[22]

Under each heading, please tick the ONE box that best describes your health TODAY.

MOBILITY

I have no problems in walking about ❑

I have slight problems in walking about ❑

I have moderate problems in walking about ❑

I have severe problems in walking about ❑

I am unable to walk about ❑

SELF-CARE

I have no problems washing or dressing myself ❑

I have slight problems washing or dressing myself ❑

I have moderate problems washing or dressing myself ❑

I have severe problems washing or dressing myself ❑

I am unable to wash or dress myself ❑

USUAL ACTIVITIES *(e.g. work, study, housework, family or leisure activities)*

I have no problems doing my usual activities ❑

I have slight problems doing my usual activities ❑

I have moderate problems doing my usual activities ❑

I have severe problems doing my usual activities ❑

I am unable to do my usual activities ❑

PAIN / DISCOMFORT

I have no pain or discomfort ❑

I have slight pain or discomfort ❑

I have moderate pain or discomfort ❑

I have severe pain or discomfort ❑

I have extreme pain or discomfort ❑

ANXIETY / DEPRESSION

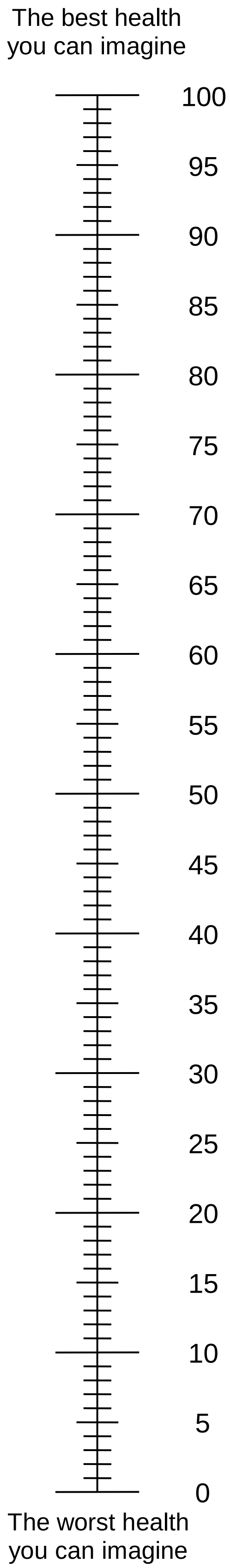
I am not anxious or depressed ❑

I am slightly anxious or depressed ❑

I am moderately anxious or depressed ❑

I am severely anxious or depressed ❑

I am extremely anxious or depressed ❑



YOUR HEALTH TODAY =

- We would like to know how good or bad your health is TODAY.
- This scale is numbered from 0 to 100.
- 100 means the <u>best</u> health you can imagine.
  0 means the <u>worst</u> health you can imagine.
- Please mark an X on the scale to indicate how your health is TODAY.
- Now, write the number you marked on the scale in the box below.

Appendix B: Ethnographic case study supportive data

Case site activity

Table B: 1 Referral and arrival activity on case study site

ACTIVITY	RESULTS		SOURCE
Peak referral time	0900-1800		Ethnographic observation
Proportion of total referrals during peak hours	Median 0.61 (0.55, 0.67)		October 2019 dataset
Proportion of patients arriving from ED sources	Peak hours (0900-1800hrs)	Median 0.22 (0.17,0.29)	October 2019 dataset
	Off peak hours (1800-0900 hrs)	Median 0.53 (0.46, 0.57)	
Travel time to AMU from ED source	15 – 360 mins Median ~75mins		Ethnographic observation (not available in AMU dataset recorded)
Travel time to AMU from non-ED source	30 – 360 mins Median ~ 180mins		Ethnographic observation (not recorded in AMU dataset)

Table B: 2 Patient arrival into the department

BEHAVIOUR	OCTOBER 2019 DATASET	ETHNOGRAPHY	COMMENTS
Proportion of arrivals during peak (0900-1800hrs)	Median 0.561 (IQR 0.403,0.738)	Large volume of activity during usual working hours extending into early evening	People accessed emergency GP clinics or attended ED after work and delays to arrivals via ambulance transport
Proportion of ED arrivals during peak	Median 0.400 (IQR 0.314, 0.530)	Limited interaction between ED and AMU doctors	Daily variability. Range consistent Monday to Friday but tended toward 45-50% at weekends and public holidays
Proportion of non-ED arrivals during peak	Median 0.738 (IQR 0.667, 0.771)	Limited interaction between ED and AMU doctors	Consistent all days of the week
Time of arrival after referral ED	Not available	Organisational preference for <120mins to meet 4-hour access standard Frequent movement when no resource in AMU available	Rightward skew with preference to move patients to the AMU regardless of resource availability in order to meet the four-hr standard and free resources in the ED.
Time of arrival after referral community	Not available	Usually 30-360mins after referral. Highly variable and skewed due to patient location, transport option, and demand on ambulance services	Highly variable but with rightward skew, as dependent upon patient access to transport, geographical location, ambulance service demand in the community (in turn influenced by the patient presentation and stability)
Proportion of bedded delays per day	Median 0.125 (IQR 0.024, 0.356)	Highly influenced by the day of the week and hospital occupancy levels. Days when delays anticipated clear from early in the day	Most patients experienced no delay. When delays were <5mins, accurate recording of times varied as these were documented by staff in the local, handwritten dataset. Staff would record these at the time or once completing several tasks.
Delay to in-patient resources access (minutes)	Median 55 (IQR 12,125) Max 634mins	Most patients placed into the correct resources upon arrival. Delays to accessing bed resources generally <30mins. Delays longer when high occupancy in the hospital. More likely to occur in the late afternoon/early evening period	If delay was <5mins due to bed/area cleaning, staff would often record delay as zero
Early morning AEC attendances	Not available	Patients arriving at AEC 0800-0900hrs were most frequently scheduled from a referral the previous evening or return Delayed attendance for as preference to use AEC services for stable patients.	Referrals towards the end of the GP working day (1700-1800hrs) often involved abnormal blood results taken from a stable patient Consultant DMs would delay attendance to ensure they arrived during AEC hours to preserve bedded area resources overnight. Also used for safe to delay when overcrowding was threatened/present or if the predicted care time for care exceeded the time left available in AEC that day

Table B: 3 Patient outcomes

BEHAVIOUR	OCTOBER 2019 DATASET	ETHNOGRAPHY	COMMENTS
Patients discharged daily	AEC: Median 0.765 (IQR 0.638, 0.912) AMU-bedded: Median 0.233 (IQR 0.200, 0.292)	Preference to keep patients in AMU until time to leave Patients tended to leave the AEC area quickly as they had access private or public transport AMU patient transport options varied due to complexity of physical needs	AEC patients were highly likely to be discharged overnight but would move to the bedded area until ready to leave. If discharge was likely, patients would remain in the AMU until ready to leave. Preference to remain in AMU based upon assumption that transfer to another ward would increase LoS AMU-bedded patients for discharge would occasionally be moved to the AEC to complete care or transferred to another area if overcrowding present/threatened
Patients admitted daily (both areas)	Median 0.656 (IQR 0.612,0.703)	Preference to compete initial stages of care before transfer to another ward. AMU-bedded patients were highly likely to be admitted especially when overcrowding was threatened or occurred. Early movement if overcrowding threatened/present	There was no reliable way to identify when patients were ready to be transferred if identified for admission in the patient notes or the electronic system. This appeared to be clinician-dependent – doctor or nurse would decide if safe to transfer. Most patients would require at least 6hrs to complete their initial evaluation and diagnostics to determine the working diagnosis and best area to transfer to (e.g., cardiology versus respiratory ward in a breathless patient)
Patients discharged within 24hr	Median 0.174 (IQR 0.141,0.224) Range 0.03-0.32	Patients remained in AMU awaiting discharge, but the short stay area was also used to facilitate non-admission to other areas of the hospital.	The AMU functioned with a medical short stay ward for patients suitable for discharge within 48hrs and a short stay frailty unit for elderly patients. Both areas were used to mitigate transfers into the main hospital beds and maintain flow from AMU once care was complete. Transfers to short stay and frailty were counted as admissions in analysis of the October dataset as patients were transferred from AMU.

Table B: 4 Evaluation and care delivery

BEHAVIOUR	OCTOBER 2019 DATASET	ETHNOGRAPHY	COMMENTS
Time to begin evaluation	Not recorded	All patients underwent the same evaluation process upon arrival: 1. Nursing staff assessment 2. Junior doctor evaluation 3. Initial blood sampling and diagnostic imaging 10-240mins in AMU-bedded Usual <60mins in AEC but longer if high volume of activity	Patients only began evaluation when placed in a clinical area (not when in a waiting area). Time taken to begin and complete varied according to volume of patients in the area, time of day (staffing), and individual care needs.
Time to complete care in mins (estimated by LoS in department)	AEC: Median 272 (IQR 165,420) AMU-bedded: Median 894 (IQR 523,1357)	Care completed after review of patient and results by consultant or senior trainee. Sometimes further investigation was requested or collaboration with specialist teams performed. Each morning, decisions to admit or discharge post-evaluation were delayed until specialist review or completion of the consultant ward round (0800-1130hrs). This extended LoS and frequently led to changes in admission plans for patients in the bedded area.	AEC patients were consistently managed in a few hours with a few taking up to 12hrs. AMU-bedded patients were mostly completed within 10hrs influenced by the twice daily presence of specialists (e.g. cardiology) and pressure to free resources for new arrivals. On rare occasions, patients would remain in AMU-bedded for several days (e.g., disagreement about specialist care team). Patients were in direct competition for staff time in the AMU and also in competition with other AMU patients and other hospital patients for diagnostic resources.

Table B: 5 Dataset assumptions and rules for missing data

Data object	Assumption	Action	Explanation
Prevalence of AEC suitability	Different for ED and non-ED populations	Posterior values via Bayesian inferential analysis taken to represent prevalence for each population	Used to calculate PPV and NPV to determine accurate representativeness in modelled behaviours
Prevalence of AEC suitability	Reasonable representativeness in historical datasets	Posterior values via Bayesian inferential analysis taken to represent prevalence for each population	Used to calculate PPV and NPV to determine accurate representativeness in modelled behaviours
Time of arrival, time of placement	Earliest time and date represents the time of arrival	Incorrect date/time removed	Dataset is informed by humans imputing values from previously completed handwritten sheets. High risk of human error
Time of arrival, time of placement	Latest time and date represents time left the area	Incorrect date/time removed	Dataset is informed by humans imputing values from previously completed handwritten sheets. High risk of human error
Time of arrival, time of placement	If date suggests left before arrival, date is incorrect as a result of human error	Date amended to make sense of patient journey	Dataset is informed by humans imputing values from previously completed handwritten sheets. High risk of human error
Clinical conditions	Clinical conditions grouped together by pathology and systems to represent common presentations, evaluation processes and treatment time	Patients conditions identified as grouped conditions according to symptom or suspected diagnosis	Group and conditions focused care is prioritised over nuanced clinical care for efficiency and according to evidence base
Bed waits	Accuracy in time spent waiting assumed in all waits greater than 5minutes long	Only waits >5mins analysed	Arrival and placement times are recorded by hand and are known to be reviewed by the organisation for bed waits. Some patients waits for a few minutes for bed area to be prepared but bed is available. Staff recording activity have other duties and may be distracted when recording
Admissions to other urgent care areas outside of AMU	All patients transferring from the AMU are admitted to the wider hospital system	Short stay area and the acute geriatric assessment unit not modelled	The AMU has two associated areas for urgent care where care is still delivered by the acute team. These patients remain under the care of the urgent care teams so are not in competition for other beds pending discharge. However, when these areas are full they do compete for in-patient wards. For ease of modelling, all patients transferred to these areas are included in admissions overall
Non-clinical patient data	No differences in patient activity according to ethnicity, gender, or age	Non-clinical information not analysed	The focus of the study of patient flow according to staff decision-making. This is condition and patient flow focused and not influenced by non-clinical features
EQ5D5L scores	Means and standard deviations for data collected via the EQ5D5L are representative of population treated in each clinical area in that location	Means and standard deviations used to create model distributions	No other data sources
EQ5D5L scores	The English dataset for estimating health via the tool is valid in Scottish populations	Direct application of English dataset values to EQ survey results	No other suitable data sources
EQ5D5L scores	Systematic error and ceiling effects of the tool are equivalent in both populations	None taken	Validate tool for health change assessment across many conditions and populations.
Patient experience	Experience is a binary phenomenon that assumes positive experience in all patients unless conditions for poor experience are met	AEC LoS >10hrs or corridor wait >1hr taken to represent poor experience	See section 6.1.1.3 patient outcomes
Patient experience	Results of the patient level data on experience reflective of the experiences of patients in this population	Direct application of findings into the model	No other suitable data sources
Patient experience	Experience of care is consistent and non-different in both areas due to geographical co-location and staffing pool with the exception of time spent waiting and/or receiving care	Only dissatisfaction related to time contributes to experience	No other suitable data sources

Patient-reported outcomes

Baseline data was collected at recruitment by me. Most follow-up occurred via email. With n=6 preferring postal follow-up and n=10 preferring telephone (performed by me). In-patient experience (IPE) surveys were reformatted onto an online questionnaire via Qualtrics. This led to greater compliance with completion and allowed anonymity for honest feedback as the participants were aware that I was also working as a clinician in the hospital during the study.

All follow-ups took place between 7-30 days after baseline survey. Median time to follow-up between groups showed no statistically significant difference. Evaluation of statistical significance between referral categories was only possible for EQ-5D-5L data (Table B:6). This was performed via the ‘gtsummary’ package for R using Pearson’s Chi-squared or Fisher's exact testing (categorical observations <5).

Patient experience results

For the IP experience data analysis, n=157 were recruited (Figure B:1 and Table B:7). Where data was missing from multiple choice questions, a 'neutral' response (e.g., neither agree nor disagree) was imputed if an available option (110 occurrences). If no neutral response was available, then no answer was imputed (17 occurrences). A question concerning patients being allowed to spend time with family was removed from analysis as there was an NHS-wide ban on visitors due to COVID restrictions.

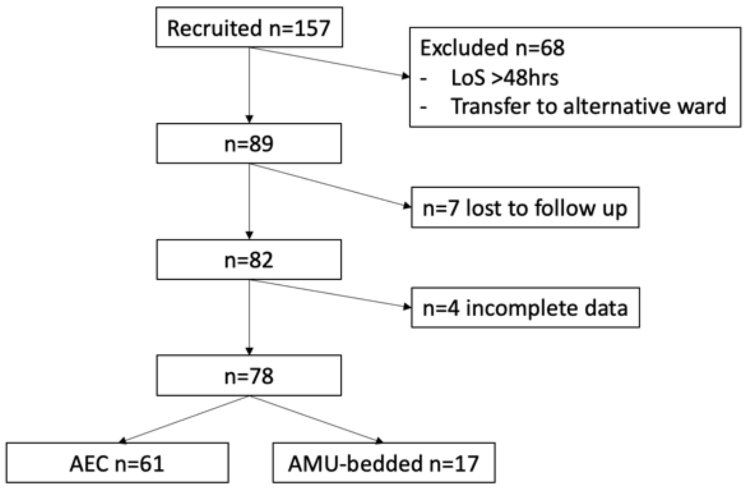


Figure B: 1 Experience survey recruitment and follow-up

Patients were contacted 7 days after attendance and followed up for a maximum of 30days from recruitment to allow for experience of follow-up to be included and minimise recall bias

Table B: 6 Demographics information of patients who completed the experience surveys

	Main Site of Care		
	AEC, N = 61[1]	**BEDDED**, N = 17[1]	**p-value**[2]
Gender			0.8
Female	32 (52%)	9 (56%)	
Male	29 (48%)	7 (44%)	
Age			0.4
	0 (0%)	1 (5.9%)	
16-25 years	2 (3.3%)	0 (0%)	
26-35 years	4 (6.6%)	1 (5.9%)	
36-45 years	3 (4.9%)	1 (5.9%)	
46-55 years	13 (21%)	2 (12%)	
56-65 years	12 (20%)	2 (12%)	
66-75 years	16 (26%)	3 (18%)	
76-85 years	8 (13%)	5 (29%)	
85-95 years	3 (4.9%)	2 (12%)	
Ethnicity			0.6
ANY other ethnic group	1 (1.6%)	0 (0%)	
MIXED or Multiple Any other Mixed or Multiple ethnic background	1 (1.6%)	0 (0%)	
WHITE -English, Welsh, Scottish, Northern Irish or British	58 (95%)	15 (94%)	
WHITE Any other White background	1 (1.6%)	1 (6.2%)	
Source			0.4
GP visit referral	35 (57%)	6 (35%)	
Remote review referral	5 (8.2%)	1 (5.9%)	
ED referral	11 (18%)	6 (35%)	
Hospital team referral	2 (3.3%)	1 (5.9%)	
Paramedic referral	6 (9.8%)	2 (12%)	
Other	2 (3.3%)	1 (5.9%)	

[1] n (%)
[2] Pearson's Chi-squared test; Fisher's exact test

No significant differences were seen between the characteristics of the patients. The case site was large teaching hospital in Dundee serving a small city with a large surrounding rural population. In keeping with the rest of Scotland, the area has a higher proportion of female than male citizens with a large proportion of 25-65year olds [23]. Note the sample had predominantly white British subjects. This is consistent with the population across Scotland (96% white)[24], but higher than the population of England and Wales (86% white)[25]. In keeping with some, but not all AMUs, the population of patients referred come from a mix of direct community referrals (GP) and the ED. Unusually, this hospital team also accepts direct referrals from paramedic crews. This is seen in other UK hospitals but is not widespread practise.

[23] https://www.nrscotland.gov.uk/files/statistics/council-area-data-sheets/dundee-city-council-profile.html#new
[24] https://www.scotlandscensus.gov.uk/census-results/at-a-glance/ethnicity/
[25] https://www.ethnicity-facts-figures.service.gov.uk/uk-population-by-ethnicity/national-and-regional-populations/population-of-england-and-wales/latest

Structured surveys

The results of the baseline survey about communication and expectations are provided in Table B:8. LoS is discussed in Section 5.1.2.1. Note this table contains information – where complete – for all patients initially recruited into the study. Patients were asked a series of 'yes/no' questions to appreciate their understanding of how their urgent care journey was likely to progress. This included all patients initially recruited to the study (n=157). Missing data in n=33. Demographic information was consistent with the findings in Table A:7.

Patients were asked to rate different aspects of care in the follow-up IPE survey (Figure B:2) and provide a final overall rating for their experience (section 5.1.2.1, Figure 5:4). For the ease of understanding, final ratings for each category of experience are presented only. These were consistent with the responses provided when each aspect of care was explored in the structured questions.

Table B: 7 Initial patient experience survey results

	Main Site of Care		
	AEC, N = 96[1]	**BEDDED**, N = 28[1]	**p-value**[2]
Aware of AEC facilities	32 (33%)	9 (32%)	>0.9
Processes explained by referrer	59 (61%)	15 (54%)	0.5
Time expectation given by referrer	32 (33%)	4 (14%)	0.051
Referrer discussed possibility of admission	30 (31%)	12 (43%)	0.3
Processes explained by AMU staff	81 (84%)	23 (82%)	0.8
Likely outcomes discussed	63 (66%)	14 (50%)	0.13
Time expectation created by AMU staff	28 (29%)	12 (43%)	0.2
AMU staff discussed possibility of admission	36 (38%)	9 (32%)	0.6

[1] n (%)
[2] Pearson's Chi-squared test; Fisher's exact test

Values show participants answering 'yes' when asked if this information was made available to them

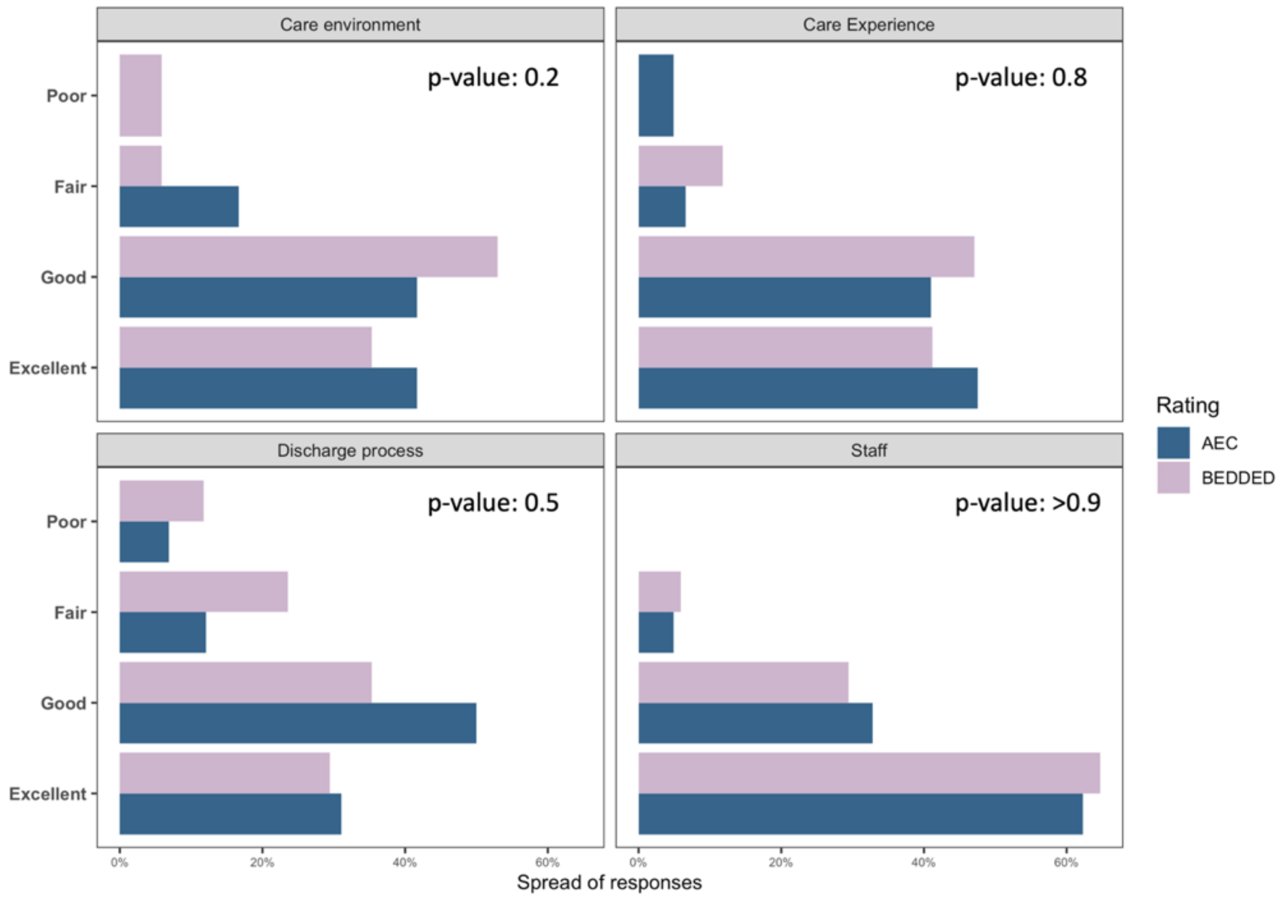


Figure B: 2 Ratings for each area of care according to patient groups

Statistical significance between the spread of responses was tested for via Pearson's Chi-squared test where numbers allow, and Fisher's exact for smaller numbers in responses. As is clear from the plot, the experience of care in each of the categories was consistent and tended towards 'good' or 'excellent'. This is likely to reflect the fact that areas of care were co-located and delivered by the same body of staff who rotated through each area across shifts.

Health-related Quality of Life results

The response to follow-up of the EQ5D5L was poor (Figure B:3). One participant was removed after initial descriptive analysis demonstrated a change in the VAS score that was highly inconsistent with the magnitude and directional change in HI.

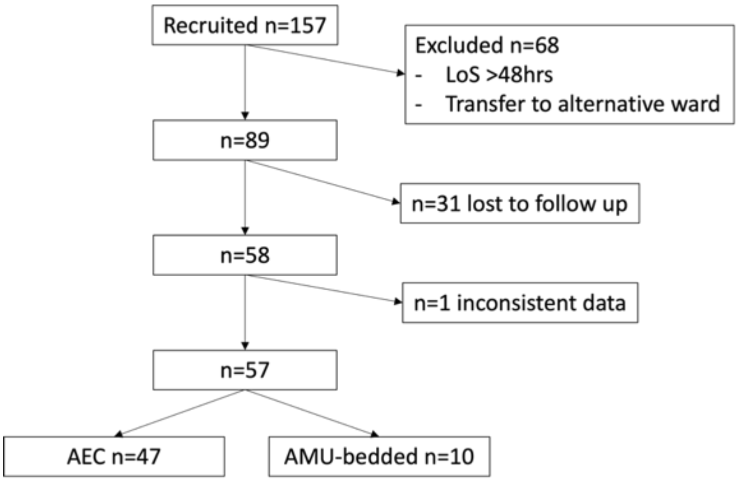


Figure B: 3 Participants in health follow up

Expert decision-maker behaviour

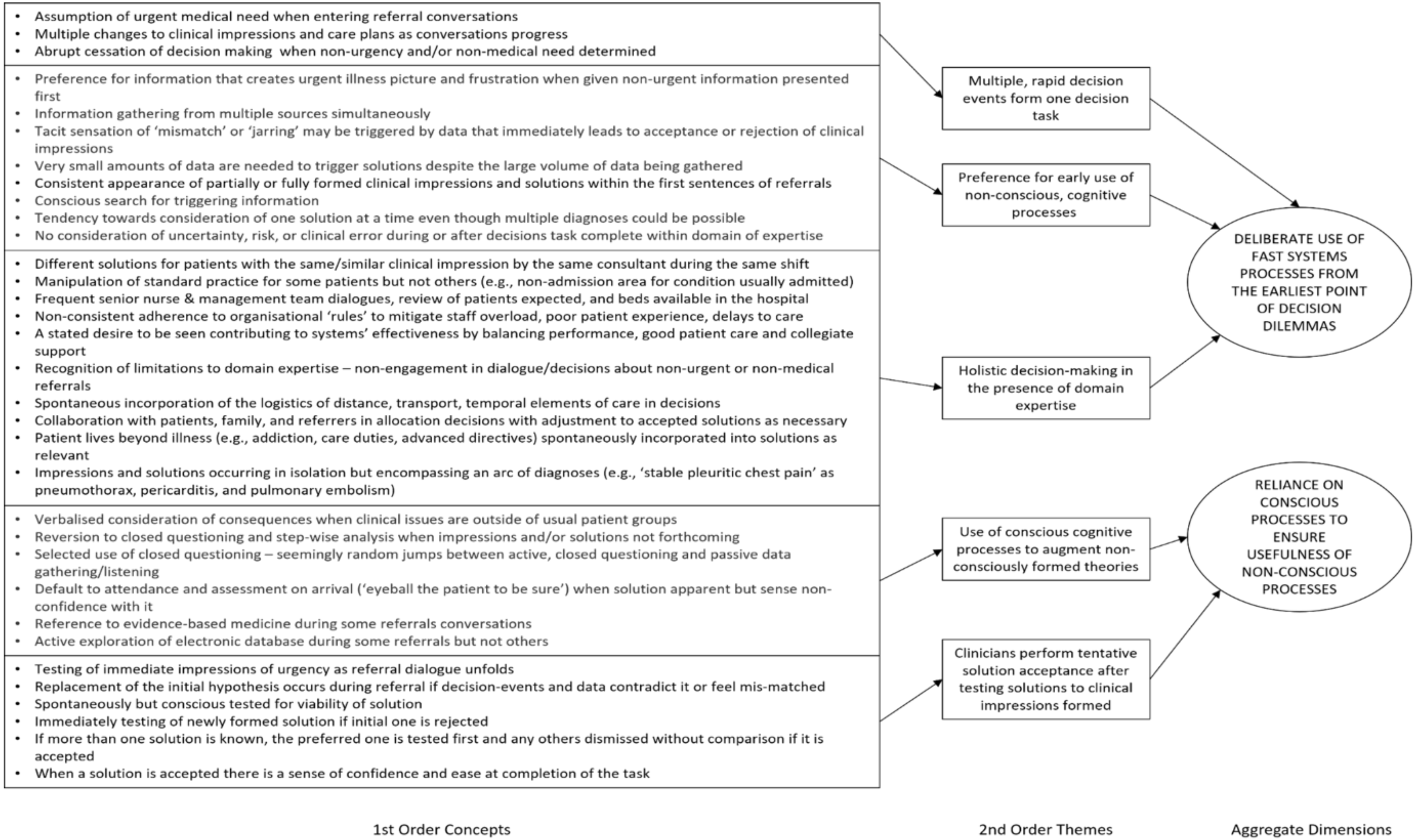


Figure B: 4 Thematic analysis of expert decision-making in the remote allocation task

First order concepts emerge directly from observed behaviour and participant descriptions. These are analysed via an iterative process of conceptual and categorical analysis until second order themes emerge. These themes are categorised in aggregate dimensions (Care Quality Commission, 2016)

Table B: 8 Observed allocation decision-making

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Consultant 1	Community referral with GP suspected GI bleed - accept to medicine or surgery. Already refused by surgical bleep holder as a medical problem. Haemodynamically stable	Acute assessment cover of full unit and AEC area (sole consultant). Crowding earlier in the day none now	GP already contacted the surgeons - continues to gather information about the patient to determine the whole picture (verbal description no review of records or previous results). Description of symptoms	Do we accept this patient to medicine given this doesn't sound like a medical problem and surgeons have already refused?	Not for AMU	Didn't feel like a medical problem	PROTOTYPE
Consultant 1	High potassium level taken earlier that day - levels not checked for an emergency reason. Reviewed blood results during call compared with previous and clinical details	Acute assessment cover of full unit and AEC area (sole consultant). Crowding earlier in the day none now; blood levels taken earlier in the day can be delayed in analysis leading to error in analysis not true abnormality	Condition explanation potassium levels scan of blood results on system	Does this patient need immediate evaluation and treatment?	AEC	Urgent concern with need to evaluate if level is truly dangerous and address if so	PROTOTYPE
Consultant 1	Bloods taken that day for patient with evolving symptoms over several weeks/months reveal gross iron deficiency anaemia. Presented as anaemia and bloods reviewed during the call for additional data	Time of day to be able to provide appropriate therapy via AEC (iron or transfusion) chronic nature of the decline in levels and haemodynamic stability of patient.	Haemoglobin level; the stability of the patient; absence of active bleeding	Admit tonight for treatment?	AEC delay	Not able to deal with adequately in the evening due to resource availability. Patient safe to wait until next day and better experience	PROTOTYPE
Consultant 1	Patient with chest pain living near the border between 2 acute hospitals	Agreement during COVID pandemic for all patients in this location to go to other hospital to manage resources (would normally come to this one outside of pandemic); awareness that the other hospital does not have all the same resources as ours and may have different strategies for evaluating new referrals	GP explains where they are calling from clinical symptoms not concerning for COVID	Decision for admission to be made by this hospital team or the other?	Not for AMU	No need to take clinical decision or get involved. Up to the other team how they would like to evaluate this patient	PROCEDURAL

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Consultant 1	Community referral for patient with anaemia whose bloods marginally worse 1 week after starting iron therapy. GP concerned about need for admission and urgent investigation and treatment	Consultation about same patient with a colleague the week before; the patient use of anti-coagulation for stroke risk; risks of bleeding; stability of clinical picture; evidence-base for emergency transfusion; GP anxiety about anaemia and anti-coagulants; protracted consultant was receiving other referrals alerts during	Style of conversation; that patient had been discussed the week before and remained stable	Does patient need to be urgently evaluated and treated?	Community care	No indication of health risk to patient	PROTOTYPE
Consultant 1	Patient with low oxygen levels and symptoms of respiratory infection	Covering both COVID and non-COVID areas for calls; aware of other calls to be attended to multiple contacts coming through	COVID symptoms oxygen levels	Does he need to attend for assessment?	COVID area	High risk of ill health with COVID symptoms and need to determine risk of decline	PROCEDURAL
Consultant 1	Patient with low oxygen levels and symptoms of respiratory infection but present for several weeks so not consistent with ?COVID	Split between COVID and non-COVID entry point; the resource impact if a COVID positive patient attends the non-COVID side/infection control issues; difficulties in accuracy of COVID diagnosis on symptoms alone	Description of cough, prolonged duration of symptoms	Does he attend COVID or non-COVID area?	COVID area	Cannot be sure of non-infection and aware of limited expertise in this novel disease. Organisational rule if COVID a differential hen COVID entry point. As he is considering COVID he follows organisational rules	DELIBERATED
Consultant 1	Patient with symptoms of COVID an potentially may need admitted	COVID & non-COVID areas	Few severe symptoms; unable to gather more information in a conversation needs to assess patient	Does he need to attend hospital?	COVID area	May not require admission as most patients with COVID don't but he has some parameters which make his risk moderate based on their experience with other COVID patients	ANALOGUE

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Consultant 1	Patient in a community hospital in COVID recovery. No transmission risk but may need transferred for supportive care and rehabilitation not available in current community hospital setting.	Patient in catchment area for other hospital but GP called this one in view of the COVID rules; the other hospital may also get concerned about the COVID rules; as he need some supportive therapy this means he could decline further and the other hospital may choose to escalate him for critical care which will mean transfer to this hospital and a poor journey for the patient but the patient is very frail and elderly and an unlikely candidate for critical care in view of co-morbidities; when he does need to leave hospital and needs MDT support he will need it from a different social work department which cannot be easily accessed if the patient is in the wrong hospital for catchment area	Catchment area of hospital timing of COVID infection	Ask the GP to refer to the other hospital for ongoing care or accept here	Not for AMU	Not a candidate for critical care if he declined; no longer a COVID risk; will need rehab and social services if he does survive this admission; calls a colleague to confirm the plan is sound	DELIBERATED
Consultant 2	Patient referred with suspected PTE	Journey to the main hospital will be a 3-4hr round trip that is unlikely to be necessary as he is fairly confident there is not an urgent illness; there is availability of Xray imaging in the patients local setting which can be accessed urgently but GPs cannot view them and will need support from the hospital team to review the images to aid exclusion of urgent illness	Lack of diagnosis; lack of signs of emergency condition in GP evaluation	How can we safely exclude acute illness without making the patient undergo an unnecessary long journey?	Community care	Doesn't feel this is an acute illness but the GP is concerned about emergency. Doesn't want to make the patient undergo long journey and this limits pressure on main hospital resource/capacity if there is available resource in the community; virtual follow up will support the GP colleague	CONSTRUCTED

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Consultant 2	Patient referred with fast heart rate and GP concern about heart attack for same day investigation.	Patient symptoms suggestive of decline of chronic illness requiring more evaluation that the GP was requesting. Patient in a rural community setting and GP may have greater capacity to manage chronic illness than he is aware of; he may be being risk averse as he sees a commonly sicker population; the extent of evaluation he suspected necessary would take some time and the journey back and forth may not be logistically possible meaning admission more likely	Conflicting information about nature of emergency and GP request; GP confidence in conversation about being able to manage if acute concern excluded	Do I allocate this patient to AEC or directly to an admission bed?	Re-assess with more info.	Decided to evaluate the patient himself on arrival to be able to determine likelihood of same day discharge - the appearance, functioning mobility of the patient on arrival will help his judgement on likelihood of same day care success	DELIBERATED
Consultant 2	Elderly patient referred after paramedic attendance to assist with fall; no acute illness or emergency medical concern but paramedics feel patient is not safe in home environment. Have arranged PT and OT assessment in the community and they are unable to support with emergency rehab	There is urgent availability of physio and occupational therapy and other community placements that can support such patients staying in the community; elderly patients admitted to acute hospital due to functional decline are at risk of harm through over medicalisation or reduced functioning; the local acute hospital has a specific team and unit to support frail elderly patients admitted without acute illness	Paramedic description of fall without injury; paramedic explanation of allied professional attendance in the community	Should this patient be brought to the acute hospital for admission?	AMU bed	All options available to support care in the community setting have been explored. He has no other access to services or skill in preventing admission in such patients but can access the frailty team on arrival to limit over medicalisation of the patient	PROTOTYPE
Consultant 2	Patient with suspected stroke	The need for COVID screening in all referrals reveals the patient has a new cough; COVID positive patient in the non-COVID area has a significant impact on resources and infection control	Cough	Should they be evaluated in COVID or non-COVID area?	COVID area	Risk to resource/capacity	PROCEDURAL

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Consultant 2	Patient referred for transfusion from an area normally served by another hospital; not unstable and no features to suggest emergency need for transfusion; underlying condition which is high risk for sudden and life-threatening blood loss	Transfusion not an emergency unless certain features are present which the patient does not have; the other hospital will normally manage such patients in non-urgent capacity; the other site cannot provide care for life threatening blood loss out of usual working hours but can do so in usual hours so could manage the next day	Location of the patient; GP names the patient's underlying condition that predisposes to anaemia	Advise to send to other hospital or admit to this hospital?	AMU bed	Has experienced patients with similar underlying conditions becoming urgently unwell overnight	PROCEDURAL
Consultant 2	GP requesting admission for a patient after the microbiology staff reported a urine sample result with an infection. Patient clinically well and asymptomatic	Microbiology staff will not have assessed the patient and will advise the GP to determine the need for admission; GP may not have had time or feel confident to determine otherwise based on the specialist recommendation; not all positive culture results require admission for investigation and treatment	GP description of reason for call; indirect instruction from non-clinician/laboratory team without context; lack of clinical symptoms in patient when evaluated by GP	Does this patient need immediate evaluation and treatment?	Community care	Feels confident in this plan but decides to confer with a colleague to check if this is a sensible plan	DELIBERATED
Consultant 2	Patient with sudden onset severe headache - suspected cerebral bleed	Will likely require CT head which the local system can access relatively easily same day; may need lumbar puncture which may not be processed for results same day but anecdotal experience (shared) amongst the team of allowing patients home whilst awaiting results; if abnormality detect unlikely to require medical admission but referral to specialist - more easily achieved via AEC than if patient admitted	Description of headache as thunderclap; patient conscious without clinical signs	Admit or AEC for investigation?	AEC	Unlikely to need admission	PROTOTYPE
Consultant 2	Confused elderly patient with functional decline at home	Risks of elderly admissions into hospital; other community resource available; GP teams experience in dealing with frailty declines in the community; unsuitability for same day care facility in view of confusion and lack of clarity	Description of decline in elderly patient; GP describes attempts to manage decline in lead up to the call	Admit or advise ongoing care in community	AMU bed	No other options available	PROCEDURAL

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Consultant 2	Worsening respiratory illness. Need to exclude COVID but COVID negative 10 days earlier.	The possibility of early/negative test; the risk of infection control if attends non-COVID area; he has referred a few patients to COVID already - their capacity may be tight; colleagues in COVID may think this is not likely to be COVID and criticise his decision making if patient is negative; COVID admission team have been feeding back that too many patients are being sent their way who should be easy to consider non-COVID on initial discussion; there is a clear organisational rule around suspected COVID; can negotiate with nursing staff to arrange for an urgent COVID test in a side room in non-COVID; nursing staff have raised concern about placing suspected COVID into non-COVID side rooms	Negative test 10 days ago; concern about collegiate opinion of decision-making and non-team working	Admit to side room in AMU and retest or admit to a COVID bed?	Re-assess with more info.	Non-COVID side room - spends sometime after the call deliberating the consequences and discussing with a mix of forwards and backwards reasoning	DELIBERATED
Consultant 2	Suspected PTE with elevated heart rate	Likely arrival outside of usual working hours meaning limited same day investigation access; patient with heavy carer duties	Elevated heart rate in presence of possible PTE; patient's carer duties	safety of out-patient care?	Patient choice	Admission may be difficult for patient to accept or cause anxiety around carer duties; clinical reasoning explained incl. risk and patient given autonomy to decide	PROTOTYPE
Consultant 2	Suspected PTE in patient with malignancy	Limitations of capacity towards the evening	Time of day; high workload in the in-patient area after 5pm	Should the patient be directed to bed for assessment as they have a high probability of PTE?	AEC	Will need admitted (feels high risk due to cancer despite stability) but stable enough for initial care to be in AEC limiting the workload in one area	PROTOTYPE

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Consultant 2	Paramedic referral for patient with suspected gastric bleeding and chest pain	Limited diagnostic skills of paramedics; extent of community teams abilities to investigate these symptoms further without hospital support; limited risk taking in view of the symptoms presented	Presence of melaena; presence of two high risk presenting complaints	Do they need to be evaluated more extensively in the community by the GP before decision about need for referral?	AMU bed	Two high risk symptoms	PROTOTYPE
Consultant 2	Suspected gastric bleed from GP; haemodynamically stable (1)	Capacity and efficiency of unit out with usual hours; low risk threshold for community referral into hospital when GI bleed is suggested despite actual life-threatening GI bleeds encountered in reality	Haemodynamic stability; time of day	Does this patient need immediate evaluation and treatment?	AEC delay	Haemodynamically stable; no features of concern re acute pathology requiring in-patient observation; feels it's not a significant blood loss and not in need of urgent investigation	PROTOTYPE
Consultant 2	Suspected gastric bleed from GP; haemodynamically stable (2)	Patient currently in a community hospital covered by GP teams; difficulties in arranging transport in time to access investigation if delayed until next day including pre-procedural preparation which may be poorly done by inexperienced staff; difficulties in transferring back to community hospital if investigation not completed early next day (hence increasing LoS for logistical reasons; current AMU IP capacity which will support transfer; current and projected capacity in the AMU	Logistics of arranging in-patient procedures and ambulance transport; limited acute competencies of community care due to nature of usual work; practicalities of pre-procedure preparation	Admit tonight or tomorrow knowing there is no actual risk to patient health if transfer delayed until next day?	AMU bed	Length of stay in acute setting will be increased if transfer delayed; current and projected capacity support the logistics of this	PROTOTYPE

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Consultant 2	Suspected diabetic ketoacidosis;	In need of immediate evaluation on arrival to determine level of care required; time of day meaning AMU capacity would be tight on arrival to allow timely assessment; need placement in another area if diagnosis correct (therefore AMU bed will be temporary); these patients generally remain haemodynamically stable when unwell; critical care area will not accept patients directly from the community	Efficiency of AMU resources - likely need admission to critical care not AMU setting shortly after arrival (therefore time in an in-patient bed would be short but could obstruct another patient accessing it in a timely manner; workload of new patients heavy this time of day - may mean delay to bed and/or assessment; AEC staff discomfort with managing patients requiring IP level care/red flag patients. Aware that the AEC area is not busy, and he can direct care on patient arrival	How can be determine placement of care rapidly to initiate preferred treatment in correct area and limit resource waste in AMU?	Re-assess with more info.	More efficient way to allocate patient	CONSTRUCTED
Consultant 2	Suspected PTE	Call taken pre-lunchtime, but arrival time of patient means unlikely full investigation that day. Day before 4-day holiday period with reduced resources so delays to OP investigation may be longer still.	Public holiday the following day may limit access to scans and safe transport home that evening. Patient has clinical condition that suggests admission may be required. Admission area from AEC (SSM) has experienced recent cardiac arrest in a patient with suspected PTE admitted from AMU - nursing staff may refuse to accept admission resource availability	Should the patient be directed to a bed in view of suspicion of admission, ward staff fears, and resources limitations?	AEC	Assess in AEC initially and then admit to other ward as needed (preserves AMU capacity), warn patient of poorly available resources in view of holiday and potential need for admission to hospital overnight	DELIBERATED

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Consultant 2	Cancer patient with suspected brain metastases in the community. Stable and not assessed by GP - GP asked palliative nurse to arrange CT scan with the acute medical team	Patient needs an emergency scan but with additional scanning needs in view of the underlying condition. Patient not necessarily suffering an acute illness and undergoing cancer therapy so has alternative team of care in the hospital who should perform urgent assessment. Aware that local cancer services are poorly responsive to such issues and asking the community team will delay and cause more anxiety. Is aware of an ability to assist and hand care back to cancer team. Day before xmas holidays so resources will be limited	Inefficiency in urgent care to address patient need; attendance plan is the easiest option to reduce decision workload but the delays to care and unnecessary time spent in AEC is inefficient for the patient and the service. Not a straightforward scan to arrange which will take up a lot of their time during other duties including and beyond call handling	How can we support the community team and patient with investigation but not disrupt the acute services/cause inefficiency	AEC delay	Aware of how quickly they can arrange this to minimise inefficiency in the system and create patient-centred care which will minimise time taken, provide patient with greater clarity on plan (better patient experience); liaise with the cancer team to transfer care thus supporting patients and colleagues	CONSTRUCTED
Consultant 3	Patient on home oxygen therapy who has needed to increase their usual oxygen delivery flow rate for shortness of breath.	COVID evaluation for all patients with new respiratory concerns	COVID consideration; COVID pathway	Does he need to go to the COVID team for assessment plan?	COVID area	Clear organisational pathway for such issues no need to consider decisions beyond this	PROCEDURAL

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Consultant 3	Local psychiatric hospital refer a patient because of concerns about worsening renal function and need for transfer	Recent admission with UTI, recent temporary medication and side effects of antibiotics on renal function limitations of medical care in the psychiatric setting; limited comfort with medical issues in non-medicine specialists; difficulties of arranging urgent test in other hospital site and transfer, back if not requiring admission; limitations of urgent care environment for patients with acute psychiatric illness; difficulties of AEC care in patients with acute psych need; emergency treatment of renal failure and triggers for urgent care	Difficulties in transfer to and from other site and inefficiency if patient doesn't require admission; nursing care of in psychiatric patients; recent antibiotic use and culprit antibiotic; concurrent medication with potential for harm; non-emergency features of referrer description of the bloods (doesn't corroborate with eRecord)	Does he need to be transferred to AMU for further evaluation and treatment of renal function?	Community care	No alarming features; clear reversible explanation and treatment plan executable in local setting	PROTOTYPE
Consultant 3	Suspected gastric bleed. Referrer presents history of 'coffee-ground vomit'	Coffee ground vomit' as a poor discriminating sign; inability to access records; GP description of background liver disease and varices	unable to access records as busy with other duties and not near records	This is almost always a sign that there is NOT an emergency GI bleed and indicates either acute illness or bowel obstruction	AMU bed	Multi task management; trust GP evaluation of risk re: liver disease	PROTOTYPE
Consultant 3	Referral from the COVID team (refused access to COVID area) of a patient with shortness of breath & oedema. Recent COVID test negative	Pressure on COVID area to ensure capacity and safety; difficult decision making in excluding COVID; professional evaluation of risk between GP and hospital clinician; likely diagnosis of CCF; limited local capacity to deal with CCF in AEC area & likelihood of admission; uncertainty of diagnosis in the patient as not previously known	Oedema & referrer concern re: heart failure; previous experience with heart failure challenges in outpatient setting; no established history of heart failure in patient meaning possible protracted out-patient investigation	Illness which is often slow to improve without daily monitoring and supervision when extreme; unclear if this is the diagnosis	AMU bed	Would be a poor experience for patient and likely to need multiple attendances therefore better under IP team initially then discharge with follow up for symptoms and diagnosis	PROTOTYPE

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Consultant 3	GP concern about malignant hypertension	Low incidence of malignant hypertension; low threshold for concern in community colleagues; clinical presentation of malignant hypertension;	Description of patient not in keeping with malignant hypertension	Does this patient need immediate evaluation and treatment?	Community care	Not an acute illness	PROTOTYPE
Consultant 3	Patient with ongoing shortness of breath 6-8 weeks after COVID	Presentation of illness post-COVID; pressure on GP to take action for ongoing symptoms in view of media stories about long COVID; heightened anxiety in the population about COVID and long COVID; duration of illness; local service specifically focused on long COVID follow up; features of emergency concern post-COVID	Symptom duration and post-COVID; no features of PTE using decision scoring tool and clinical parameters	Does this patient need immediate evaluation and treatment?	Community care	No acute illness and service available to assist with this; no merit in assessing just due to family pressure;	PROTOTYPE
Consultant 4	Referrer is unclear from the presentation what their urgent concern is - patient who has felt unwell since COVID diagnosis 14 days before and provides considerable detail without clarity on the reason for concern about urgent illness	Performing clinical duties alongside; caller uncertainty on diagnosis in view of recent COVID; much concern in community about post-COVID symptoms and care; has already discussed with the COVID team who advised no acute concern but now calling other acute team; has performed some investigation but demonstrates limited knowledge of clinical use of results; rambling and unfocused nature of referrer	Long presentation of symptoms and history without any evidence of acute illness; stability of patient; normal blood test and risk profile; lack of acute signs/triggers	Does this patient need immediate evaluation and treatment?	Community care	Assessment by GP reveals no evidence of presence of acute illness therefore no need for urgent care evaluation	PROTOTYPE
Consultant 4	Patient with new headache and vomiting	Atypical presentations of COVID; degree of investigation required in headaches; likelihood of admission	Possibility of bleed; nature of headache	Attend hospital of not?	AMU bed	Need to exclude bleed therefore risk to health	PROTOTYPE
Consultant 4	GP referral of patient with jaundice and low blood pressure	Availability of rapid clinic access for such patients run by other team; potential for urgent illness in such patients; GP use of urgent care service for contact	Suitability for alternative area of elective care; blood pressure levels	Does this patient need urgent services?	AMU bed	Low blood pressure suggests physiological instability	PROTOTYPE
Consultant 4	Patient with COVID symptoms unsure if admission required	Separate COVID pathway; risks of COVID patient in wrong area	Need to assist referrer with decision around need for admission suspicion of COVID	Should the patient be assessed in AMU or COVID	COVID area	Organisational pathway	PROCEDURAL

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Consultant 4	Patient with shortness of breath for 1-2 weeks and chest pain on exertion	Has contacted 999 for the same condition twice in last 2 weeks; protocols for evaluating patients with ACS by cardiology in local area; AMU capacity	Heart attack suspicion patients often managed on standardised pathway if low risk; description of symptoms as moderate to high risk	Is this patient likely to go home following assessment in AEC on standardised chest pain pathway?	AMU bed	Standardised pathway not suitable as blood markers may not be useful and likely to require in-patient observation for symptoms describes; if capacity tight would manage in AEC initially as safe for assessment but admit for observation; patient anxiety will likely call 999 again	PROTOTYPE
Consultant 4	Known person who injects drugs with skin infection in groin area and general malaise	High likelihood of vascular infection/abscess in PWIDs and need for urgent scan to exclude; access to safe OPHAT; possible need to involve surgical team	Infection likely needing IV antibiotics; drug injection history high risk	Will scanning be possible via AEC?	AMU bed	Need urgent scan to exclude deep-seated or vascular infection in groin	PROTOTYPE
Consultant 5	Patient with diarrhoea and vomiting under care of heart failure team at home (referring specialist nurse)	Heart failure medications commonly used and nephrotoxic risks; infection risks of gastroenteritis; common association of heart failure and chronic renal disease; risks of renal failure	Fluid loss in context of patient with heart failure; background of renal impairment confirmed on database; infection risks	Does this patient need urgent care? Should the GP be getting involved to assess first?	AMU bed	Needs urgent evaluation of renal function and review of meds; not safe for AEC due to infection risk to other patients - needs isolation	PROTOTYPE
Consultant 5	Young adult with pancytopenia & tachycardia	Other blood parameters; age of patient and risks of viral illnesses	Likely reversible causes of pancytopenia in young adults; likely diagnosis and other stable parameters; infection risks with low neutrophils	Does this patient need admission, or can they be evaluated in AEC first?	AEC	Despite tachycardia the clinical picture suggests stable; suspicion that heart rate is not accurate reflection of illness state	CONSTRUCTED

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Consultant 6	Chest pain now resolved in community - GP advise paramedic for ED. Paramedics not sure urgency is present	Previous attendance with same complaint; paramedic experience in emergency chest pain; patient anxiety in seeking help	Patient concern; Patient satisfaction with plan	Unlikely clinical benefit from attendance but patient anxiety may lead to ongoing poor well-being if not assessed again	Community care	Patient reassured with paramedic evaluation and previous investigation	CONSTRUCTED
Consultant 6	Epigastric pain in patient in long-term facility with dementia; limited duration of symptoms; no history of atypical cardiac disease	Advanced dementia; limitations of facility care with urgent illness; limitations of investigation as dictated by advanced care plan; logistics of transport; mental well-being of patient; benefit versus risk; inexperience of referrer; proxy care decisions of NoK due to capacity of patient	Presentation style of referrer; lack of urgent medical symptoms; site of long-term care; advanced dementia history	Is this an urgent medical problem?	Community care	Nil to support need to attend and exclude urgent illness; patient unable to voice opinion; clear advanced care plan; lack of need for ongoing supportive treatment not available onsite	CONSTRUCTED
Consultant 6	Description of transient change in stool suggestive of GI bleeding in patient on anticoagulant; GP witness mix of normal and possible bleeding stool	normal clinical picture of significant gastric bleeding; danger of anticoagulation; need for urgent investigation; resource availability at time-of-day call made; patient preference to not be admitted	Mix blood and normal stool; patient wish to avoid admission	Urgent evaluation of bleeding risk needed and investigation but not available until the following day n- should we advise admission overnight?	AEC	Wants to explore the extent of bleeding and present the patient with more information to determine their preferred plan of action; can arrange urgent investigation at same time	CONSTRUCTED
Consultant 6	Young patient with headache and previous investigation in to same phenomenon.	No clear emergency but GP and patient concerned about need for repeat evaluation; patient anxiety about recurrent symptoms without diagnosis or good self-management plan;	Patient reports neurological signs; referred mid-afternoon; usual management of headache in AEC safe	Neurology needs reassessed	AEC	Patient attended late in the day unable to attend to symptoms due to limited resource capacity in the AEC will mean poor patient experience; evening team may consider discharge same day	PROTOTYPE

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Consultant 6	Nursing home patient with dementia and suspected GI bleed	Non-typical presentation of urgent bleeding; previous recent investigation into the same phenomenon and disease course; safety or nursing home facility; experience of GP team in community care; risks and benefits of further investigation in patient with advanced dementia	Description of bleed; previous investigations results from <1month ago; GP satisfaction with results to exclude urgent illness; GP comfort with managing symptoms in community	Does this need immediate transfer?	Community care	Referrer and decision-maker both happy with the clinical presentation in relation to known chronic disease; GP able to provide symptom control; no benefit to patient in transfer will recontact if symptom control suggests need for transfer	CONSTRUCTED
Consultant 6	Young patient with possible skin or joint infection already discussed with orthopaedics who advised admission to medicine	Orthopaedic teams limited knowledge of medical processes; GP expertise in identifying non-medical condition initially; Ortho team expertise in excluding joint infection; availability of non-admission pathways for SSTI; age of patient and logistical ease of non-admission; presentation at weekend when OP antibiotic team not available; my presence in the department all weekend to provide care	GP recognition of focal infection rather than diffuse SSTI; description of infection appearance; physiological stability; age of patient	Borderline orthopaedic and medical care needs evaluation before plan as may be suited for OP care	AEC	Likely bursitis and suitability for out-patient antibiotic via AEC over weekend and follow up with specialist team	PROTOTYPE

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Consultant 6	Patient recently self-discharged because of alcohol addiction with a low phosphate level in the community - checked that day	Alcohol addiction behaviours when engaging with hospital care; patients ongoing engagement with health as OP (assumed preference); risks of low phosphate levels; presence of low phosphate levels in alcohol addiction population and risks in this group; limited expertise of GP following advise; advice letter written by junior medical team; patients EPR with historical phosphate and other electrolyte levels; recent admission team management of phosphate with partial IV replacement due to self-discharge (non-prescription of oral replacement); options for safe phosphate replacement and other electrolytes associated	Time of day and duration of therapy other electrolytes normal; patient preference for non-admission to alcohol addiction; risks of admission and withdrawal treatment	Phosphate infusion needed will take several hours and arrival during the busiest time of the day will require overnight stay	AEC delay	Safe to remain in community overnight but replacement starting next day will cover need and prevent risks of non-engagement due to preference for out-patient care;	CONSTRUCTED
Consultant 6	Acute confusional state in 51yr old	time of day and investigation availability; stability of patient for AEC; range of speciality overlap; diagnosis of new non-organic illness	Age of patient; stability of patient; time of day	Is this medical or psychiatric?	AEC	Time to fully evaluate and determine better differentials	PROTOTYPE
Trainee 1	Patient with swollen abdomen of unknown cause referred by another speciality clinician	Patient already in the hospital anticipating OP care; other pathways available for management via other OP teams; capabilities of other OP pathway	Creation of likely chronic illness causing symptoms; referrer's description of the degree of ascites	Does this patient need IP symptom management & diagnosis for a new but chronic condition?	AMU bed	Awareness of the limitations and delay to pathway as out-patient - lack of established diagnosis	PROTOTYPE
Trainee 1	Patient with pleuritic chest pain of unknown cause	Limitations of community access to x-rays urgently	Need to exclude PTE; unable to recall the scoring system to determine safety for OP care for PTE; subsequent thoughts about other diagnoses	Can the GP safely exclude PTE without the need to come to hospital?	AEC	Wanted to exclude other diagnoses	DELIBERATED
Trainee 1	Patient referred for repatriation from another hospital site	Rules around transfer of patients between sites; junior doctors' inexperience in arranging repatriations	Non-acute illness; clear rules around organisational transfer	Do I accept the patient to AMU to facilitate transfer?	Not for AMU	Not an acute illness not for urgent care	PROCEDURAL

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Trainee 1	Young patient with breast mass weight loss reduced mobility and back pain	Cancer pathways; other teams of care	Cancer in young patient; suggestion of urgent blood dyscrasia	Do I admit this patient or manage as outpatient?	AMU bed	Surgical team will not accept; these things always come to medicine	PROTOTYPE
Trainee 1	Paramedic call for admission about patient with groin pain	Limitations of paramedic expertise in medicine	Symptom of groin pain not medical; recent GP assessment	Is this an urgent or medical problem?	Community care	No acute illness identified and no medical illness	DELIBERATED
Trainee 1	Patient with jaundice and tachycardia		Clinical features; tachycardia	Does this patient require IP assessment?	AMU bed	Main suspected diagnosis	PROTOTYPE
Trainee 1	Patient with pneumonia and low oxygen levels	Business of COVID team; feedback about excessive AMU referrals to COVID ; infection risk to non-COVID area	Suspicion of COVID; not clear	Should I defer this patient to the COVID area	COVID area	History strongly suspicious of COVID	DELIBERATED
Trainee 1	Patient with severe sepsis	Capabilities of the AMU in resuscitation; roles of ED	Blood pressure	Can I safely accept this patient to AMU?	Not for AMU	No resuscitation facilities; even though not explicit rules exist there aware of the 'tacit rules' about unstable patients in AMU without ED team evaluation first	PROTOTYPE
Trainee 2	Patient with worsening chronic hyperkalaemia	None demonstrated	Potassium levels felt high but not sure if life threatening; not clear	Should I admit or manage through AEC?	AEC	Not sure of significance may not be high on recheck	PROTOTYPE
Trainee 2	Frailty falls	None demonstrated	Frailty falls in older patient	None stated	AMU bed	Usual course of action	PROTOTYPE
Trainee 2	Chronic history of shortness of breath with lows oxygen levels not COVID	COVID & non-COVID areas	Oxygen levels; chronic history so not COVID	COVID or non-COVID?	AMU bed	Low oxygen; COVID unlikely	PROTOTYPE
Trainee 2	GP with concern about renal impairment	None demonstrated	Blood results; senses not serious	Not sure if safe for AEC care (doesn't consider other options)	AEC	Senses this is not serious (but doesn’t compare with recent results or attendances)	DELIBERATED

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Trainee 2	Patient with COVID symptoms	COVID & non-COVID areas	COVID suspicion of referrer	COVID or non-COVID?	COVID area	Clear organisational pathway for such issues no need to consider decisions beyond this	PROCEDURAL
Trainee 2	Chest pain for two days	Low risk chest pain pathway	Chest pain and known pathway; normal heart tracing	AEC or admit for suspected heart attack?	AEC	Low risk chest pain	PROTOTYPE
Trainee 3	Suspected COVID	COVID & non-COVID areas	COVID symptoms	COVID or non-COVID?	COVID area	Clear organisational pathway for such issues no need to consider decisions beyond this	PROCEDURAL
Trainee 3	Persistent cough with low sats	COVID & non-COVID areas	cough	COVID or non-COVID?	COVID area	Clear organisational pathway for such issues no need to consider decisions beyond this	PROCEDURAL
Trainee 3	Young female with headache for >1 week	Second presentation to GP practice; recognition by GP of non-acute nature (had referred to another non-acute specialty; usual AEC pathways; presentation of headache in non-medical specialties recently worked in; GP has not seen the patient personally (phone consultation)	Presenting complaint; gender; age; recent work in obstetric work	AEC or in-patient?	AEC	Wants to exclude one specific diagnosis	PROTOTYPE
Trainee 3	Suspected PTE	AEC pathways for PTE; that the GP has physically assessed this patient	Language of referrer; non-acute nature of symptoms	AEC or in-patient?	AEC	Wants to exclude PTE despite scepticism	PROTOTYPE
Trainee 3	Facial cellulitis	OPHAT service (but not that they can take direct referrals; presence of collections requiring surgical assessment rather than medical	Common out-patient condition; physiological stability	AEC or in-patient?	AEC	Physiologically stable; can quickly evaluate and exclude abscess	PROTOTYPE

DECISION-MAKER	DETAILS OF REFERRAL	CONTEXT (OBSERVATION and/or IMMEDIATE RECALL)	TRIGGERS RECALLED BY PARTICIPANTS	PARTICIPANT RECALL OF DECISION	SOLUTION	RATIONALE	DECISION TYPE
Trainee 3	Chest pain for 2 days with normal heart tracing		Suspected heart attack with ongoing pain	AEC low risk chest pain pathway or in-patient bed?	AMU bed	Ongoing pain would trigger AEC staff to immediately move the patient to in-patient bed so prevent delays	PROTOTYPE

Appendix C: Overview, design, and development (ODD)

The model description follows the ODD (Overview, Design concepts, Details) protocol (Grimm et al., 2006, 2020)

Purpose

This work models a single hospital's acute medical unit (AMU) functioning in the urgent healthcare system in the UK (Scotland). It represents the outcomes of remote decisions about suitability for urgent in-patient (AMU bedded) or out-patient, ambulatory emergency care (AEC) of adult, medical patients. Patients are referred via clinicians in the community, out-patient clinical, or the Emergency Department (ED). The simulation model reproduces the allocation of patients upon referral (to AEC or the Bedded area) by different categories of staff. The outputs provide a measure of the impact of those decisions on health-related quality of life (HRQoL), patient experience, efficiency of local services, and hospital system efficiency. The purpose of this model is to replicate how these outcomes emerge in a real-life case study and explore if/how these outcomes change when different combinations of staff are used to allocate.

Figures C:1 provides an overview of the model. This was generated following an observational study of allocation decision-making and of hospital system behaviours on the case study site. The model is a hybrid of agent-based and discrete event modelling. Decision-maker and hospital system behaviours facilitating or limiting transfer were created as agent-based models. Patient movements into and through the hospital were modelled as discrete events over time (patients as passive groups)

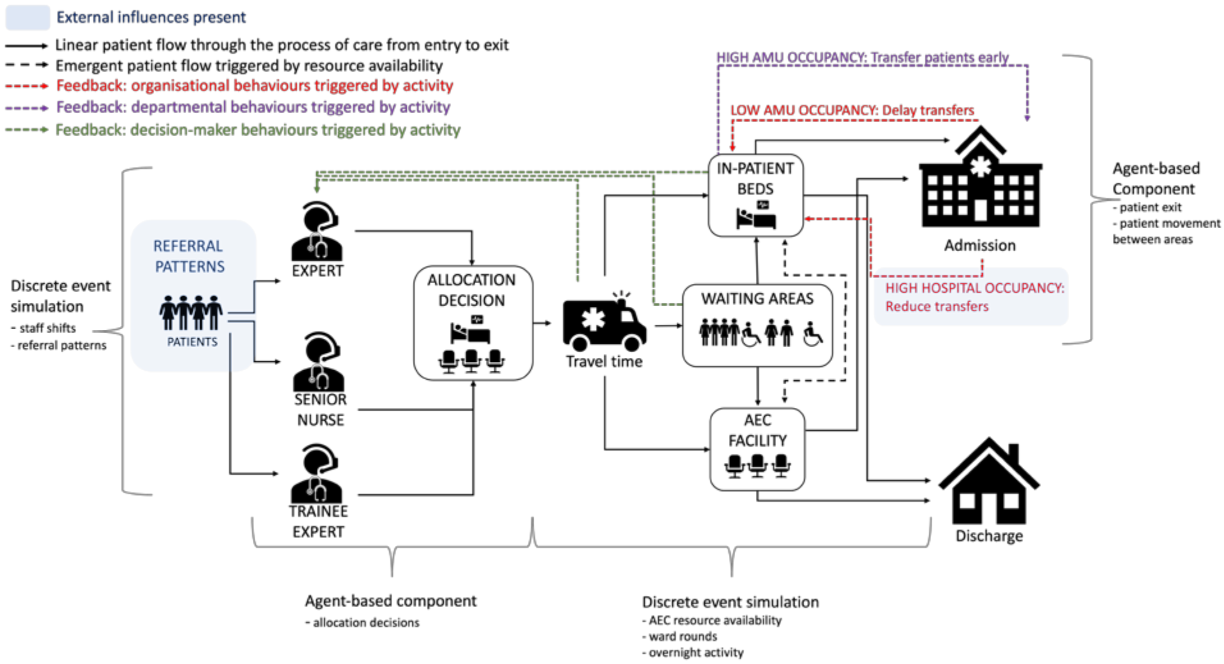


Figure C:1 Overview of behaviours and feedback

On taking a referral call, the decision-maker allocates the patient to an in-patient bed of the Ambulatory Emergency Care (AEC) facility. Decision-makers fall into one of 3 categories: experts, trainee-experts, and nursing staff but are categorised in the model outputs as expert (consultants) and non-experts (trainees and nurses) for ease of analysis. The local environment influences some allocation decisions and the hospital behaviours to create capacity for anticipated patients. In-patient occupancy influences expert decision-making (but not non-experts) by increasing AEC allocations when overcrowding is sensed or anticipated as shown by the black dotted line. The hospital (managerial) system behaviours are indicated by the red dotted line. This includes transferring patients into alternative hospital beds when overcrowding is sensed, delayed transfer of admissions when AMU occupancy is low, delayed transfer out of hours, and delayed transfer during the morning ward round. Patient demand and hospital occupancy levels (which limit transfer of patients) are external events. All other activities/events are modelled to occur or are emergent.

Entities, state variables, and scales

Entities are patients, decision-makers, decision patches, and the wider hospital system. These are described in Tables C1:C4.

Table C: 1 Decision-maker, patch, and environment state variables

Decision-maker variables		
Variable	Description	Format; nature; range of potential values
expert-adjust	Proportion of patients that a decision-maker feels could be managed via AEC relative to prevalence of AEC suitability in that population	Rational number; static; 0.0 – 3.8
max-AEC-risk	Additional proportion of patients allocated to AEC when overcrowding is sensed.	Rational number; static; 0.0 – 0.15
Decision-patch variables		
high-risk-adjust	Variable that allows a patch to adopt the max-AEC-risk profile of any decision-maker on that patch	Rational number; static; 0.0 – 0.15
expert-adjust-local	Variable that allows a patch to adopt the expert-adjust value of any decision-maker on that patch	Rational number; static; 0.0 – 3.8
Global environment variables		
Occupancy-AMU	Proportion of AMU-care beds occupied. Total number of patients in the bedded area (including waiting-bedded)/number of AMU-care beds	Rational number; dynamic; 0 – 1.53
Occupancy-AEC	Proportion of AEC-care spaces occupied. Total number of patients in the AEC area (including waiting-aec)/number of AEC-care spaces	Rational number; dynamic; 0 – 1.25
Occupancy-total	Proportion of all clinical spaces occupied. Total number of patients in the AEC-care and AMU-care (including all waiting areas)/number of AEC-care and AMU-care clinical spaces/beds	Rational number; dynamic; 0 – 1.43

Table C:2 Patient variables

Variable	Description	Format; nature; range of potential values
condition	Variable representing probability of an individual patient's condition being suitable for AEC	Integer; static; 0 - 1 drawn from a uniform distribution
AEC-ok?	Variable that indicates suitability to attend the AEC area for care	Logical; static; true/false
ed	Variable indicating if patient has been referred from the emergency department	Logical; static; true/false
expert-dm	Variable indicating if the allocating decision-maker was a consultant or not	Logical; static; true/false
time_referred	Variable indicating model time when patient entered the model	Integer; static >0 (model ticks)
time_arrived	Variable indicating anticipated time arrival into the department	Integer; static >0 (model ticks)
aec-possible	Variable indicating if patient arrived during AEC opening hours	Logical; static; true/false
treatment_started	Variable indicated when patient started receiving care	Integer; static; >0 (model ticks)
treatment_time	Variable indicating time required to undergo investigation and care according to area and initial for-discharge value	Integer; static; 30-2150 (model ticks)
los	Variable indicating model time spent in the department from arrival to model exit	Integer; dynamic; >0 (model ticks)
delayed	Variable indicating model time spent in waiting to start treatment	Integer; dynamic >0 (model ticks)
time_complete	Variable indicating model time when care expected to finish	Integer; dynamic >0 (model ticks)
complete?	Variable indicating if patients is ready to leave the area	Logical; static; true/false
for-discharge	Variable indicating route of exit from the model	Logical; dynamic; true/false
final-area	Variable indicating area where care was predominantly received	Binary; dynamic; 0 or 1

Variable	Description	Format; nature; range of potential values
early-move	Variable indicating if the patient has been selected for admission and transfer to create capacity before treatment complete	Logical; dynamic; true/false c
aec-move	Variable indicating if the patient has been moved from the AMU-bedded to AEC-care area pending discharge to create capacity before treatment complete	Logical; dynamic; true/false

Table C:3 Hospital system behaviours

Variable	Description	Format; nature; range of potential values
expected-to-current-capacity-ratio	Variable that triggers the conversion of patients nearing end of care into admission/transfer into hospital. Patients are identified to move if the ratio of expected AMU-care patients to currently available beds exceeds this value. Reflects ability to proactively create capacity for new arrivals	Integer; dynamic; 1 – 25
amu-crowding	Variable representing the wider system tolerance of overcrowding in AMU-care area. Triggers reactive creation of resources for new patients	Integer; dynamic; 90 - 150
max-ip-waits	Variable representing the number of patients waiting in the AMU-care area that triggers a decision-maker to increase their allocations to AEC-care	Integer; static; 0-20
waiting-time	Time a patient will wait for a bed resource before being moved to the next available space in any part of the area to begin treatment	Integer; static; 0-240
sufficient-beds-to-cope-night	Minimum number of empty beds overnight before delays to transfer/admission occur to limit high workload in areas outside of department and boarding of patients	Integer; static; 0-15
sufficient-beds-to-cope-day	Minimum number of empty beds during the day before delays to transfer/admission occur to limit high workload in areas outside of department and boarding of patients	Integer; static; 0-15

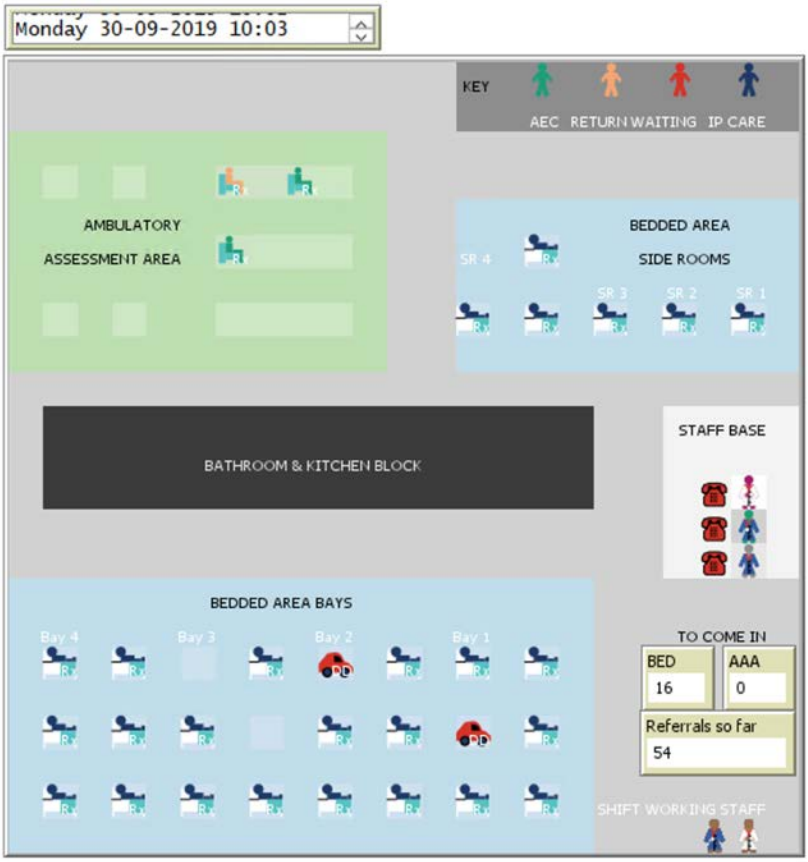
Variable	Description	Format; nature; range of potential values
random-aec-adm	Proportion of patients allocated to AEC-care whose assumed outcome of discharge will change as a natural course of illness	Rational number; dynamic; 0.10-0.40
random-amu-dis	Proportion of patients allocated to AMU-care whose assumed outcome of admission will change as a natural course of illness	Rational number; dynamic; 0.075-0.20
Overnight-transfer-end	Variable that indicates when downstream transfer of patients ends unless there is poor capacity	Integer; dynamic >0 (model ticks)
non-urgent	Proportion of patients that will be sensed by a consultant DM as not requiring attendance	Rational number; static; 0.90-0.99

Table C:4 Scheduled environmental events variables

Variable	Description	Format; nature; range of potential values
aec-available	Variable that indicates when the AEC-care area is open	Logical; dynamic; true/false
peak	Variable indicating peak activity for referrals	Logical; dynamic; true/false
Overnight-start	Variable indicating time when the AEC is not available and the department runs with overnight facilities and behaviours	Set to mirror Close_AEC Integer; dynamic; ≥0 (model ticks)
Overnight-end	Variable indicating time when the AEC is available and the department runs with overnight facilities and behaviours	Set to mirror Open_AEC Integer; dynamic; ≥480 (model ticks)
Start-of-weekend	Model tick time that equals Saturday 0000 in the 24hr clock date/time display	Integer; dynamic; ≥7200 (model ticks)
End-of-weekend	Model tick time that equals Monday 0000 in the 24hr clock date/time display	Integer; dynamic; ≥10080 (model ticks)
weekend	Variable to indicate if the model time is a weekend	Logical; dynamic

Variable	Description	Format; nature; range of potential values
Open_AEC	Model time that equate to the time of AEC opening set by the user.	Integer; dynamic; ≥0 (model ticks)
Close_AEC	Model time that equate to the time of AEC closing set by the user	Integer; dynamic; ≥60 (model ticks)
Mean_weekday_attendances	Mean number of referrals Monday-Friday. Used to calculate rate of attendance	Integer; dynamic; 0-100
Mean_weekend_attendances	Mean number of referrals Saturday and Sunday. Used to calculate rate of attendance	Integer; dynamic; 0-100
Slow-overnight-arrivals	Model time set to mirror 0300hrs in the 24hr clock date/time display when the rate of arrivals reduces	Integer; dynamic; ≥38880 (model ticks)
aec-returns-start	Model time that equates to the time of AEC opening set by the user for return patients attending AEC-care	Integer; dynamic; ≥0 (model ticks)
aec-clinic	Duration of the AEC-care returns session	Integer; static; 60-1440

The landscape is the urgent care environment consisting of 11 x 11 square patches (Figure D:2). There is a block of 15 patches labelled ‘Ambulatory Assessment Area’ representing AEC-care and block of 31 patches representing labelled ‘Bedded Area Bays’ which represent AMU-care. There is also a block of 18 patches for the bedded waiting area (waiting-bedded) that run along the area between the bedded are bays and the bathroom & kitchen block. Four patches representing the AEC-care waiting area (waiting-aec) lie between the ambulatory assessment are and the bathroom and kitchen block. There is a patch for entry the unit from each source (not visible) and three patches to represent patients pending who are travelling to or waiting to be transferred to the unit (under the ‘To come in’ monitors. There are three decision patches where decision-makers position themselves to receive patients when in shift.



AEC: Ambulatory emergency care
AAA: Ambulatory assessment area

Figure C:2 Screenshot of the model landscape

Ambulatory emergency care is called the ambulatory assessment area on the study site. The bedded area contains four six-bedded bays. The pool of staff working in shifts are visible in the lower right-hand corner along with the number of patients allocated to bedded and ambulatory care. Staff next to the telephones at the staff base are those actively performing decision-maker duties. The key identifies to type of patient present in the unit and the time. Date and time are anchored to the model ticks.

The model tick counter is anchored to time and set to start on Monday 30th September at 00:00. Each time step is one minute, and simulations run for 181441 time-steps representing 18 weeks of ward activity (inclusive of 2-week model warm-up period). This is assumed to be sufficient time to identify recurring patterns in activity representative of year-round activity.

Process overview and scheduling

Schedule

set-demand

This procedure and sets the mean volume of referrals that will arrive over the next 24hrs according whether or not the weekend period is sensed (*start-of-weekend; end-of-weekend*). The *weekend* variable is set to true from Saturday 0000hrs to Monday 0000hrs and false outside of this period. A global variable *expected-to-current-capacity-ratio-capacity-threshold* is set here via the user-set *proactive-capacity-creation-threshold* variable at each model tick according to the total number of patients attending the day before:

if ≤65 then *expected-to-current-capacity-ratio = proactive-capacity-creation-threshold*
if >65 then expected-to-current-capacity-ratio = (proactive-capacity-creation-threshold + 5)

start-work

Any DMs situated on a **decision** patch (one per patch) indicate their decision-maker type and that they are available to newly referred patients. The **decision** patch mirrors the current DM's variables to allocate patients and adopts a colour unique to that category of staff. Patches with no DMs are instructed to indicate non-availability to patients by reverting back to their original colour.

shift-work

Procedure that instructs any one from a DM group working shifts at random to move to any available **decision** patch with no other DMs present on that patch at the start of their shift' Also instructs movement back to the pool of DMs at the end of their shift. Uses user-set *expert-shift-starts expert-shift-finish; trainee-shift-start; trainee-shift-finish; shift-change-am; shift-change-pm* according to category of staff). If there are no shift workers selected in the model, then no changes are made.

resource-shifts

The procedure has four roles:

1. Identifies the end of the current nightshift (model starts 0000hrs) and the start of the next nightshift:

night-shift not ended, *aec-available* is set to false, otherwise it is true.

patients on AEC-care at start of night-shift are relocated using according to how much model time is left until their *time_complete:* >120mins left to move to AMU-care for the remainder of their stay, otherwise complete care in AEC

2. Senses occupancy in the AMU-care area by counting the beds without patients present and comparing with *sufficient-beds-to-cope-day* (if aec-available true) or *sufficient-beds-to-cope-night* (aec-available false). If counted beds ≥ *sufficient-beds-to-cope-day/night* then 2mins are added to the *time_complete* variable of all patients with *for-discharge* false at each model tick until counted beds ≤ *sufficient-beds-to-cope-day/night*. If the counted beds are ≥ *sufficient-beds-to-cope-day/night*, then the sub-model *avoid-overnight-moves* is performed.

3. Resets the *expected-to-current-capacity-ratio* to equal initialisation *proactive-capacity-creation-threshold* value (proactively capacity creation at night)

4. Alters patient movement during the morning senior review by adding a unique delay to time_complete variable for each patient from a reporter. If >0 available beds and < 3 patients expected into the bedded area, any patients previously identified as early moves remain in the department and update their *time_complete* variable from the same reporter

patients-referred

This procedure creates new patients from ED and non-ED sources, and AEC-returns patients. New patients enter the model via a Poisson distribution. The rate is set according to time of day and source of referral as shown in the sub-models section (*Rate of arrivals*).

Upon creation patients are assigned their state variables *condition* and *ed* (according to source). *complete?* is set to false. They are labelled to reflect a call waiting. This is displayed for the user. The global tally of referrals since 00:00hrs that day is updated at each patient creation.

The number of AEC-return patients for the day is drawn from a random uniform distribution and divided by the duration of the AEC return clinic to create the rate informing a Poisson distribution of return patient arrivals. AEC-return patients have their variables *AEC-ok*? and *for-discharge* are set to true, and they are assigned an individual *treatment-time* that is no longer than the duration of return clinic.

present

This procedure instructs patients to move, at random, to a decision patch if they sense that a patch matching their preferred DM type is available and has no other patients on it. IF preferred DM is note available, they will seek another. Patients from ED prefer a nurse DM. If there are no nurses they default to a trainee, then an expert if no trainees are available. Patients from non-ED sources prefer an expert but will default to a trainee if none, then nurse if no trainee is available.

Patients update their variable *expert-dm* according to DM category. DMs can only allocate one patient at a time, but multiple DMs can allocate simultaneously.

decide

This procedure allocates patients to areas for care using the allocate and adjust sub-models. If the patient presents to an expert and non-attendance is sensed (*condition* ≥ *non-urgent*) the patient exits the model.

Trainee and nurse DMs only ever decide using the *allocate* procedure as they cannot sense overcrowding. Expert DMs will perform the *allocate* procedure when there is no overcrowding and *adjust* procedure if they sense overcrowding. Overcrowding is sensed in one of two ways:

1. patients currently occupying **waiting-bedded** ≥ *max-ip-waits*

2. patients allocated to **AMU-care** currently occupying **to-come-in** ≥ *max-expects-trigger*

If both conditions are met the adjust procedure is unaltered. In both the *allocate* and *adjust* procedures, *AEC-ok?, treatment_time, time_referred, for-discharge,* and *time_arrived* are set. Patients then move to the **to-come-in** patch and are labelled according to their allocation. **to-come-in** queues are updated in the user interface.

get-treatment

All patient progress in the model occurs in this procedure. All patient collectives in the model update individual *los* since arrival at each model tick excluding those on the **to-come-in** patch. Sequence for progress according to patient collectives is as follows:

1. Patients on **to-come-in**:

   once *time_arrived* = ticks, move to allocated area (sub-model relocate). *aec-possible* is updated according to *aec-available* is true or false

2. Patients on **waiting-bedded** or **waiting-aec**:

   If *los* < *waiting-time* then follow the *wait-for-resource* sub-model, otherwise follow the *skip-queue* sub-model

3. Any patients on **AMU-care** or **AEC-care** update *final-area* (0/1) to identify where they are receiving care. If *aec-move* = true, a patient sets their *final-area* = 0

4. Patients on **AMU-care** identified as delayed discharge:

   if *aec-available* = true, move to **AEC-care** until *complete?* = true when overcrowding is sensed and set *aec-move* = true

5. Patients moved to **AEC-care** awaiting transport home:

   once *time_complete* = ticks: set *complete?* true

6. Patients identifying as *early-moves* to create capacity:

   once time_complete = ticks they set complete? = true

7. Patients on **AEC-care** or **AMU-care** with *complete?* = false:

    a. 0800-0300hrs

    Once time_complete = ticks, if not *early-move* = true update their *for-discharge* variable to reflect changes in discharge plan since referral as follows:

    AMU-care patients identified as *for-discharge* = false:

    If random-uniform 1.0 < *random-amu-dis* they change *for-discharge* = true and set *complete?* = true

    AEC-care patients with *for-discharge* = true:

    If random-uniform 1.0 < *random-aec-adm* they change *for-discharge* = false and set *complete?* = true

    b. 0300hrs - 0800hrs

    Patients with *AEC-ok?* = true update *for-discharge* via the reporters described in 7a. If *for-discharge* = true, they exit the model.

    Patients with AEC-ok? = false: if for-discharge = true set their label to identify as a delayed discharge and update *time_complete* to be the current overnight-end time plus a delay via a reporter (60-360mins); if *for-discharge* = false, follow the process as described in 7a.

8. All patients with *complete?* = true are asked to undergo the *dispose* procedure as a final step.

readjust-location

This procedure forces all patients with *AEC-ok?* = false who moved to **AEC-care** due to long delays to move to an **AMU-care** resources when available at random. If treatment has started it continues as before; if not, treatment starts at the next time-step. They assimilate with other AMU-care patients and update their *delayed* variable to reflect all time in the department until placed in **AMU-care**. If *delayed* <5 ticks it is set to zero.

leave

The procedure instructs patients who have undergone the dispose procedure to undergo the *exit-model* sub-model.

update

If ticks = *peak-start*, the start-peak sub-model is initiated. This sub-model sets *peak* = true until ticks = *peak-end* when *peak* is set to false, and *peak-start* is recalculated for the following day. If 0000hrs is sensed, daily departmental outcomes for final model analysis are updated and the global variables that accumulate the daily tallies are reset. Daily values are only stored after a two-week warm-up period.

random-amu-dis and *random-aec-adm* that inform changes in discharges plans (see *get-treatment*) as set for the next 24hrs via reporters. If previous day's attendances >65 *amu-crowding* is set to (*amu-crowding-tolerance* + 10), otherwise *amu-crowding = amu-crowding-tolerance*.

redirect

This procedure provides a safety net to prevent the model from crashing in event of extreme over-crowding. If there is no patients space available anywhere (clinical and waiting), patients exit the model, and a system failure event is recorded in the global outputs. This will repeat on every tick until capacity becomes available.

This procedure also triggers the sub-model *system-crowding-reaction* when overcrowding is sensed. System-crowding-reaction creates AMU-care resources by identifying patients to transfer which sets *early-move* = true during the process. If no overcrowding is sensed, any delayed discharge patients with *early-move* = true by previous *system-crowding-reaction* runs, have *early-move* set to false, change their label to identify as a delayed discharge, and exit the model as per the *get-treatment* procedure.

Outputs

Primary (collated at end of model run)

- Tally of 'true/false AEC' and 'true/false AMU' patients per day according to expert or non-expert DM
- Total daily attendances in each area

- Total number of patients allocated to each area
- Total discharges from each area
- Total discharges within 24hrs
- Total admissions into the hospital from each area
- Total number of patients moved in the out-of-hours period
- Total number of patients placed in the waiting-bedded area
- Cumulative health index for each area
- Proportion of patients with a positive experience
- Total number of patients starting care in their non-allocated area
- Total number of patients refused attendance (by expert-DM)
- System failure events

Secondary (stored as lists during model run)

- Individual health index change for all discharged patients
- Area that care was delivered prior to completion
- Individual patient length of stay (all patients)
- Individual delay to starting treatment (all patients)
- Occupancy levels for each area at each tick

Occupancy, daily waits and system failure events are updated continuously and displayed in the graphic user interface. Graphic interface also displays the number of patients expected in each area, the type of care they are undergoing (according to colour-code), and the number of referrals waiting to be answered.. Individual patient outputs are stored in a csv. file. Data informing the occupancy plot on the GUI is collected in a csv. file at the end of model run.

Design concepts

Basic principles

Behaviours are modelled to follow three aims:

1. Limit overcrowding
    a. Experts increase AEC allocations in response to environmental feedback

    b. Patients will complete care early, move within the model, or transfer their for-discharge status to reproduce the hospital system behaviour of creating capacity when overcrowding is present or threatened
2. Limit waste – the system automatically avoids large numbers of empty beds in AMU
3. Prevent inefficiencies in other areas of the hospital via:
    a. Tolerance of some overcrowding
    b. Limit transfer of for-discharge false patients from 0300-0800hrs to allow more time for discharge after the morning ward round

Emergence

Efficiency outcomes of occupancy, delays, overnight moves, and admissions emerge as allocation decisions at referrals create or mitigate queues of patients who cannot access allocated resources upon arrival. Tolerance of overcrowding and delays provides time for patients to complete care and realise discharge, but early movement to mitigate overcrowding leads to higher occupancy levels for longer periods and risks more patients converting to admission.

Patients' health change on discharge is directly related to the area of care they completed care in. Thus, if allocated to AEC but moved to AMU to complete care (e.g., overnight when facilities close) they will reflect an AMU-related health change. Patient experience is directly influenced by delays to starting care and time spent in the AEC area receiving care. These emerge as a result of bottlenecks created by allocation decisions and tolerance of crowding.

System behaviours (reproduced by patients moving through the model) are outside of the control of other agents in the model. Only DMs may control their allocation decisions

Adaption

In periods of inefficiency, expert DM agents adapt their allocation decision directly in response to patterns of actual or anticipated crowding. Patients adapt their time to complete care if overcrowding beyond the tolerated limit is sensed. Patients will alter their discharge status, care completion time, and/or location in response to overcrowding.

Objectives

No direct-objective seeking is built into the model.

Learning

No learning is built into the model.

Prediction

Decision-makers explicitly predict the type of care required (and thus the discharge potential) for each patient according to condition and their level of expertise. This occurs in real life as a clinician-to-clinician discussion is the mode of referral into the system meaning some objective clinical information, plus access to historical records, is available.

Sensing

Expert DMs sense the condition of the patient, the source of referral, and the prevalence of AEC in the population groups according to source of referral. They also sense the number of patients waiting for AMU-care resource and the number expected to arrive that day requiring an AMU-care bed. The decision-maker does not sense that the system has failed.

Patients are programmed to sense the variables that influence hospital system behaviours in managing the flow of patients:

- the number of expected arrival and the current capacity (this reproduces the hospital system behaviours to mitigate overcrowding and inefficiencies)
- the overcrowding tolerance level and the number of beds needed to mitigate wasteful use of AMU resources
- the care completion, discharge, and delay status of themselves and all other patients, the availability of AEC facilities, and the timing of scheduled events

The hospital department senses the previous day's and current days demand to set overcrowding tolerance and delays to transfer.

Interaction

Decision-makers interact with patients by allocating them to their resource for care. Patients interact indirectly as they compete for the resources.

Stochasticity

Patient arrival rate is stochastic and drawn from a Poisson distribution. Time for patients to arrive on to the unit is taken from a random-normal distribution that accounts for government rules for ED transfer time and observed variation in arrival from different parts of the region and different modes of transport (e.g., private versus ambulance).

condition and treatment_time are randomly assigned from distributions as shown in Tables 1 and 3. This reproduces the wide variation of clinical pathology and patient need experienced on the case study site. Although for-discharge is initially determined by the patient condition and prevalence of AEC suitability in each patient group (ED or non-ED), stochasticity is added at the end of their treatment time (random-adm-aec and random-dis-amu) to represent unanticipated results and further health decline. Health change (hrqol) is taken from a random normal distribution according to area of care at completion. Patient moves are random except where patients have been waiting ≥1hrs for a bedded resource or any area for ≥4hrs. Patients waiting ≥4hrs are prioritised.

Collectives

Patient collectives emerge as they are allocated, from the exogenous influence of patient demand on the unit when they arrive, and from their assigned for-discharge status. Collectives that emerge upon arrival compete for DM time to be allocated, AEC-care, AMU-care, and waiting area resources. Collectives that emerge after treatment has commenced are in competition for transfer if identified for admission. Collectives that emerge if for-discharge true may compete with AEC-care patients for resources whilst awaiting transport home. Return AEC patients compete for AEC and waiting area resources only.

The presence of waiting area collectives and anticipated AMU-care patients encourages the decision-maker agents to increase allocation to AEC resources and patients to complete care early.

Observation

The view shows the position of each patient in the urgent care landscape.
Plots display:

- Bar chart of daily AMU-care waits (≥5mins waiting)
- Occupancy in each area of care

Monitors display:

- Referral calls waiting to be answered
- Anticipated AMU and AEC patients
- Total referrals so far that day
- System failure events
- Patients placed in AEC-care due to long waits

There is a fixed output window to display the day, date, and time to orientate users as they interact with the model.

Initialisation

Default settings exist for all inputs (see Table C:5), but the user is prompted to change these as necessary. They are then prompted to confirm their choices by pressing the ‘Set time and attendance parameters’ button. After this they are prompted to initiate the model which creates the visual reproduction of the urgent care environment shown in Figure 3 with the chosen staffing groups allocated. The model may be start/stop the model as required after this point. A list is created to collect individual patient outcomes.

Table C:5 Parameters set at initialisation

Variable	Description	Value	User access?	Source
expert-rota-staffing	Number of consultants rotating through shifts	15	Yes	MA
trainee-rota-staffing	Number of trainees rotating through shifts	30	Yes	MA
random-aec-adm	See Table D:1 – D:4	0	Yes	MA
random-amu-dis	See Table D:1 – D:4	0	Yes	MA
non-urgent	Patient conditions refused at referrals	0.96		MA
ed-aec-prev	Conditions with potential for AEC in ED population	0.15	Yes	Expert opinion & HDS
noned-aec-prev	Conditions with potential for AEC in non-ED population	0.30	Yes	Expert opinion & HDS
peak-split	Proportion of ED patients arriving during peak hours	0.20	No	HDS
off-peak-split	Proportion of ED patients arriving during off-peak hours	0.50	No	HDS
peak-demand	Proportion of all patients arriving during peak hours	0.6	No	HDS
Overnight-transfer-duration	Period of time that hospital is willing to transfer patients for admission once the overnight period has started	240mins	No	MA
slow-overnight-arrivals	See Table D:1 – D:4	1620	No	MA
slow-arrivals	See Table D:1 – D:4	false	No	MA
Start-of-weekend	First weekend detected in the model	7200	No	HDS
End-of-weekend	End of first weekend detected in the model	10080	No	HDS
weekend	See Table D:1 – D:4	False	No	HDS
aec-available	See Table D:1 – D:4	False	No	HDS
Open_AEC	Opening time of AEC facilities	8	Yes	MA
Close_AEC	Closing time of AEC facilities	23	Yes	MA
aec-returns-start	Return patient clinic start time	Open_AEC		MA
aec-returns-end	1600hrs finish	960	No	MA
expected-to-current-capacity-ratio capacity-threshold	See Table D:1 – D:4	10	Yes	MA

Variable	Description	Value	User access?	Source
amu-crowding-tolerance	See Table 1	110	Yes	MA
max-ip-waits	Max number of patients in waiting-bedded that triggers capacity creation behaviours	3	No	MA
Max-expects-trigger	Max number of expected AMU-care patients that triggers capacity creation behaviours	8	No	MA
waiting-time	Delay tolerated by patients in waiting-bedded before actively seeking to start care in any area	1	No	MA
sufficient-beds-to-cope-night	Number of available AMU-resources that triggers a delay in transfer of patients at night	6	No	MA
sufficient-beds-to-cope-day	Number of available AMU-resources that triggers a delay in transfer of patients during day	6	No	MA
peak-start	Start of high volume of referrals	9	Yes	HDS
peak-end	End of high volume of referrals	18	Yes	HDS

MA - Modeller assumptions based on Ethnographic case study; HDS – Historical dataset

Input data

There are no input data

Sub-models

Small sub-models have been described in the relevant procedure in the schedule section. Here, more complicated sub-models are explained in flow diagrams with relevant reporters tabulated.

Rate of arrivals

The model senses high demand periods via peak = true or false. When peak = false, if the period of slow arrivals is sensed, the rate is halved. For all scenarios:

mean-demand = Mean_weekday_attendances (or Mean_weekend_attendances if weekend sensed) * 0.75

Multiplication by a factor of 0.75 is required to prevent unnaturally large volumes of referrals that occurs as a feature of the demand rate requiring separation into three different time periods. This allows the user interface selection of Mean_weekend_attendances and Mean_weekday_attendances to reflect activity seen in real-life creating a meaningful interaction with the model as the input value can directly relate to their day-to-day activity. Rate is calculated as follows:

peak = true:

ED source rate =

(mean-demand * peak-demand * peak-split) / duration of peak

Non-ED source rate =

(mean-demand * peak-demand * (1 - peak-split)) / duration of peak

peak = false & slow-arrivals = false:

ED source rate =

(mean-demand * (1 - peak-demand) * off-peak-split)/ duration of off-peak

Non-ED source rate =

(mean-demand * (1 - peak-demand) * (1 – off-peak-split))/ duration of off-peak

peak = false & slow-arrivals = true:

ED source rate =

(mean-demand * (1 - peak-demand) * off-peak-split)/ (duration of off-peak * 2)

Non-ED source rate =

(mean-demand * (1 - peak-demand) * (1 – off-peak-split))/ (duration of off-peak * 2) *avoid-overnight-moves*

Sub-model is shown in Figure C:3. Delays are modeller assumptions based on the ethnographic study.

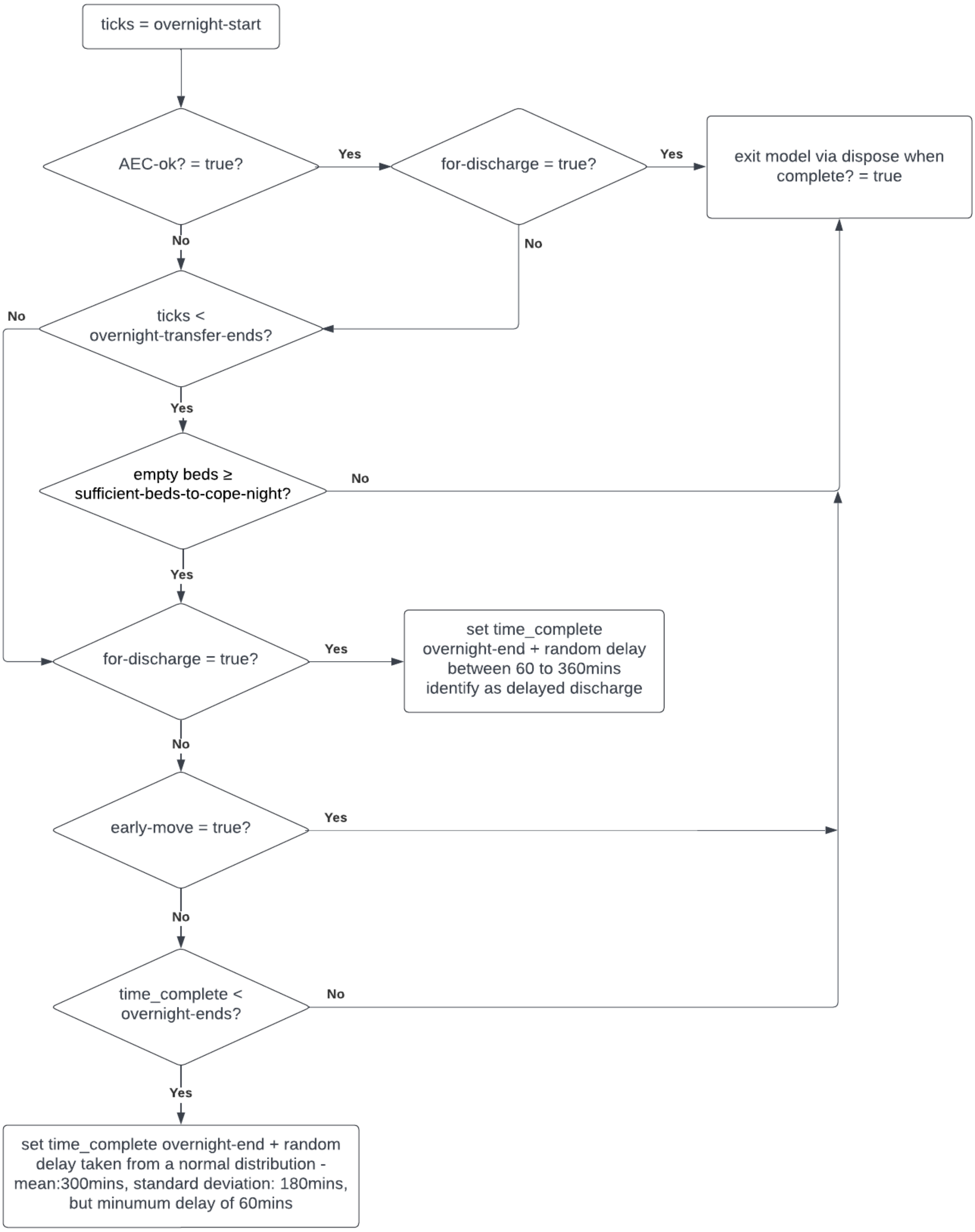


Figure C:3 avoid-overnight-moves

allocate and adjust procedures

The logic for allocate and adjust is shown in Figure C:4 with reporters in Table C:6.

Table C:6 Parameters and reporters used in allocation decisions

Parameter	Type	Description	Values	Source
AEC-ok?	Logical Static	Suitability for ambulatory care	**Allocate** reports true if: condition ≤ expert-adjust-local = true *and* aec-available = true **Adjust** reports true if: Condition ≤ expert-adjust-local + high-risk-adjust = true *and* aec-available = true	Ethnographic observation and modeller assumptions
time_arrived (ticks)	Rational Number	Non-ED patients travel time	If AEC-ok? = true then samples from random gamma distribution: $\alpha = 2\ \beta = 0.045$ If AEC-ok? = false then randomly samples from distribution according to time: 0800-2300hrs: • gamma distribution $\alpha = 11\ \beta = 0.08$ 2301-0759hrs: • gamma distribution $\alpha = 6\ \beta = 0.06$ In all cases resamples if reports <5mins	Ethnographic observation and modeller assumptions. Assumes travel to department is longer during peak and AEC-care patients use private transport (quick)
	Rational Number	ED patients travel time	Randomly samples from distribution according to presence/absence of peak Peak = true: • normal distribution $mean = 90\ sd = 45$ Peak = false: • normal distribution $mean = 60\ sd = 30$ In all cases resamples if reports <0mins	Ethnographic observation and modeller assumptions. Assumes arrivals take longer during working hours.
treatment_time (ticks)	Rational Number	AEC-care discharges	Random sample from gamma distribution $\alpha = 4.5\ \beta = 0.02$	Historical case site dataset October 2019 and modeller assumptions
		AEC-care admissions	Random sample from gamma distribution $\alpha = 24\ \beta = 0.04$	
		AMU-care discharges	Random sample from gamma distribution $\alpha = 24\ \beta = 0.04$	
		AMU-care admissions	Random sample from gamma distribution $\alpha = 3\ \beta = 0.008$	

sd = standard deviation; α and β refer to the shape and rate parameters for the gamma distributions

Figure C:4 Sub-models to allocate and adjust

relocate

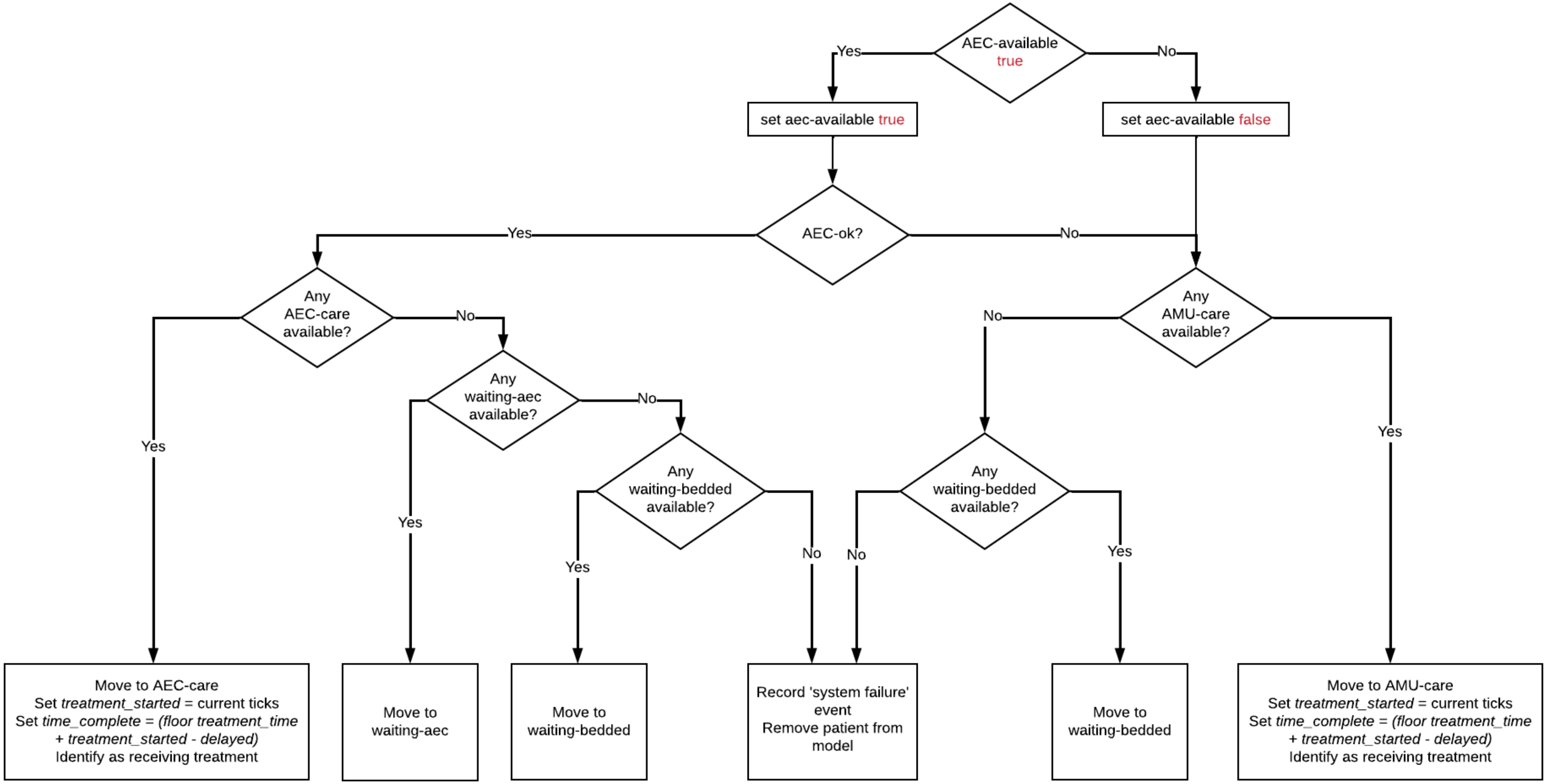


Figure C:5 Sub-model to relocate

Note when AEC-care is closed all patients default to AMU-care but those allocated to AEC-care at referral retain their AEC-ok = true status.

wait-for-resource & skip-queue in AEC-waiting

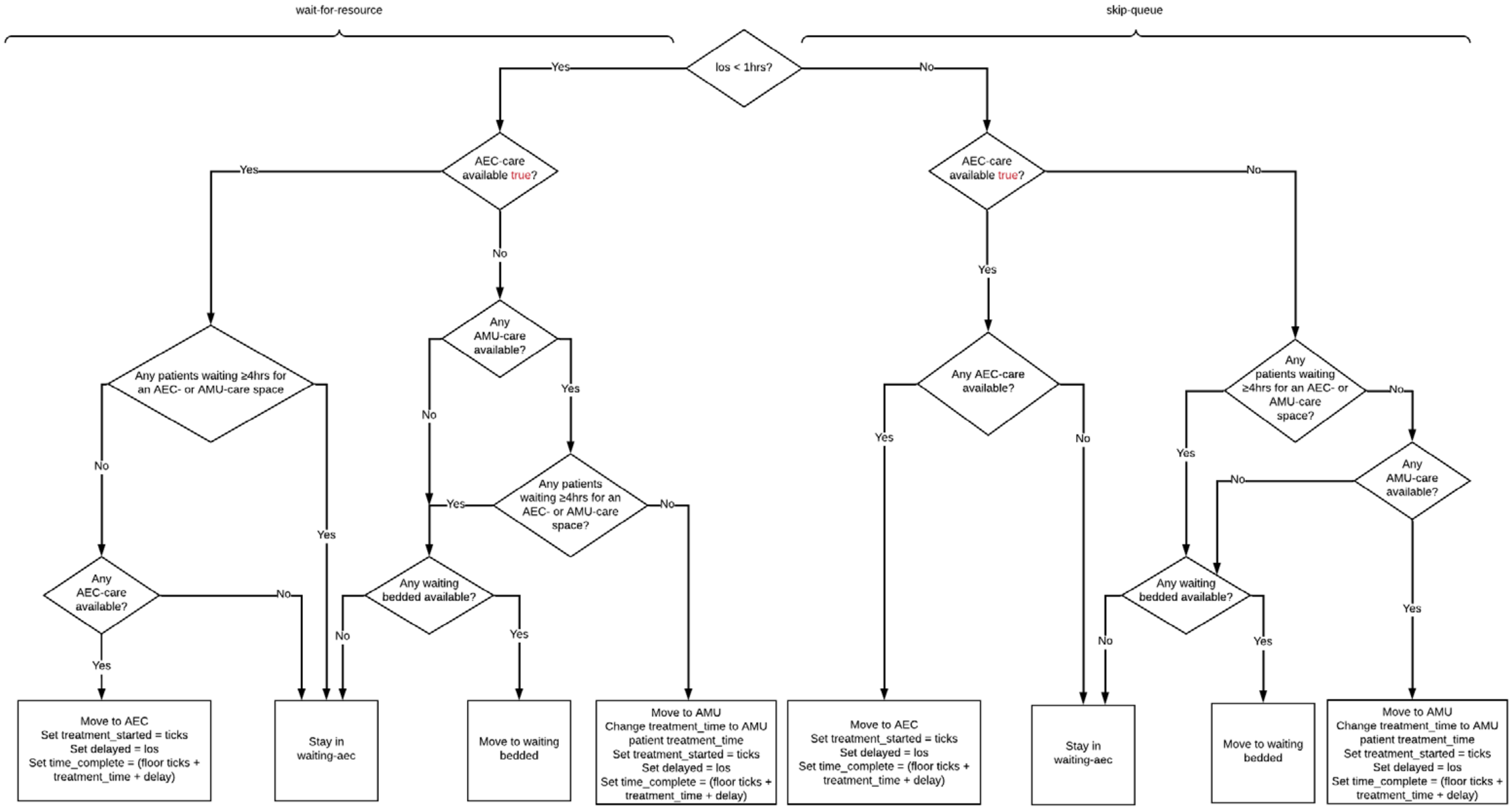


Figure C:6 Sub-models wait-for-resource and skip-queue for patient in AEC-waiting

Patients will preferentially move to AEC-care spaces when available, but will seek any space if waiting >1hr provided no patients have been waiting longer than 4hrs *wait-for-resource & skip-queue in Bedded-waiting*

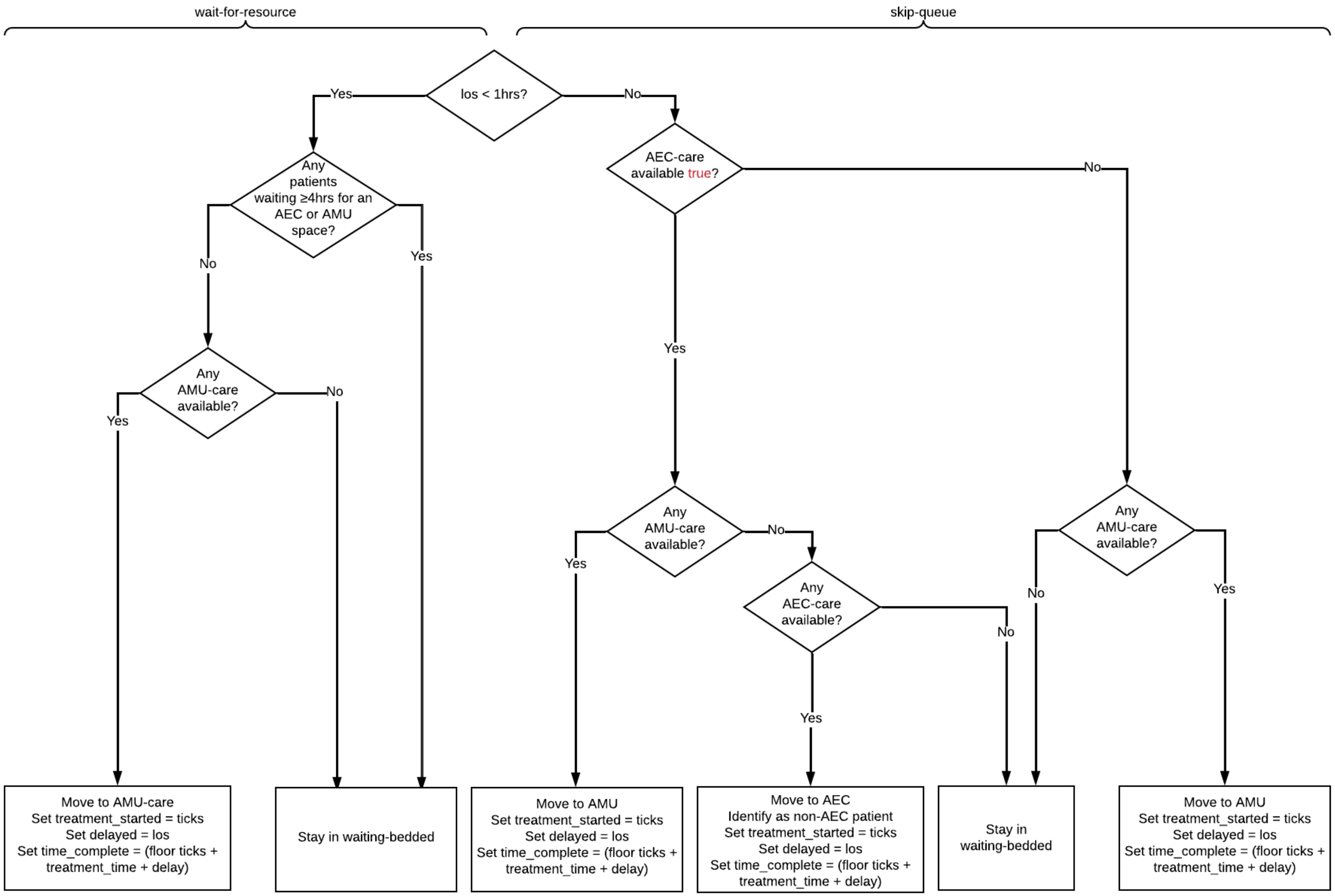


Figure C:7 Sub-models wait-for-resource and skip-queue for patient in Bedded-waiting

Patients will preferentially move to AMU-care spaces when available, but will seek any space if waiting >1hr provided no patients have been waiting longer than 4hrs

Dispose

Only patients identified as complete undergo. Sub-model to collect daily tallies of patients discharged within 24hrs, patients discharged (all areas), patients admitted (all areas), and daily tally of patients completing care in each area for analyses (not performed in the model). Asks patients to identify as ready for home or transfer for the leave procedure. Also determines health change and experience for each patient as shown in Table C:7.

Table C:7 Parameters used in dispose procedure

Variable	Description	Type	Patient group	Values	Source
hrqol (for-discharge = true patients only)	Health change	Rational number	AEC-care	Random normal distribution mean 0.068 sd 0.117	Distribution created from locally collected data using EQ5D5L survey
			AMU-care	Random-normal distribution mean 0.111 sd 0.131	
exp-daily-aec	Experience	Integer	AEC-ok? true	$\begin{cases} 1 = default \\ 0 = los \geq 480mins \\ 0 = delayed \geq 240min \end{cases}$	Ethnographic observation, experience survey (locally collected), and modeller assumptions
exp-daily-amu	Experience	Integer	AEC-ok? false	$\begin{cases} 1 = default \\ 0 = delayed \geq 60mins \end{cases}$	

sd = standard deviation

exit-model

A global (daily) tally of ED and noned patients is updated.

A global (daily) tally of patients transferred between Close_AEC and Open_AEC is updated.

A global tally of patients transferred to a hospital bed during out-of-hours period (aec-available = false) is updated

A global (daily) tally of the outcomes of expert and non-expert DMs is updated using the decision-logic shown in Figure C:8

If the model is still in the warm-up period, patients are removed. After warm-up the following variables for each patient exiting are stored in a list of lists for analysis after model runs are complete: area of care, disposal outcome, los, delay; hrqol

system-crowding-reaction

Procedure to create urgent care capacity when overcrowding sensed by the hospital system (observer). See Figure C:9 This procedure is triggered if overcrowding is present or if the ratio of expected AMU-bed patients to currently available beds ≥ expected-to-current-capacity-ratio. expected-to-current-capacity-ratio is determined in the set-demand procedure This reflects the variation in hospital capacity to accommodate early moves from the AMU when recent demand has been high. The model will only accept ≤ 3 early-moves at any time.

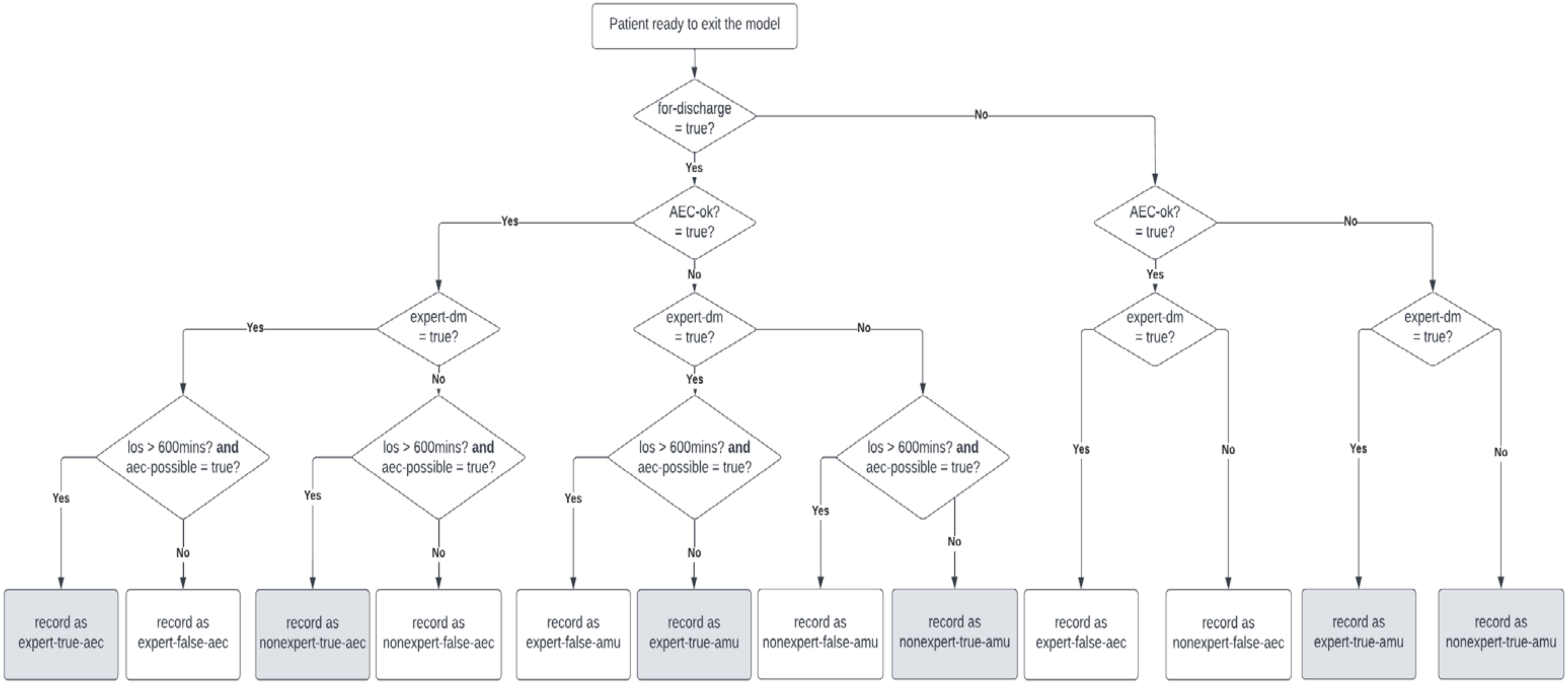


Figure C:8 Logic for collecting outcomes of expert and non-expert allocation decisions

Data is tallied daily and presented in the final model output for sensitivity and specificity analysis

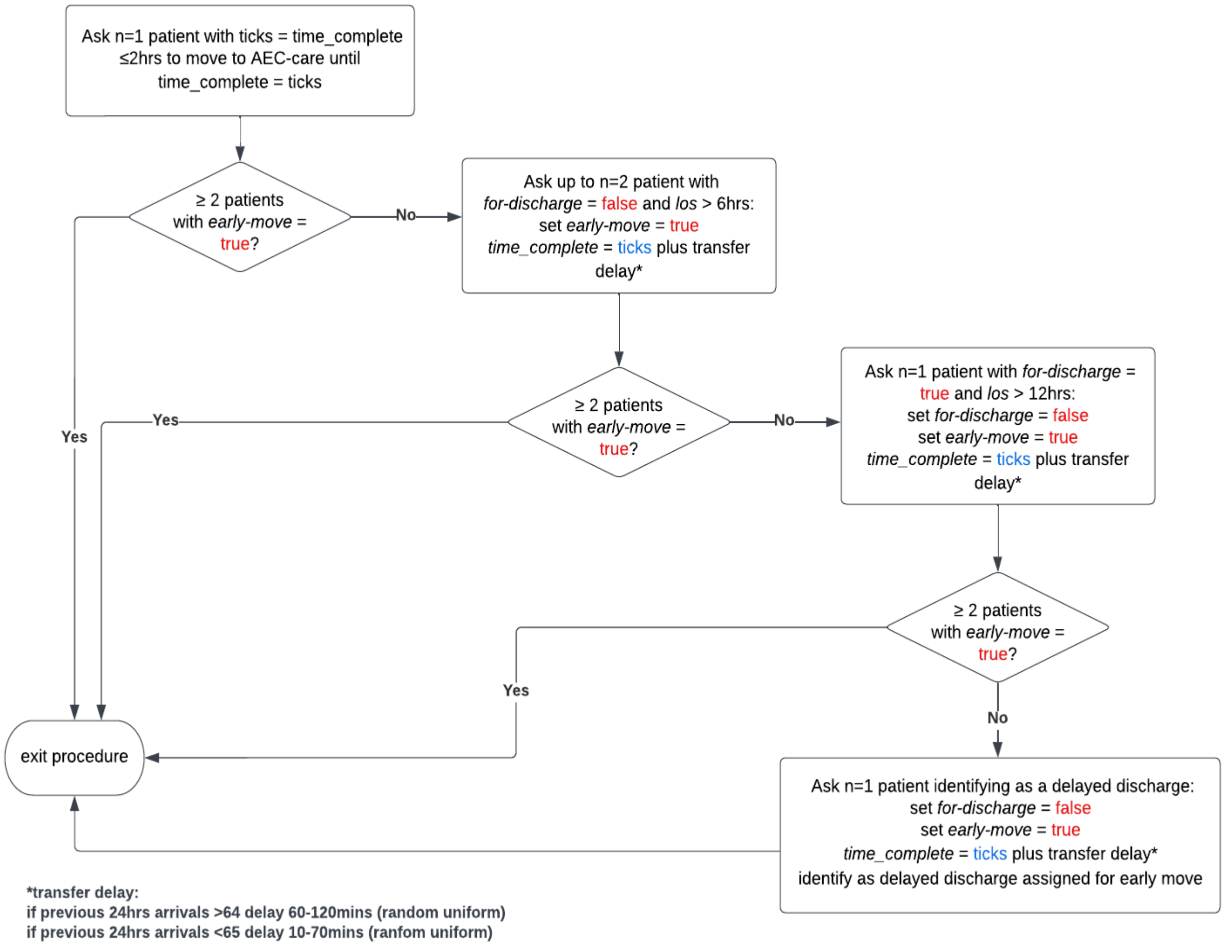


Figure C:9 system-crowding-reaction

Appendix D: Assumptions

Table D:1 Model assumptions

Area of activity	Assumption	Modelled behaviour	Explanation	Source/ Evidence
Patient referrals	Current referral-time patterns are unchanged from 2016	No variation in arrival rates throughout model runs	The referral times taken from the local study of senior decision-making provide insight into referral times as these are not locally recorded with any accuracy or consistency. There is no evidence that the timing of urgent care seeking behaviour has changed in the last five years and the working pattern and hours of referrers is similarly unchanged	Ethnographic study and modeller assumptions
Patient referrals	Proportion of patients arriving during peak hours and from each source is stable	Static, deterministic values applied	This site has an established pathway for arrival directly into the urgent care specialises to prevent ED crowding. Referrals are made through the team the referrer thinks is most appropriate and all arrivals go straight to their assigned urgent care area. When community teams are functioning with an out of hours service there is less referral activity from this source	Local data and ethnographic observation
Patient referrals	Patients not referred via ED or GP teams (e.g., out-patient clinics) assumed to behave as GP team referrals	Not separately modelled	This population of patients is very small. Any difference in time taken to arrive from setting unlikely to have significance in model dynamics and outputs	Ethnographic study and modeller assumptions
Patient referrals	Stochastic arrival times at rate that varies across the day	Poisson distribution sampling according to peak split and time of day	The historical data on decision-making shows a skewed referral pattern (assuming midnight to midnight) reflective of GP working hours	Historical data of attendances October 2019 & Historical data on decision-making in local setting (contains referral times)
Arrival patterns	AEC allocated patients arrive more quickly than bedded allocates	Drawn from a different distribution than bedded allocates	Access to private transport or use of public transport as stable to travel without paramedic support; reproduces decisions to delays presentation until following day when more resources available	Ethnographic observation and historical data of attendance in October 2019
Arrival patterns	Arrivals to AMU-bedded area will be quicker overnight than during the day	Drawn from a different distribution than daytime bedded allocates	Greater access to private transport from relatives (if stable) and ambulance services less busy as fewer referrals	Ethnographic observation and historical data of attendance in October 2019
Arrival patterns	Delay to arrival for ED populations is longer during daytime periods	Arrival time distributions different overnight	Patients referred form ED are located in the hospital but are referred shortly after arrival by the triage nurse meaning a delay between referral and arrival as they undergo full clinical assessment. There is also a local policy to move patients from the ED within 2hrs of arrival and a central mandate to move patients within 4hrs of arrival	Historical data of attendances October 2019 & Historical data on decision-making in local setting (contains referral times)

Area of activity	Assumption	Modelled behaviour	Explanation	Source/Evidence
Daily demand	Lower demand on weekends than weekdays	Mean weekday demand 45; Mean weekend demand 37	Patient preference to attend GPs for non-life-threatening health decline and no practices open at weekends. Will delay until weekday	Ethnographic study and modeller assumptions
Daily demand	Demand patterns consistent across all seasons	Mean demands fixed throughout model run	Loss of seasonal variation has emerged in UK urgent care over the last 10years with consistently high demand year-round	Modeller assumptions and data source
Daily demand	A proportion of patients referred every day will have urgent need for attendance excluded by an expert in acute internal medicine	A small proportion of patients exit the model after referral if the decision-maker is an expert	Variation in clinical knowledge across fields and limited knowledge of hospital resources available in urgent care results in some patients wrongly referred by risk averse clinicians. Consultants are able to identify these patients and reassure referrers of non-urgency or collaborate on a clinical plan that avoids urgent care attendance	Ethnographic study and modeller assumptions
Clinical decision-makers	Nursing staff make few AEC allocation decisions beyond what is suggested by the referrer or established local practice	Modelled distribution	Nursing staff rarely questioned the allocation decision of the referring ED triage nurse and only placed patients into AEC from the ED when locally agreed pathways were present. Performing multiple decision-tasks in other areas meaning limited band-width for clinical decision outside of their skillset	October 2019 dataset , Ethnographic observation, & Westall et al study
Clinical decision-makers	Trainees demonstrate wide variation in ability to recognise AEC suitability with most poorly performing compared to consultants and a few outliers equally early career consultants	Modelled distribution	Trainees in urgent care vary in their length of training, exposure to urgent care, and comfort with risk. Those nearing the end of training will practice medicine consistent with newly qualified consultants whilst those at the lower end will be risk averse and lack knowledge. There are a greater number of early years trainees (before specialisation) than senior trainees (specialising in hospital medicine)	Ethnographic observation and modeller assumption
Clinical decision-makers	Variation in expertise across consultant staff due to time spent delivering urgent care in the department and individual speciality training prior to becoming a consultant	Modelled distribution	Categories of staff learn risk management collectively and adopt practices in their location through mutual learning events. As they work in a close group in an environment with high validity feedback, behaviours are influenced by local learning and collegiate feedback with poor performance identified and managed within the team. Some practitioners will display high risk allocation behaviours with less expert consultants being more risk averse early in their career.	Ethnographic observation and modeller assumption

Area of activity	Assumption	Modelled behaviour	Explanation	Source/Evidence
Clinical decision-makers	All experts are able to identify patients without need to attend and will prevent attendance into the system. No other staff are capable of this	refuse attendance of non-urgent patients	Expert clinicians possess the greatest system and clinical knowledge to recognise safe non-attendance of patients referred. Exact numbers will vary according to patients presenting and the risk profile of the expert, but number are small enough to be represented as a group behaviour. Experts will also have credibility with referring clinicians to prevent an unnecessary attendance and be able to collaborate an alternative plan to satisfy all parties involved	Ethnographic observation; modeller assumption; literature search results Section 3.4
Exiting the model	Downstream resources are always available for patients requiring admission at the point that care completion is identified	All discharged patients exit the model at the time care is complete unless a delay has been added in the model. Exits the model at the time of care complete unless there is deemed to be excess free resources in the AMU:	The reasons for delay to transfer are multiple and complex. As the hospital is assumed to consistently function with high occupancy rate, treatment time distributions have been coded to include regularly observed delays to transfer such as receiving ward preparedness/protected mealtimes. Because of variable occupancy rates, if the AMU has patients requiring transfer but is experiencing moderately good bed availability, transfers will be delayed allowing the wards to prepare patients for discharge in anticipation of new arrivals	Ethnographic observation
Exiting the model	During periods of high occupancy in the hospital, out of hours when staffing is low, or if the AMU is deemed to have sufficient capacity to cope for that point in time, there is a delay to transferring patients to downstream bed resources	When sufficient beds detected: delay of 2mins for every tick this remains true	For the purposes of simplification, assumptions about movement from the unit have to be made. The real-world behaviour is highly stochastic but follows general rules as delays due to time of day, time for wards to create discharges, time to board patients and create capacity will be present in periods of high demand. Managerial staff will also prevent high volumes of transfers to lower resources areas if the AMU is not crowded/overcrowded	Ethnographic observation and modeller assumption
Exiting the model	During high occupancy in the hospital, when staffing is low, or when the AMU is deemed to have sufficient capacity, there is a delay to transferring patients to downstream bed resources	If demand in the last 24hrs has been <65 or if referrals so far <65 delay is 10-70mins taken from a uniform distribution	For the purposes of simplification, assumptions about movement from the unit have to be made. The real-world behaviour is highly stochastic but follows general rules as delays due to time of day, time for wards to create discharges, time to board patients and create capacity will be present in periods of high demand. Managerial staff will also prevent high volumes of transfers to lower resources areas if the AMU is not crowded/overcrowded	Ethnographic observation and modeller assumption

Area of activity	Assumption	Modelled behaviour	Explanation	Source/Evidence
Exiting the model	During high occupancy in the hospital, when staffing is low, or when the AMU is deemed to have sufficient capacity, there is a delay to transferring patients to downstream bed resources	If demand in the last 24hrs has been ≥65 or if referrals so far ≥65 delay is 60-120mins taken from a uniform distribution	For the purposes of simplification, assumptions about movement from the unit have to be made. The real-world behaviour is highly stochastic but follows general rules as delays due to time of day, time for wards to create discharges, time to board patients and create capacity, will be present in periods of high demand. Managerial staff will also prevent high volumes of transfers to lower resources areas if the AMU is not crowded/overcrowded	Ethnographic observation and modeller assumption
Patient waiting	Patients waiting >1hr for a bed will be moved to AEC to start their assessment process to prevent delays	Forced movement to available resource if los in waiting area >1hr	When capacity is exceeded, patients wait in a visible, but non-clinical part of the unit. Staff running the unit are aware how long patients have been waiting for IP beds and will try to start the assessment process. They will do this by transferring patients to the AEC area for care is capacity exists and they can be safely monitored there. Once a bed is available they will move. Staff know this is inefficient for other AEC patient so only do this when time spent waiting has been long	Ethnographic observation, modeller assumptions
Exiting the model	Proactively creation resource availability for patient referred into the system but not yet arrived if large volumes expected and few beds available to accommodate them	Threshold at which the ratio of expected bedded allocates to bed available triggers identification of patients to transfer to another ward before care is scheduled to complete	The hospital will support the AMU in preventing overcrowding but will try to limit large volumes of patient transfer into the hospital to prevent pressure in downstream areas to board patients unnecessarily. It may also not have sufficient beds to prevent overcrowding. This means that there will sometimes be an expectation for the AMU to accept overcrowding until they have discharged a sufficient number of patient to empty their waiting area	Ethnographic observation, expert opinion, modeller assumption
Exiting the model	When overcrowding occurs, patients for admission will transfer earlier than scheduled and patients for discharge will move to AEC area additional assumption that patients for discharge are suitable to wait in non-clinical areas	Preference to move patients ready for discharge to AEC	If patients have been identified as safe for home but occupying a bed they will be moved to a non-clinical waiting area	Ethnographic observation, modeller assumptions

Area of activity	Assumption	Modelled behaviour	Explanation	Source/Evidence
Exiting the model	When overcrowding occurs, patients for admission will transfer earlier than scheduled and patients for discharge will move to AEC area additional assumption that patients for discharge are suitable to wait in non-clinical areas	Preference to move patients who have been present longest to ensure stability of illness	The local system struggles to cope when overcrowding occurs. Staff will accept moving patient and handing tasks over to new teams.	Ethnographic observation, modeller assumptions
Exiting the model	If overcrowding persists patients identified for discharge will be transferred	Only move patients identified for discharge if no other options	Although there will be preference to keep patients identified for discharge in the urgent care area, at times of high demand these may represent the only safe transfers to create capacity. Patients will be transferred to a downstream in-patient bed on the assumption that the new team (on the downstream ward) will facilitate discharge when ready	Ethnographic observation, modeller assumptions
Exiting the model	The AMU will not be allowed to move patients that results in low occupancy rates, only sufficient to cope with their current demand	Only move patients to create sufficient capacity for known patients arrivals	Preference not to move patients about the area once care is started but if discharge anticipated this will be done to limit bed waits for potentially unstable patients	Ethnographic observation, modeller assumptions
Exiting the model	Some patients will experience a change in condition that will alter the intended disposal plan once evaluation is complete.	A proportion of AEC patients identified for discharge will have disposal changed to admission; a proportion of bedded patients identified for admission will have disposal plan changed to discharge	The urgent care assessment process includes a senior clinician review once initial evaluation is complete. This also involve other specialist input such as cardiologists. Clinical conditions may change, patients may choose not to stay, or specialists may support strategies for early discharge	Ethnographic observation
Other clinical activity	AMU care for all patients is undertaken by staff on the unit other than the decision-makers	DES element of group behaviours according to model structure	AMUs function with a larger body of staff compared with non-urgent areas. As this was not the focus of the research, once patients have arrived on the unit their care is assumed to continue under non-modelled staff	Ethnographic observation & modeller assumptions

Area of activity	Assumption	Modelled behaviour	Explanation	Source/Evidence
Other clinical activity	AEC area also provides care for follow up patients who compete for resources but are not part of the allocation decision behaviours	Up to 7 patients per day, not included in outputs	These patients present competition for resources but have already attended on a previous day. Local preference for no follow up where possible so number are generally small	Ethnographic observation & modeller assumptions
Other clinical activity	COVID induced changes to presentations and activity will be short lived	COVID impact not modelled	COVID had not occurred when the model concept was built and currently UK hospital systems anticipate return to usual structure/process although it is not clear when. I assume my model will be useful post-COVID	Modeller assumptions
Other clinical activity	Peak duration is the same every day of the week	User set at interface	Peak can vary at by one or two hours at weekends but as attendances are lower at weekends this has no impact on modelled activity or outcomes	Ethnographic observation and modeller assumptions
Delays	Only bed waits >5mins are an accurate reflection of the system	Any patients waiting for >1 model tick in the IP bed wait area	The dataset is created from handwritten, contemporaneous notes. Observation of staff found that recording of exact times of arrival and bed placement varied widely when the delay to placement was a few minutes - some staff would record this exact wait and others would record the time of placement only. The database records all patients who arrived without immediate IP bed placement (not AEC waits). To account for this human behaviour in recording bed waits a 5min interval before recording was added as this is equal to 1 model tick	Ethnographic observation, local handwritten database, & modeller assumptions
Delays	when no physical space is left in the area, all new arrival are redirected to an alternative area - e.g., the Emergency Department	If there are zero IP Bed spaces and zero IP Bed wait spaces at moment of arrival of an IP Bedded allocated patient then the patient is redirected to another area of care	If the unit is full and the waiting area is full there is no space to observe a patient and the workload has greatly exceeded resources. This is deemed as highly unsafe, and patients are redirected to other urgent care areas or kept in the ED for longer until capacity can be addressed. This is an exceptionally rare event. Although not witnessed on the case site, it is seen in other areas where patients are redirected to the emergency department due to concerns for safety. This assumption also allows the model to keep running without crashing if this does occur.	Ethnographic observation and modeller assumptions
Patient outcomes	HRQoL change in patients who are discharged follows a normal distribution set by their area of care	Modelled outcome form a normal distribution according to area	There are no available data on the health changes seen in the ambulatory management of urgent conditions beyond that collected by me during the observation study. As not all patients who could be categorised as AEC suitable are managed in the AEC, the HRQoL of these patients may be compare with those who did meet criteria and were managed via AEC to appreciate any difference that could be seen according to the area of care allocated	Data collection of patient outcomes in patients discharged within 48hrs during ethnographic study and modeller assumptions

Area of activity	Assumption	Modelled behaviour	Explanation	Source/Evidence
Patient outcomes	Patients attending either area have a positive experience of care unless they undergo delays to starting care or experience a long length of stay in the AEC area	All patients allocated experience = 1 upon creation, changed to 0 if poor experience criteria met	Easier modelling based on results discussed in Chapter Five, Section 5.1.2.1	Ethnographic observation, data collection on case site patient experience, and modeller assumptions
Decision-maker outcomes	Arrival within AEC opening hours, and length of stay ≤10hrs, and a discharge outcome.	True/False outcome if met/not met	See Chapter Four, Section 4.7.3.4	Expert opinion, patient experience survey, and modeller assumptions
Decision-maker outcomes	Arrival outside of AEC opening hours, or Length of stay >10hrs, or admission outcome	True/False outcome if met/not met	See Chapter Four, Section 4.7.3.5	Decision-maker outcomes
Patient variables	Equal probability of any medical condition across both populations	Conditions modelled as a number taken from a uniform distribution (0-1) that represents probability of AEC suitability and discharge	The AMU covers all adult medical emergencies meaning a large variety of illness with co-morbidities and social needs. All conditions equally likely to present and at random due to nature of urgent care. No two similar conditions may be suitable for the same care of social needs or co-morbidities differ	Ethnographic observation & historical dataset
Patient variables	Patients will undergo a group behaviour pattern of treatment time based on the area of care and probability of discharge	Distributions created according to allocation and initial plan for disposal based on patient condition	Patients in healthcare exhibit group behaviours enforced by the system as they are managed as collectives for economies of scale. The time taken to complete assessment and diagnostics in the separate areas follow broadly similar distributions according to types of illness. These types of illness determine suitability for AEC and suitability for discharge meaning that they can be represented by random allocation from defined distributions. Patients with conditions that are commonly managed as out-patient undergo less extensive evaluation and require less direct observation due to clinical stability.	Modeller assumption, ethnographic study, local data from October 2019
Patient variables	Patient reported outcomes used are validated by the successful validation of the explanatory model	Health index change is drawn from a distribution according to area of care informed by the data collected during the ethnography	As individual patient outcomes (beyond mortality) are unknown in these populations, assumptions about the validity of the inputs used were required. As the data was collected on the case site and the case site was successfully reproduced, the use of this data to explore trends in health and experience was reasonable	Prospective data collection via EQ5D5L and patient surveys during ethnography

Area of activity	Assumption	Modelled behaviour	Explanation	Source/Evidence
Patient variables	Once resource in the allocated place of care is accessed by a patient, they will receive all care in that are for the duration of their treatment	No movement between AEC and AMU unless the system forces it due to lack of resources	Ethnographic observation did reveal patients who are allocated to one area and then move to the other after initial stages of evaluation reveal them to be more suited for the non-allocated are (e.g., a patient allocated to AEC whose condition on arrival is more unstable than initially perceived). Local recording of this activity is poor (manually recorded) and unverifiable in the electronic database. The ethnographic case study revealed a very small number of patients experiencing this and that it occurred in both directions. To minimise model complexity the assumption is that the number of patients moved from AEC to bedded is equivalent to the number moved from bedded to AEC to maintain the assumption	Ethnographic observation and modeller assumptions
Exiting the model	There is a preference not to move patients who have completed care overnight until they have been reviewed on the morning ward round	Delay to model exit	at 0800hrs there is a staff handover and a review of all patients. This can identify more discharges from both the AMU clinicians and the specialists who visit later in the morning. To prevent unnecessary admissions, there is a preference to wait until senior review unless overcrowding is present. Patients requiring admission also delayed to ensure they see a clinician that morning in case the transfer means they miss a ward round review on the receiving ward	Ethnographic observation
Exiting the model	Patients with AEC potential have a high likelihood of discharge regardless of allocation decision	All patients meeting within the prevalence range for AEC in their population are identified for discharge on initial referral	Allocation to AEC suggests no need for admission and AEC services will strive to ensure discharge. This is the default assumption of staff and patients upon arrival	Ethnographic observation
Daily demand	Prevalence of patients with the potential for AEC is stable across all days and times in both ED and non-ED populations	Deterministic prevalence values for ED and non-populations	AEC suitability is largely determined by local resource capabilities which are relatively stable. Population presenting may vary from day to day but this is reflected by the random distribution of patient need (condition)	Ethnographic observation
Patient variables	Patients behave as passive entities I urgent care setting. Preference assumed to align with allocation and discharge plan that emerges in the model	No patient variable for preference	Experts shown to consider patient preference but system not always able to accommodate this. Patients largely behave as passive entities in hospital settings	Ethnographic observation

Area of activity	Assumption	Modelled behaviour	Explanation	Source/Evidence
Prevalence of AEC suitability	Constant over model runs	Posterior values via Bayesian inferential analysis taken to represent prevalence for each population	Used to calculate PPV and NPV to determine accurate representativeness in modelled behaviours	Modeller assumption
Prevalence of AEC suitability	whole presenting urgent care population may be considered for AEC suitability	Posterior values via Bayesian inferential analysis taken to represent prevalence for each population	Used to calculate PPV and NPV to determine accurate representativeness in modelled behaviours	Modeller assumption
AEC waits	Patients in the AEC waiting area not considered at risk of health decline (no safety concerns in overcrowding)	AEC waits not specifically explored in outputs	AEC patients are anticipated to be safe to wait for care as a result of their presenting complaint. Not considered a high-risk populations	Modeller assumption

Appendix E: Supportive data for SSM Validation

Tests of variance

Comparisons of the variances around the outputs' means with the historical dataset against the null-hypothesis was performed using both parametric (Tukey) and non-parametric (Kruskal-Wallis) tests. The p-values for tests are presented in Tables A5:1 – A5:3.

Table E:1: Tests of variance around the mean for departmental outputs

	AMU-bedded discharged[1]	AEC-care discharges[1]	Admissions[1]	24hrs discharges[1]	AEC allocations per day[1]	Proportion of bed-wait per bed allocations[2]
Truncated Normal	0.076	<0.01	<0.01	<0.001	<0.001	0.151
Truncated Normal no extra AEC	0.315	<0.01	<0.01	<0.001	<0.001	0.132
Gamma	0.637	0.021	<0.01	<0.001	<0.001	0.064
Gamma no extra AEC	0.380	0.023	<0.01	<0.001	<0.001	0.053
Fixed	0.067	<0.01	<0.01	<0.001	<0.001	0.119
Fixed no extra AEC	0.035	<0.01	0.011	<0.001	<0.001	0.197

[1]Tukey
[2] Kruskal-Wallis

No difference (green) | Rejection of null hypothesis (orange)

Table E:2 Tests of variance around the mean for patient level outputs against the three-month historical dataset

	Length of delay[2] (≥5mins)	LoS in AEC-care discharges[1]	Los in AEC-care admissions[2]	LoS in AMU-bedded discharges[1]	LoS in AMU-bedded admissions[2]
Truncated Normal	<0.001	<0.001	0.024	0.99	<0.001
Truncated Normal no extra AEC	<0.001	<0.001	0.005	0.99	<0.001
Gamma	<0.001	<0.001	0.177	0.99	<0.001
Gamma no extra AEC	<0.001	<0.001	0.155	0.99	<0.001
Fixed	<0.001	<0.001	<0.01	0.99	<0.001
Fixed no extra AEC	<0.001	<0.001	<0.01	0.99	<0.001

[1]Tukey
[2] Kruskal-Wallis

No difference (green) | Rejection of null hypothesis (orange)

Table E:3 Tests of variance around the mean for decision-maker outputs

	Expert Sensitivity[2]	Non-expert Sensitivity[1]	Expert Specificity[1]	Non-expert specificity[2]	Expert Positive predictive value[2]	Non-expert Positive predictive value[2]	Expert Negative predictive value[2]	Non-expert Negative predictive value[2]
Truncated Normal	0.644	<0.01	0.259	0.037	0.205	0.056	0.752	<0.001
Truncated Normal no extra AEC	0.884	<0.01	0.831	0.041	0.612	0.033	0.938	<0.001
Gamma	0.717	<0.01	0.244	0.023	0.151	0.054	0.605	<0.001
Gamma no extra AEC	0.971	<0.01	0.111	0.035	0.111	0.088	0.885	<0.001
Fixed	0.536	<0.01	0.462	0.030	0.348	0.046	0.628	<0.001
Fixed no extra AEC	0.463	<0.01	0.571	0.028	0.453	0.042	0.550	<0.001

[1]*Tukey*
[2] *Kruskal-Wallis*

No difference (green) — Rejection of null hypothesis (orange)

Sensitivity analyses

Table E:4 describes the parameters and distributions used in the explanatory model. In all parameter spaces explored, uniform distributions were adopted. This was justified for several reasons. Firstly, there were no empirical data from the local site to support alternative distributions. Secondly, expert opinion of the how other staff, departments, or resources in the hospital may have behaved in times of high hospital occupancy was too unreliable to inform triangular distributions, Thirdly, the uncertainty surrounding unknown influences upon these parameters (e.g., staffing crises, fluidity in available resources, diagnostic technology adoption, the impact of high elective waits on urgent care services seen since the pandemic) was assumed too great to apply any other distribution under modeler assumptions. Expert opinion informed plausible bounds to each distribution.

PARAMETER	DESCRIPTION & RATIONALE	DISTRIBUTION	SOURCE
ed-aec-prev	Proportion of patients from the ED who may be suitable for admission avoidance given information at referral. Shown to be of moderate influence on outputs in explanatory model	0.05 – 0.25 Uniform (rational number)	Modeler assumptions
noned-aec-prev	Proportion of patients from non-ED sourced who may be suitable for admission avoidance given information at referral. Shown to be of moderate influence on outputs in explanatory model	0.15 – 0.40 Uniform (rational number)	(Corley & Gioia, 2004; Gioia et al., 2013) Modeler assumptions
refuse-attends	Proportion of patients that an expert decision-maker will determine do not need to attend hospital	0.96 – 1.0 (rational number)	Modeler assumptions based on the ethnographic study
expert-adj-con	The shape parameter for the gamma distribution from which the allocation value assigned to individual consultants is drawn	5.0 – 10.0 Uniform (rational number)	Modeler assumptions
expert-adj-trainee	The mean for the truncated normal distribution from which the allocation value for trainees is drawn	-1.0 – 2.0 Uniform (rational number)	Modeler assumptions
expert-adj-sn	The limits of the uniform distribution from which the senior nurse allocation value is drawn	0.025 – 0.20 Uniform (rational number)	Modeler assumptions
aec-admits	The daily proportion of AEC allocated patients admitted following completion of treatment	0.10 – 0.40 Uniform (rational number)	Modeler assumptions
amu-discharge-plan	The daily proportion of Bedded allocated patients discharged following completion of treatment	0.075 – 0.20 Uniform (rational number)	Modeler assumptions
amu-crowding-tolerance	The maximum % occupancy in the Bedded area before reactive capacity creation may occur	90 – 150 Uniform (rational number)	Modeler assumptions
Proactive-capacity-creation-threshold	The ratio of expected bed-allocates to current bed availability that triggers proactive capacity creation	5 – 20 Uniform (rational number)	Modeler assumptions
Mean_weekday_attendances	Mean number of patients referred every 24hrs Monday-Friday	43.0 – 50.0 Uniform (rational number)	Modeler assumptions

Table E:4 Parameters and sample space explored in global sensitivity analysis

Appendix F: Supportive data for predictive modelling

Table F: 1 AEC Utilisations at different level of enforced occupancy

	AEC utilisation at 100% enforced occupancy			
scenario	mean	sd	99% CI Lower	99% CI Upper
C	0.338	0.049	0.335	0.341
CT	0.192	0.035	0.190	0.194
BL	0.168	0.042	0.166	0.170
CN	0.167	0.043	0.164	0.170
T	0.065	0.013	0.064	0.066
TN	0.047	0.013	0.046	0.048
N	0.014	0.010	0.013	0.015

	AEC utilisation at 115% enforced occupancy			
scenario	mean	sd	99% CI Lower	99% CI Upper
C	0.337	0.047	0.334	0.340
CT	0.198	0.038	0.196	0.200
BL	0.181	0.045	0.178	0.184
CN	0.171	0.044	0.168	0.174
T	0.064	0.014	0.063	0.065
TN	0.047	0.013	0.046	0.048
N	0.012	0.010	0.011	0.013

	AEC utilisation at 130% enforced occupancy			
scenario	mean	sd	99% CI Lower	99% CI Upper
C	0.333	0.050	0.330	0.336
CT	0.193	0.037	0.191	0.195
BL	0.178	0.043	0.175	0.181
CN	0.172	0.044	0.169	0.175
T	0.065	0.013	0.064	0.066
TN	0.047	0.013	0.046	0.048
N	0.014	0.010	0.013	0.015

C: Consultants, N: Nurses, T: Trainees, CN: Consultants/Nurses,

CT: Consultant/Trainees, TN: Trainees/Nurses, BL: Baseline

Table F: 2 24hr discharges at increasing levels of enforced occupancy

	24hr discharges at 100% enforced occupancy			
scenario	mean	sd	99% CI Lower	99% CI Upper
N	0.374	0.026	0.372	0.376
TN	0.366	0.026	0.364	0.368
T	0.362	0.025	0.361	0.363
BL	0.347	0.027	0.345	0.349
CN	0.347	0.027	0.345	0.349
CT	0.340	0.026	0.338	0.342
C	0.318	0.028	0.316	0.320

	24hr discharges at 115% enforced occupancy			
scenario	mean	sd	99% CI Lower	99% CI Upper
N	0.377	0.026	0.375	0.379
TN	0.369	0.026	0.367	0.371
T	0.366	0.026	0.364	0.368
CN	0.349	0.028	0.347	0.351
BL	0.347	0.027	0.345	0.349
CT	0.343	0.027	0.341	0.345
C	0.320	0.028	0.318	0.322

	24hr discharges at 130% enforced occupancy			
scenario	mean	sd	99% CI Lower	99% CI Upper
N	0.377	0.025	0.376	0.378
TN	0.369	0.025	0.368	0.370
T	0.366	0.026	0.364	0.368
CN	0.349	0.028	0.347	0.351
BL	0.348	0.027	0.346	0.350
CT	0.344	0.027	0.342	0.346
C	0.321	0.027	0.319	0.323

C: Consultants, N: Nurses, T: Trainees, CN: Consultants/Nurses,

CT: Consultant/Trainees, TN: Trainees/Nurses, BL: Baseline

Table F: 3 Differences in time spent in crowding per week with different strategies (minutes)

100% tolerated occupancy: time in crowding per week between strategies

	BL	CT	TN	CN	C	T	N
BL	0	-69	360	49	-668	286	446
CT	69	0	429	118	-599	355	515
TN	-360	-429	0	-311	-1028	-74	86
CN	-49	-118	311	0	-717	237	397
C	668	599	1028	717	0	954	1114
T	-286	-355	74	-237	-954	0	160
N	-446	-515	-86	-397	-1114	-160	0

115% tolerated occupancy: time in crowding per week between strategies

	BL	CT	TN	CN	C	T	N
BL	0	-29	394	45	-496	350	481
CT	29	0	423	74	-467	379	510
TN	-394	-423	0	-349	-890	-44	87
CN	-45	-74	349	0	-541	305	436
C	496	467	890	541	0	846	977
T	-350	-379	44	-305	-846	0	131
N	-481	-510	-87	-436	-977	-131	0

130% tolerated occupancy: time in crowding per week between strategies

	BL	CT	TN	CN	C	T	N
BL	0	-60	368	37	-529	295	438
CT	60	0	428	97	-469	355	498
TN	-368	-428	0	-331	-897	-73	70
CN	-37	-97	331	0	-566	258	401
C	529	469	897	566	0	824	967
T	-295	-355	73	-258	-824	0	143
N	-438	-498	-70	-401	-967	-143	0

C: Consultants, N: Nurses, T: Trainees, CN: Consultants/Nurses,
CT: Consultant/Trainees, TN: Trainees/Nurses, BL: Baseline

Crowding was defined as 90-100% occupancy of the Bedded area. Tables should be read across strategies. Moving from the strategy in the row name to the strategy in the column name provides the difference between time spent. For example, comparing other strategies with BL crowding at 100% tolerance, CT saw 69 fewer minutes in crowding and TN saw 360mins more. Tukey's Test for variance saw significant differences between scenarios CT-BL non-significant at 115% tolerance and CN-BL non-significant at 130% tolerated occupancy.

Table F: 4 Differences in time spent in overcrowding per week with different strategies (minutes)

100% tolerated occupancy: time in overcrowding per week between strategies

	BL	CT	TN	CN	C	T	N
BL	0	-35	272	12	-128	223	393
CT	35	0	307	47	-93	258	428
TN	-272	-307	0	-260	-400	-49	121
CN	-12	-47	260	0	-140	211	381
C	128	93	400	140	0	351	521
T	-223	-258	49	-211	-351	0	170
N	-393	-428	-121	-381	-521	-170	0

115% tolerated occupancy: time in overcrowding per week between strategies

	BL	CT	TN	CN	C	T	N
BL	0	-43	473	73	-442	370	681
CT	43	0	516	116	-399	413	724
TN	-473	-516	0	-400	-915	-103	208
CN	-73	-116	400	0	-515	297	608
C	442	399	915	515	0	812	1123
T	-370	-413	103	-297	-812	0	311
N	-681	-724	-208	-608	-1123	-311	0

130% tolerated occupancy: time in overcrowding per week between strategies

	BL	CT	TN	CN	C	T	N
BL	0	-56	479	54	-458	391	662
CT	56	0	535	110	-402	447	718
TN	-479	-535	0	-425	-937	-88	183
CN	-54	-110	425	0	-512	337	608
C	458	402	937	512	0	849	1120
T	-391	-447	88	-337	-849	0	271
N	-662	-718	-183	-608	-1120	-271	0

C: Consultants, N: Nurses, T: Trainees, CN: Consultants/Nurses,

CT: Consultant/Trainees, TN: Trainees/Nurses, BL: Baseline

Overcrowding was defined as >100% occupancy of the Bedded area. Tables should be read across strategies. Moving from the strategy in the row name to the strategy in the column name provides the difference between time spent. For example, comparing other strategies with BL overcrowding at 100% tolerance, CT saw 35 fewer minutes in crowding and TN saw 272mins more. Tukey's Test for variance revealed significant difference between all strategies with the excepting for difference between CN-BL at 100% occupancy tolerance.

Table F:5 Proportion of patients starting care in the wrong area per week

scenario	Proportion of patients starting care in the wrong area at 100% forced occupancy			
	mean	sd	99% CI Lower	99% CI Upper
N	0.015	0.014	0.014	0.016
TN	0.012	0.011	0.011	0.013
T	0.010	0.010	0.009	0.011
BL	0.004	0.005	0.004	0.004
CN	0.004	0.006	0.004	0.004
CT	0.003	0.005	0.003	0.003
C	0.002	0.003	0.002	0.002

scenario	Proportion of patients starting care in the wrong area at 115% forced occupancy			
	mean	sd	99% CI Lower	99% CI Upper
N	0.052	0.020	0.051	0.053
TN	0.043	0.019	0.042	0.044
T	0.038	0.017	0.037	0.039
CN	0.028	0.014	0.027	0.029
BL	0.025	0.013	0.024	0.026
CT	0.022	0.013	0.021	0.023
C	0.010	0.009	0.009	0.011

scenario	Proportion of patients starting care in the wrong area at 130% forced occupancy			
	mean	sd	99% CI Lower	99% CI Upper
N	0.062	0.024	0.061	0.063
TN	0.052	0.023	0.051	0.053
T	0.046	0.021	0.045	0.047
CN	0.032	0.017	0.031	0.033
BL	0.030	0.017	0.029	0.031
CT	0.027	0.016	0.026	0.028
C	0.012	0.010	0.011	0.013

C: Consultants, N: Nurses, T: Trainees, CN: Consultants/Nurses,

CT: Consultant/Trainees, TN: Trainees/Nurses, BL: Baseline

Although differences between scenarios frequently met statistical significance, only the difference between the Consultant only (C) and Nurse only (N) strategies at 130% tolerated overcrowding was meaningful (≥0.05)

Table F:6 Proportion of patients experiencing transfer in the overnight period per week

	Proportion of overnight transfers at 100% forced occupancy			
scenario	mean	sd	99% CI Lower	99% CI Upper
CN	0.185	0.036	0.183	0.187
BL	0.183	0.036	0.181	0.185
CT	0.180	0.034	0.178	0.182
C	0.170	0.030	0.168	0.172
N	0.163	0.037	0.161	0.165
TN	0.155	0.034	0.153	0.157
T	0.153	0.033	0.151	0.155

	Proportion of overnight transfers at 115% forced occupancy			
scenario	mean	sd	99% CI Lower	99% CI Upper
C	0.163	0.031	0.161	0.165
CT	0.161	0.033	0.159	0.163
BL	0.159	0.033	0.157	0.161
CN	0.157	0.034	0.155	0.159
N	0.142	0.040	0.140	0.144
TN	0.134	0.035	0.132	0.136
T	0.131	0.034	0.129	0.133

	Proportion of overnight transfers at 130% forced occupancy			
scenario	mean	sd	99% CI Lower	99% CI Upper
C	0.159	0.031	0.157	0.161
CT	0.154	0.035	0.152	0.156
CN	0.152	0.035	0.150	0.154
BL	0.151	0.034	0.149	0.153
N	0.140	0.043	0.137	0.143
TN	0.131	0.037	0.129	0.133
T	0.129	0.036	0.127	0.131

C: Consultants, N: Nurses, T: Trainees, CN: Consultants/Nurses,

CT: Consultant/Trainees, TN: Trainees/Nurses, BL: Baseline

Table F: 7 Median delay in bedded area populations

Occupancy forced	Baseline	Consultants	Consultants/Trainees	Consultants/ Nurses	Trainees/ Nurses	Trainees	Nurses
100%	23(13,42)	22 (12,42)	22 (13,42)	23 (13,44)	23 (12,42)	22 (12,42)	23 (13,43)
115%	38 (16,97)	33 (15,75)	38 (16,96)	39 (17,104)	33 (15,78)	33 (15,76)	33 (15,77)
130%	39 (17,114)	38 (16,109)	38 (16, 109)	40 (17, 118)	34 (15, 90)	33 (15, 88)	35 (15, 92)

Delays in minutes with 2nd and 4th quartile in brackets

Table F: 8 Median delay in AEC populations

Occupancy forced	Baseline	Consultants	Consultants/Trainees	Consultants/Nurses	Trainees/ Nurses	Trainees	Nurses
100%	35 (17,60)	38 (19,60)	37 (18,60)	39 (19, 60)	34 (17, 71)	35 (20, 67)	37 (19, 79)
115%	46 (21,65)	46 (21, 64)	54 (24, 84)	46 (20, 60)	81 (36, 48)	71 (31, 127)	80 (38, 154)
130%	52 (22,74)	55 (23, 98)	38 (16, 109)	45 (20, 60)	81 (36, 155)	79 (35, 159)	88 (37, 172)

Delays in minutes with 2nd and 4th quartile in brackets

Table F: 9 Lengths of stay for AEC patients

scenario	median	2nd quartile	4th quartile
100% forced occupancy			
C-100%	248	165	427
CN-100%	243	163	399
BL-100%	240	162	388
CT-100%	238	160	376
N-100%	212	148	293
TN-100%	212	150	289
T-100%	211	148	291
115% forced occupancy			
C-115%	251	166	435
BL-115%	247	165	414
CN-115%	244	163	404
CT-115%	242	163	392
T-115%	212	150	296
N-115%	211	148	289
TN-115%	211	149	292
130% forced occupancy			
CN-130%	246	164	411
BL-130%	243	163	397
C-130%	239	161	380
CT-130%	239	161	380
T-130%	213	149	294
TN-130%	212	149	292
N-130%	210	148	291

Table F: 10 Lengths of stay for bedded area patients

scenario	median	2nd quartile	4th quartile
100% forced occupancy			
C-100%	986	405	1491
CT-100%	813	388	1324
BL-100%	792	385	1301
CN-100%	784	388	1297
T-100%	706	354	1214
TN-100%	691	355	1200
N-100%	663	353	1175
115% forced occupancy			
C-115%	1006	404	1503
CT-115%	842	388	1340
BL-115%	828	386	1321
CN-115%	818	389	1313
T-115%	732	350	1228
TN-115%	713	350	1214
N-115%	683	348	1187
130% forced occupancy			
C-130%	849	388	1340
CT-130%	849	388	1340
BL-130%	834	388	1323
CN-130%	823	387	1316
T-130%	735	348	1231
TN-130%	719	349	1217
N-130%	689	346	1193

C: Consultants, N: Nurses, T: Trainees, CN: Consultants/Nurses, CT: Consultant/Trainees, TN: Trainees/Nurses, BL: Baseline.

Suffixes in scenario abbreviations relate to the enforced occupancy levels of 100%, 115%, and 130%