Bridging the gap: how human factors can support the development of AI technology in healthcare

Kate Elizabeth Preston

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Strathclyde Institute of Biomedical and Pharmaceutical Science

University of Strathclyde, Glasgow, Scotland

Acknowledgements

I dedicate this work to my late grandad, John, who, if given the chance, would have read my whole thesis and thoroughly enjoyed it.

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Presentations

- Preston K., Dunlop E., Ferguson A., Maclellan C., Dong F., Bennie M. Assessing the needs of clinicians in adult critical care in Scotland for a sepsis fluid management Artificial Intelligence tool using a human factors approach. Poster presented at: DigiFest Conference; 2023 November 14th; Glasgow, Scotland.
- Preston K., Dunlop E., Ferguson A., MacLellan C., Dong F., Bennie M. Assessing the needs of clinicians working in adult critical care in Scotland for a sepsis fluid management Artificial Intelligence tool. Oral presentation at: European Drug Utilization Research Group (EuroDURG) Conference; 2023 June 27th-30th; Bologna, Italy.
- Preston K. Artifical Intelligence in Hospital – An interview with Kate Preston (Podcast). 1202 – The Human Factors Podcast; 2023 June 5th. Available from: https://www.1202podcast.com/kate-preston/
- Preston K., Dunlop E., Dong F., Bennie M. Bridging the gap: Human factors and hospital artificial intelligence technology. Oral Presentation at Chartered Institute of Ergonomics & Human Factors Conference Doctoral Consortium; 2023 April 25th-26th; Birmingham, UK.
- Preston K., Dunlop E., Dong F., Bennie M. User needs assessment for an Artificial Intelligence-based decision support for fluid management of sepsis in Scotland. Poster presented at: Health and Care Future Showcase Event; 2022 October 10th; Glasgow, Scotland.

Non-academic publications (members only access)

- Preston K., Sujan M. Is Healthcare Ready for the Rise of AI? The Ergonomist; 2023 September.
- Preston K., Sujan M. Do clinicians need to know about AI or should designers know about clinicians? The Ergonomist; 2023 December.

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Abbreviations

ACCP	Advanced Critical Care Practitioner
AF	Aimee Ferguson
AI	Artificial Intelligence
AI-CDS tool	Artificial Intelligence-based Clinical Decision Support tool
AI-SFM	Artificial Intelligence-based Sepsis Fluid Management
BOE model	Behaviour-Organisation-Environment model
(e)CDS(S)	(Electronic) Clinical Decision Support (System)
CIEHF	Chartered Institute of Ergonomics and Human Factors
CIS	Computer Information System
CM	Calum MacLellan
CVI	Content Validity Index
EHR	Electronic Health Record
ED	Emma Dunlop
GGC	Greater Glasgow and Clyde
HCP	Healthcare Professional
HEPMA	Hospital Electronic Prescribing and Medicine Administration
HF(E)	Human Factors (and Ergonomics)
HDU	High Dependency Unit
ICU	Intensive Care Unit
IQR	Interquartile Range
KP	Kate Preston
MB	Marion Bennie
ML	Machine Learning
MS	Mark Sujan
MS Teams	Microsoft Teams
NHS	National Health Service
NICE	National Institute for Health and Care Excellence
PRISMA-ScR	Preferred Reporting Items for Systematic Reviews and Meta-Analysis for Scoping Reviews
P	Participant
SEIPS	Systems Engineering Initiative for Patient Safety
SME	Subject Matter Expert
SOP	Standard Operating Procedure
TOE model	Technology-Organisation-Environment model
UK	United Kingdom
USA	United States of America
UTAUT	Unified Theory of Acceptance and Use of Technology
WHO	World Health Organisation

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Thesis Abstract

Introduction: Artificial intelligence (AI) technology has the potential to support healthcare, however, often due to a a limited understanding of the work system the technologies performance reduces once integrated. The discipline of human factors can be applied from the outset of development to support a better understanding of the work system.

Methods: A scoping review was completed to gain an understanding of how human factors approaches had been previously applied to AI-based clinical decision support technology. Semi-structured interviews, based on an extended Work System Model were conducted with Scottish adult critical care clinicians to assess their need for an AI-based sepsis fluid management (AI-SFM) tool. A review of the resources developed to measure organisational readiness for AI technology in any sector was conducted. The factors within these resources were analysed using the extended Work System Model.

Results: Sixty-four studies in the review applied a human factors approach at the three stages of the AI technologies lifecycle: Design, Implementation and Use. The studies highlighted approaches that should be applied from the outset of AI technology development, including assessing user needs which was then applied to an AI-SFM tool in Stage 2. Twenty clinicians in Scottish adult critical care were interviewed. Clinicians felt the tool would be useful but highlighted barriers within the work system, including a lack of organisational readiness. To further understand organisational readiness, a review of resources highlighted 17 studies that had applied ten resources, the most common being the *Technology-Organisation-Environment (TOE) model.* The majority of the factors were found under the organisation component of the extended Work System Model.

Conclusions: The application of human factors has the potential to support the development of AI technology for the healthcare setting, and a systems perspective should be considered from the outset. Future work should continue to apply these approaches, and resources should be created to help this process.

Thesis Summary

Introduction: Artificial intelligence (AI) technology can potentially support healthcare, especially within the hospital setting. Previous research has described the development of AI tools for healthcare, including for sepsis, which have shown positive outcomes for tasks such as patient diagnosis. However, research suggests that the performance may be reduced once AI tools are implemented in the chosen setting. This reduction may result from developers focusing solely on the technological aspects of AI technology development rather than how it will interact with the work system where it will be integrated.

It is important to consider how a new AI tool interacts within the whole work system as the technology may change how work is done within the setting and should be considered as another multi-disciplinary team member. To help ensure that future AI technology is created for the work system, human factors approaches can be applied from the outset of its development. Therefore, this thesis aimed to understand further how human factors can be applied to developing AI technology for healthcare.

Methods: To understand further how human factors could be used to support the development of AI technology for healthcare, a three-stage approach was taken. Stage 1 aimed to understand how previous human factors approaches had been applied to developing AI technology for clinical decision support in the hospital setting. A systematic scoping review was completed to ensure that all research on this area was captured. Stage 2 completed an assessment of user needs in adult critical care for an AI tool for sepsis fluid management (AI-SFM tool) to further show the importance of considering the human factors discipline early in development. A qualitative methodology was used for this study in the form of semi-structured interviews based on the extended Work System Model. Participants were shown a vignette of the AI-SFM tool and asked about their current work system and what within that work system would need to change to use the tool. Stage 3 aimed to complete a review of resources that had been developed to measure organisational readiness for AI technology across any sector. The factors within these resources were then analysed using the extended Work System Model.

Results: The review completed in Stage 1 of this thesis found that 64 studies had applied a human factors approach to hospital AI clinical decision support technology over a ten-year period (2013-2023). These approaches were categorised under the AI development lifecycle of Design, Implementation and Use, with most studies

completing an approach under Use. Studies also highlighted approaches that should be completed at the outset of AI technology design, including assessing user needs prior to a prototype being developed.

In stage 2, 20 clinicians from nine Scottish health boards participated in semi-structured interviews (six trainee doctors, five pharmacists, four consultants, four advanced critical care practitioners, and one nurse). Participants felt that the AI tool would be useful in adult critical care but provided suggestions for its development, including that it should be integrated into the current or future electronic platforms. However, participants indicated potential barriers within their work system for using the AI-SFM tool, such as the tool being compatible with all job roles, a lack of knowledge of AI technology, the current variation in the use of tools and technologies, and the adult critical care unit's design. These barriers suggest that there may be a lack of organisational readiness for AI technology within the hospital setting. Stage 3 found ten resources in 17 studies that focused on organisational readiness for AI technology across sectors, with the most common resource being the *Technology-Organisation-Environment (TOE)* model. The analysis of the organisational readiness factors within the included resources found that only one resource or study that had applied a resource had factors associated with all six components of the Work System Model, with the majority being associated four or five components. Results also found that the factors within the included resources were most relevant to the organisation component of the extended Work System Model.

Conclusions: This thesis provides an understanding of how the discipline of human factors may be used to support the development of AI technology in healthcare. The studies highlight the importance of applying a human factors approach from the outset of AI technology development to ensure that it is designed for the work system in which it will be integrated. It would be beneficial for future research to update the scoping review completed in Stage 1 to understand any new approaches that can be applied to AI technology. Further, it is hoped that the work in Stage 2 can be used to highlight the importance of taking a human factors approach early in the development of AI technology, as it highlighted potential barriers to the future integration of AI technology, including a lack of organisational readiness. The results found in stage three describe key organisational readiness resources and provided future researchers with an initial understanding of the key factors that should be considered to ensure successful integration of AI technology into the chosen work system.

Chapter 1: Introduction

This thesis focuses on how the discipline of human factors can support the development of AI technology in healthcare. This chapter aims to provide an overview of the healthcare settings relevant to this thesis and insight into AI technologies developed for healthcare. It starts with an introduction to healthcare in general, including how it is delivered and relevant global and Scotland-specific strategies. This chapter then details adult critical care units within Scotland and how technology use has evolved in healthcare in general. Furthermore, the chapter also provides a brief history of the use of AI technology and summarises the types of AI technology currently being developed. In addition, examples of how AI technology has been developed for healthcare previously, along with those specifically for treating and diagnosing sepsis, are discussed. Finally, potential challenges with the real-world application of AI technology are highlighted.

1.1. Introduction to healthcare

1.1.1. Healthcare delivery

Healthcare and its provision can be defined as the:

"…efforts made to maintain or restore physical, mental, or emotional well-being, especially by trained and licensed professionals…" (1).

Healthcare delivery includes diagnosing, treating, and preventing mental and physical disease and injury (1, 2). The delivery of healthcare can span across several settings, which can be seen in Figure 1.1.

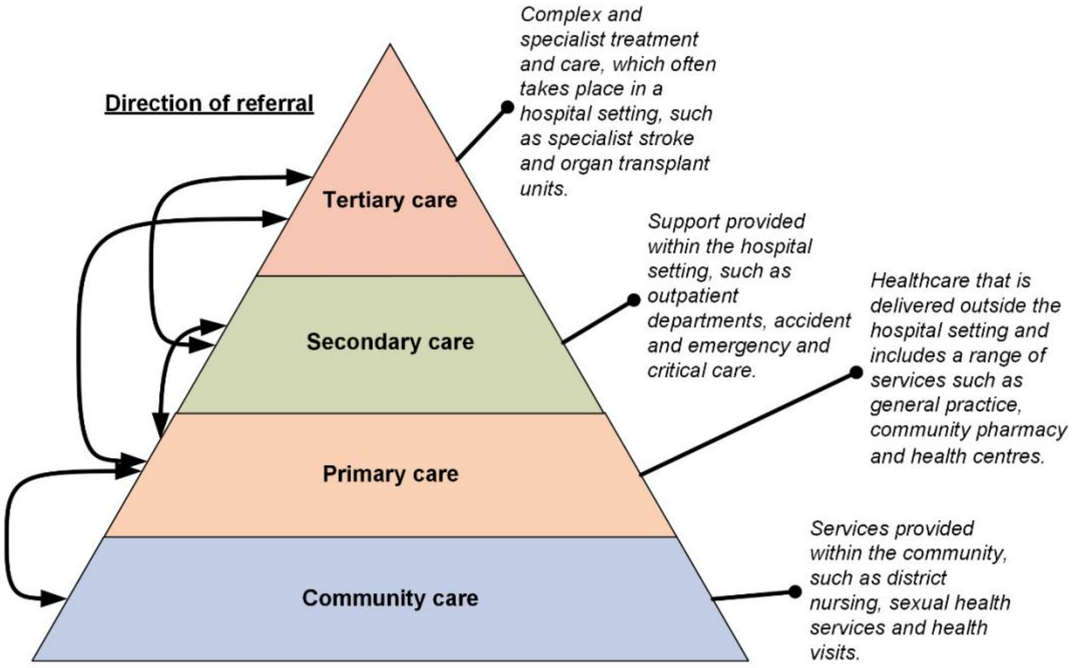

Figure 1.1: Different healthcare settings
Adapted from (3-6)

Within different healthcare settings, various clinicians, including doctors, nurses, pharmacists, and other allied health professionals, including dietitians, physiotherapists, and psychologists, can deliver and manage services. While many countries will operate within the remit of the healthcare setting stated above, there will be a variety of setups depending on country-specific factors.

1.1.2. Models of healthcare

Internationally there are four main models for the delivery of healthcare within industrialised nations, which can be seen in Figure 1.2. While many countries use a single model for their healthcare, some use a combination. This includes the United States of America (USA), which combines all four models, with private health insurance used primarily, however schemes such as Medicare (similar to the national health insurance model) are also available. Some countries also utilise different models concurrently; for example, the UK has the option for private health care and those over the age of 26 years pay for government-subsidised dental treatment. Another example is China, which uses a mix of public health insurance and out-of-pocket insurance depending on the location. While there are four main healthcare models, individual countries may utilise several or apply them differently.

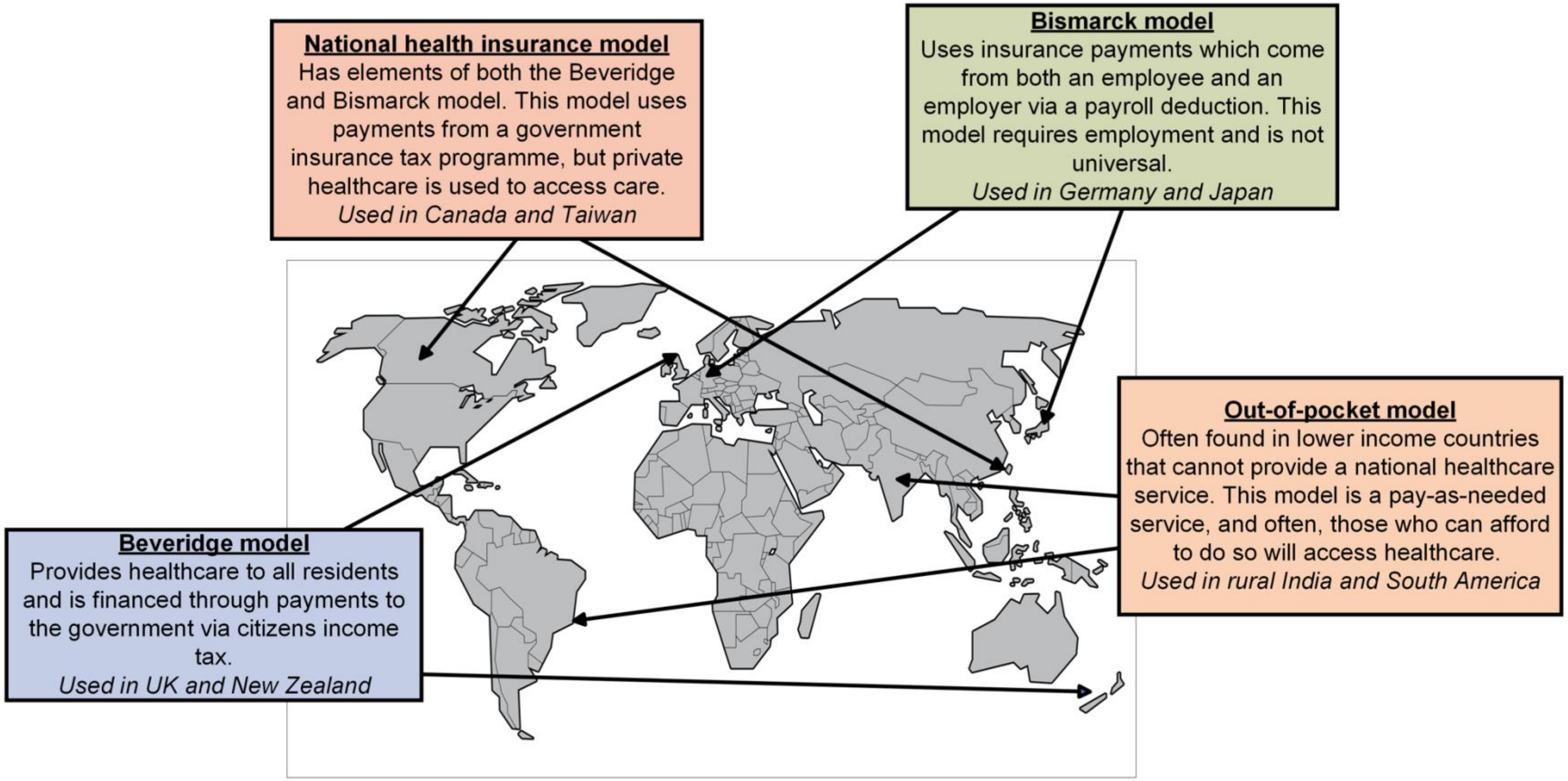

Figure 1.2: Models of healthcare
Adapted from (7)

1.1.3. Global healthcare strategies

Several World Health Organisation (WHO) strategies have been published globally, including plans and policies to improve health outcomes and increase access to healthcare. Three of these strategies which have a focus on technology for healthcare are outlined below:

Universal Health Coverage

Universal Health Coverage was set out by the World Health Organisation (WHO) to provide universal access to quality health services without the worry of financial hardship. The health services where universal access was considered necessary include prevention, treatment, and other forms of care, which should be provided throughout the person's lifespan. Further, those providing these health services should have suitable skill levels and access to the necessary tools, technology and equipment. Some progress has been made towards Universal Health Coverage, but there are still inequalities worldwide for services such as vaccines and maternal care (8).

The Global Action Plan on Aging and Health

This strategy developed by the WHO aims to improve health outcomes for older adults worldwide by promoting healthy aging. Focusing on ageing and health is important as it is indicated that by 2050, one in five people will be aged 60 or over, resulting in increased or new healthcare needs. The global action plan set goals to be achieved, including the development of appropriate technology, which should allow for established evidence and partnerships to support a 'Decade of Healthy Ageing from 2020 to 2030' (9).

The Global Digital Health Strategy

Developed by the WHO this strategy aims to improve health outcomes worldwide and increase universal health coverage using digital technologies (10). This strategy also hopes to bridge the digital divide and increase information and communication between global communities. It is suggested that while implementing digital technology in healthcare can be disruptive, these new technologies have increased benefits in areas such as medical diagnosis and person-centred care. The strategy provides objectives to follow, a framework for action, and implementation principles that will help advance the use of digital health globally.

1.1.4. The Scottish healthcare context

The UK uses the Beveridge model (see Figure 1.2) for a large portion of its healthcare delivery through the National Health Service (NHS). The NHS was founded on the 5th of July 1948 when healthcare services were made accessible at the point of use. Scotland was part of the UK-wide NHS health system until 1999, when the country voted for the devolution of powers from the UK Government, creating the Scottish Parliament. This devolution of powers resulted in the creation of NHS Scotland, which is under the direction of the Scottish Government (11). NHS Scotland comprises 14 local health boards responsible for providing health care for each population (Figure 1.3). Alongside this there are eight special health boards that provide a range of specialist services.

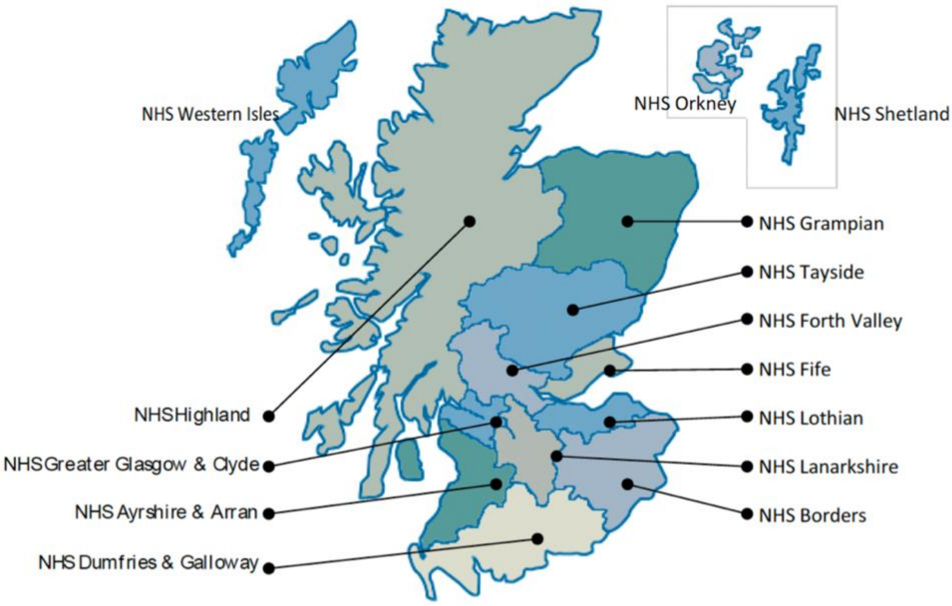

Figure 1.3: National Health Service (NHS) Scotland health boards
Taken directedly from (12)

As of January 2024, there are currently 275 (excluding the state hospital) NHS hospitals in Scotland covering acute, community, and tertiary care, etc., and providing multiple services and procedures, including but not limited to emergency care, elective surgery, outpatient care and diagnostics. Some hospitals care for patients with the most severe and complex illnesses or injuries within adult critical care, for example, patients with sepsis. Out of the 275 hospitals in Scotland, it is estimated that 23 include one or more adult critical care units, with the most being within the Greater

Glasgow and Clyde (GGC) health board (which serves the largest regional population in Scotland), followed by NHS Lothian (see Table 1.1) (13, 14). However, it is difficult to establish an accurate number as each health board has different care provisions (13).

Table 1.1: Number of hospitals/critical care units in each Scottish health board
Adapted from (13, 14)

Health board	Population	Number of hospitals *	Hospitals with adult critical care units	Estimated number of adult critical care units per hospital
Greater Glasgow and Clyde	1,185,040	44	1. Queen Elizabeth University Hospital	5
			2. Glasgow Royal Infirmary	4
			3. Inverclyde Royal Hospital	1
			4. Royal Alexandra Hospital	1
Lothian	916,310	33	1. Royal Infirmary of Edinburgh	5
			2. Western General Hospital	2
Lanarkshire	664,030	20	1. University Hospital Hairmyres	2
			2. University Hospital Monklands	2
			3. University Hospital Wishaw	2
Grampian	586,530	35	1. Aberdeen Royal Infirmary	4
			2. Dr Gray's Hospital	1
Tayside	417,650	31	1. Ninewells Hospital	4
			2. Perth Royal Infirmary	1
Fife	374,730	13	1. Victoria Hospital	3
Ayrshire and Arran	368,690	17	1. University hospital Crosshouse	3
			2. University hospital Ayr	2
Highland	324,280	32	1. Raigmore Hospital	3
Forth Valley	305,710	8	1. Forth Valley Royal Hospital	1
Dumfries and Galloway	148,790	21	1. Dumfries and Galloway Royal Infirmary	1
Borders	116,020	15	1. Borders General Hospital	1
Western Isles	26,640	3	1. Western Isles Hospital	1
Shetland	22,940	1	1. Gilbert Bain Hospital	1
Orkney	22,540	1	N/A	0
Golden Jubilee national hospital**	N/A	1	1. Golden Jubilee National Hospital	1

*As defined by Public Health Scotland
**Special health board

Adult critical care units comprise Intensive Care Units (ICUs) and High Dependency Units (HDUs). These units can be specific to a type of care; for example, the Surgical High Dependency Unit focuses on providing care to those who have undergone surgery. Furthermore, there are different levels of care provided in adult critical care, depending on the severity of the patient's condition. The levels of care can be seen in Table 1.2 (15).

Table 1.2: Level of care provided in adult critical care in NHS Scotland
Adapted from (15)

Level of care	Description
Level 1	Patients who need detailed observations or interventions, patients who need interventions to stop deterioration or rehabilitation or patients who need monitoring that cannot be provided in a ward setting.
Level 2	Patients who need increased levels of observations or interventions (more than Level 1), patients who need two or more basic organ system monitoring, patients who need long-term advanced respiratory support or patients who need nursing or therapy more frequently than at Level 1.
Level 3	Patients who need advanced monitoring for respiratory or on two or more organ systems, patients with delirium in addition to Level 2 care, patients with complex support for multiple organ failures or patients with chronic impairments of one or more organs that restrict daily activity.

Adult critical care units are highly complex and specialist hospital areas. As a result, the settings require a highly trained multi-disciplinary team of clinicians, including doctors, nurses, pharmacists, and advanced critical care practitioners (16). Furthermore, as set out in Section 1.1.5, Scotland has a drive to increase the use of digital solutions in healthcare. This includes healthcare technology, which can be harnessed to support multi-disciplinary teams in providing effective and accurate patient care within adult critical care.

1.1.5. Relevant healthcare strategies in Scotland

There has been a drive within NHS Scotland to increase the development and use of different technological innovations within healthcare. Two strategies that have been developed to support the increased use of technology in healthcare are outlined below:

Digital Health and Care Strategy

In October 2021, the Scottish Government published the Digital Health and Care Strategy, which sets out the vision for using technology to deliver healthcare services that will improve Scottish citizens' care and well-being with three main aims (taken verbatim from (17)).

Aim 1: Citizens have access to, and greater control over, their own health and care data – as well as access to the digital information, tools, and services they need to help maintain and improve their health and well-being.

Aim 2: Health and care services are built on people-centred, safe, secure, and ethical digital foundations which allow staff to record, access and share relevant information across the health and care system, and feel confident in their use of digital technology, in order to improve the delivery of care.

Aim 3: Health and care planners, researchers and innovators have secure access to the data they need in order to increase the efficiency of our health and care systems and develop new and improved ways of working.

To achieve the aims, there are six priority areas, which can be seen in Table 1.3.

Table 1.3: Six Priority areas in Scotland's Digital Health and Care Strategy
Taken directly from (17)

Priority area	Description
Digital access	People have flexible digital access to information, their own data and services which support their health and wellbeing, wherever they are.
Digital services	Digital options are increasingly available as a choice for people accessing services and staff delivering them.
Digital foundations	The infrastructure, systems, regulation, standards, and governance are in place to ensure robust and secure delivery.
Digital skills and leadership	Digital skills are seen as core skills for the workforce across the health and care sector.
Digital futures	Our wellbeing and economy benefits as Scotland remains at the heart of digital innovation and development.
Data-driven services and insight	Data is harnessed to the benefit of citizens, services and innovation.

Alongside this strategy, there will be a delivery plan that will be continually updated which will ensure that the strategy will go from 'what' or 'why' to 'how', allowing for greater choice and control for the people of Scotland (17).

Scotland's Artificial Intelligence Strategy

The Scottish Government has produced a strategy for using Artificial Intelligence (AI), which states that "*Scotland will become a leader in developing and using trustworthy, ethical and inclusive AI*" across several sectors, including healthcare (18). To help guide this roadmap, the strategy uses the Economic Cooperation and Development's five complementary values-based principles, which are as follows (taken verbatim from (19)).

1. AI should benefit people and the planet by driving inclusive growth, sustainable development and well-being.
2. AI systems should be designed in a way that respects the rule of law, human rights, democratic values and diversity, and they should include appropriate safeguards – for example, enabling human intervention where necessary – to ensure a fair and just society.
3. There should be transparency and responsible disclosure around AI systems to ensure that people understand AI-based outcomes and can challenge them.
4. AI systems must function in a robust, secure and safe way throughout their life cycles and potential risks should be continually assessed and managed.
5. Organisations and individuals developing, deploying or operating AI systems should be held accountable for their proper functioning in line with the above principles.

The strategy sets out the actions that will be taken, which include creating a Scottish AI alliance, developing foundations to increase success and building an AI powerhouse that will lead to adopting new AI technology (18). It is concluded that by applying this strategy, Scotland will become a leader in the development of AI technology.

1.1.6. Evolution of healthcare technology

Healthcare technology can be defined as any technology, such as medical devices and health information systems, developed to support healthcare (20). Technology is used routinely within healthcare and has undergone considerable changes as shown through the waves of technological advancement in healthcare (see Figure 1.4).

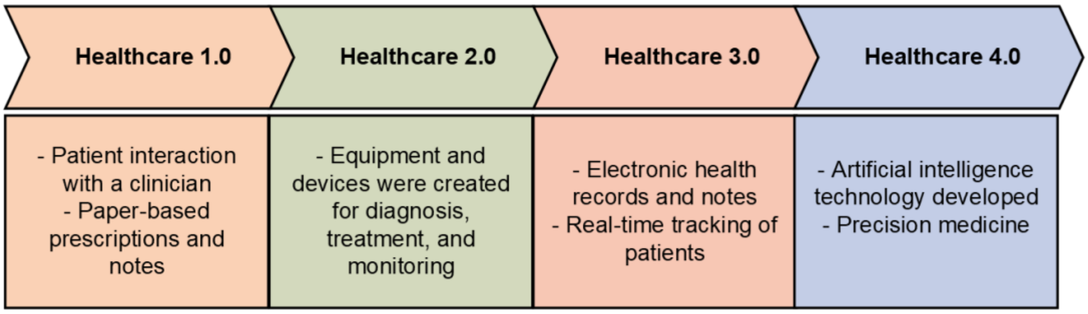

Figure 1.4: Waves of technological advancement in healthcare
Adapted from (21-23)

Healthcare 1.0 can be considered as healthcare at its most basic, with the patient meeting with a clinician, and through consultation a care plan is created, prescriptions written, and follow-ups decided. It has been suggested that the elements of Healthcare 1.0 have been around for centuries. Healthcare 2.0 refers to the period when new medical devices and equipment were developed for monitoring, life support and imaging (23). This new equipment is consistently used within healthcare to help support patients' diagnosis, treatment and monitoring. Healthcare 3.0 introduced technology such as electronic health records (EHRs) and a shift from paper-based tools to electronic platforms (24). This shift increased access to patient information, allowing for quick and accurate diagnosis and treatment (24). The Healthcare 1.0-3.0 waves supported the development and integration of technology across healthcare. In primary care, specifically, there has been a drive to use digital technologies, including EHRs and telemedicine services, to help with patient monitoring and diagnosis (25). In community care, wearable technology is now used for monitoring, and mobile apps for mental health services are increasingly utilised (26). In secondary and tertiary care, several technologies are currently used, including EHRs (27), electronic prescribing (28) and remote consultations (29), which are used to help with both the management and provision of patient care (30).

However, there is increasing pressure on healthcare due to various factors, including the COVID-19 pandemic, the ageing population, and the complexity of care (31, 32). With these pressures comes the need to establish and integrate new innovations and increase patient-centred care, including more personalised healthcare and precision medicine, which may be achieved with the increased use of healthcare technology. This need for increased use of healthcare technology has led to the creation of Healthcare 4.0. Healthcare 4.0 can be considered the fourth wave of technological advancement and development within the healthcare setting and aims to create a highly digital and interconnected system that brings about personalised care (33). One of the main components of Healthcare 4.0 is taking a personalised approach to healthcare, which is effective and efficient (33). This personalised approach to their care will consider an individual patient’s characteristics, including their medical history and, in some cases, their genetic profile (34). Several technologies are related to Healthcare 4.0, including Blockchain, wearables and big data analytics (35). However, one the key technologies that can bring about the personalised care Healthcare 4.0 introduces is using Artificial Intelligence (AI) to support care-related decisions (35).

1.2. AI technology in healthcare

AI technology (also termed AI tools) can be defined broadly as technology that aims to imitate human functionality by making decisions (36-38). AI technology is used in several sectors, including but not limited to, applications in the transportation (39), social media (40) and military sectors (41). Furthermore, within healthcare specifically, AI has the potential to transform practice and influence how care is provided to individual patients (36, 37, 42).

1.2.1. A brief history of AI technology in healthcare

When understanding how AI technology can be used in the healthcare setting, it is beneficial to understand the history of its development. The following section will provide a brief history of healthcare AI technology.

The term AI was first stated in 1956 by John McCarthy, which began the development of rules-based systems, specifically production systems (see Section 1.2.2. for a description) that were used for the automation of tasks, especially within assembly lines (43, 44). It was not until the 1960s that further applications, such as chatbots and robotics, were developed (44-46). However, while there was an increase in the development of these early AI systems, there was little adoption within healthcare despite the suggested benefits (44). After the initial wave of investment and development, from the mid-1970s to 1980, there was an ‘AI winter’ (44), which is considered a period of time with limited funding and interest in developing AI systems, resulting in significantly fewer applications (47).

This first AI winter ended in the 1980s when there was renewed excitement for developing AI systems and for the creation of expert rules-based systems for healthcare. One example of these technologies was DXplain, where the clinician, for example, would input the patient's symptoms, and the AI would output a diagnosis alongside a detailed description of the disease (43). Despite the potential of these systems, there was another AI winter from around the late 1980s to the early 90s (44). However, by the late 1990s, there was increasing interest in the application of AI, especially within the healthcare setting (44). The early application of AI, while not focused on healthcare, did set the groundwork for the modern period of AI development for the setting.

On the back of the increasing interest in AI from the late 1990s, the early 21st century saw the initial development of what can be seen as modern AI applications. This was brought on by the increased popularity of 'deep learning' after a paper published by Hinton and Salakhuydinov showed how this type of AI technology could be applied in practice (48). A significant development in AI technology was seen at IBM, where an open-domain question-answering system (also known as DeepQA) named 'Watson' was developed in 2007, which came first place on the American television programme Jeopardy! against human participants in 2011 (49). IBM Watson was also important for healthcare, as in 2013 it was applied to the sector showing the potential use of modern AI technology for patient care (49). The DeepQA technology used by Watson was seen as useful as it could use patient EHR information to provide evidence-based decisions. In 2017, Bakkar et al. successfully used IBM Watson to identify new RNA-binding proteins in Sclerosis (50). Overall, the development of IBM Watson and DeepQA can be considered the cornerstone of modern AI technology applications and has led the way to evolve the application of the technology in healthcare.

Since the development of IBM Watson, AI technology has increased dramatically. Currently, the use of AI technology is mainly seen within secondary care (Section 1.2.1) focusing on clinical decision support (CDS), where the technology aims to aid clinicians in making judgements about patient care (51). An example of the type of AI-based clinical decision support provided in secondary care is diagnosis (52, 53). Diagnosis support refers to AI-based clinical decision support that provides guidance on what disease, for example, the patient presents with and has been applied to several conditions, including cancer (54). One study used Convolutional Neural Networks to help with skin cancer diagnosis where the AI-based clinical decision support was trained using a large dataset of different skin cancer lesions (54). Once trained, the AI-based CDS was compared with expert radiologists to test its performance, and the results found the technology performed the same or better than the clinician. Overall, AI-based clinical decision support can support various tasks and conditions in secondary care. As a result of the increased application of AI technology in healthcare, recent publications have been developed to ensure that future use of AI technology is regulated, such as the AI Act by the European parliament (55). The AI Act is the first comprehensive AI law which sets out rules which should be followed based on the level of risk the technology poses (55). This AI act will continue to be developed and is in the process of becoming a European Union law (55).

1.2.2. *Types of AI technology relevant to healthcare*

Previous literature describes three levels of AI technology; a summary of these can be seen in Figure 1.5.

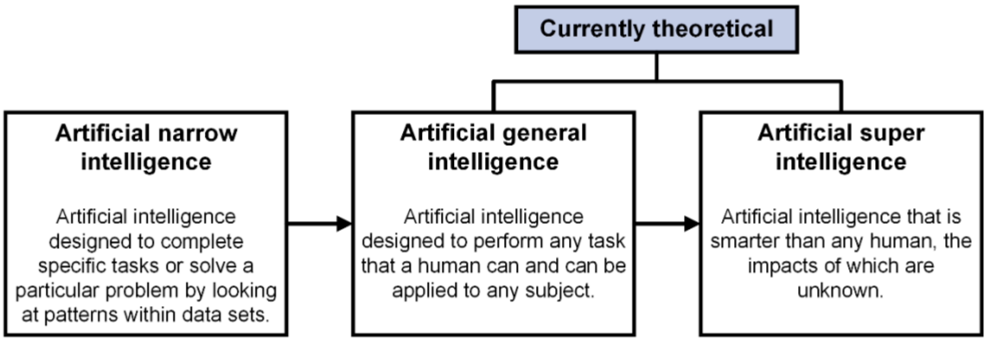

Figure 1.5: Levels of AI technology
Adapted from (42)

Within artificial narrow intelligence, two subsets of AI technology are suggested, which can be seen broadly as rules-based and learning-based. Rules-based AI, also known as knowledge-based systems, is considered the simplest form of AI technology currently used. These rules-based systems are developed to represent the knowledge of relevant experts in the field where the AI technology will deploy. They are often used to automate processes and imitate the decision-making of subject matter experts, for example, with advice on what they should do or what to conclude based on the information the AI technology has been given (51, 56). Learning-based AI refers to machine learning technology trained to make inferences in the patient data (51). This learning-based AI aims to improve over time through experience without extra programming (57). Different subtypes can be used within rules-based and learning-based AI, depending on input data, the objective, or the architecture of the technology. A selection of the different subtypes of both rules and learning-based AI can be seen in Figure 1.6.

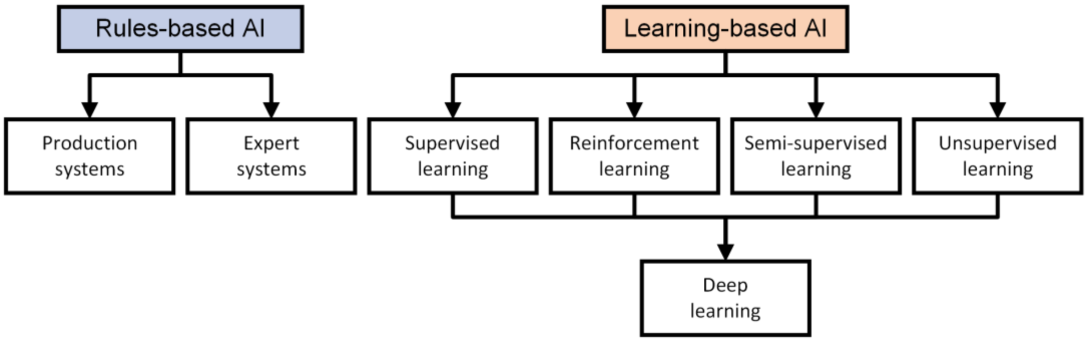

Figure 1.6: Examples of the subtypes of artificial intelligence (AI)
Adapted from (58)

Two subtypes within rules-based AI are production systems and expert systems. Production systems use rules and inputs to decide what action to take and can be used to automate a number of tasks (59). While similar, expert systems are created to mimic the decision-making of experts or organisations (60). For both of these subtypes, rules and inputs are established, which allow the technology to make its own decisions based on the information it is provided. For both production and expert systems, there can be forward and backwards chaining, with the latter relating to using facts to conclude a situation, and the former using facts to predict what will happen next.

The four main subtypes of learning-based AI are supervised, semi-supervised, unsupervised and reinforcement learning. Supervised learning involves training a model on labelled data, so the model knows the correct output. The model then learns the correct output based on the data inputted (61). The types of algorithms used for this AI subtype include linear regression, decision trees, and random forests. Unsupervised learning relates to a model that independently finds patterns in the data provided (61). The algorithms used for this AI subtype include clustering, dimensionality reduction, and anomaly detection algorithms. Semi-supervised learning uses techniques and algorithms from both supervised and unsupervised learning by using labelled data to understand the correct output and then unlabelled data to find independent patterns. Reinforcement learning involves training a model using feedback through rewards and punishments. Over time, the model learns what to do to get a reward. The algorithms used for this AI subtype include value-based, policy-based, and model-based methods (62). Any of these four subtypes can then be used to create deep learning involving multiple layers of artificial neural networks. Each layer learns a specific function on the input data to learn complex patterns (63).

The algorithms used for this AI subtype include convolutional neural networks, recurrent neural networks, and generative adversarial networks. The field of AI is constantly developing, and therefore, as research progresses, the types, and ways this technology is used and created will change and expand.

1.2.3. AI technology in sepsis

Sepsis occurs when a patient has an adverse response to an infection and can result in life-threatening organ dysfunction and, consequently, severe complications or death (64-66). Research suggests that in 2017, there was an estimated 48.9 million cases of sepsis globally, resulting in 11 million sepsis-related deaths (67). As a result, there has been a drive to promote the knowledge of sepsis, including in Scotland, where a national campaign was created to raise awareness of the signs and symptoms of the condition (68). This level of understanding is necessary as diagnosing sepsis can be difficult due to the variation in patient presentation. This variation is caused by many factors, such as the area of infection entry, the pathogen, and the patient characteristics, such as age, weight and medical history (69). Once sepsis is diagnosed, or clinicians suspect the condition is present, treatment must start as soon as possible to prevent the condition from becoming severe or life-threatening (64). This includes antibiotic and fluid administration, which are considered the cornerstones of sepsis treatment (65). Specifically, administering fluids for sepsis treatment is one of the main recommendations in the Surviving Sepsis Campaign, where guidelines on diagnosis and treatment are presented (64). While it is universally accepted that fluids in sepsis treatment are necessary, the volume that should be administered is widely debated. Previous research has suggested that giving a patient either insufficient or too much fluid can harm their survival and recovery (70). Therefore, an individualised volume tailored to patients' physiological characteristics is recommended (70). However, this individualised or precision medicine fluid decision can be difficult and time-consuming for clinicians to calculate due to the number of patient data points necessary to make the calculation. Therefore, AI tools can be developed to support clinicians calculating fluid volume for patients with sepsis through evidence-based and patient-specific means.

AI technology for clinical decision support in diagnosing and treating sepsis is evolving and showing positive outcomes (36). One tool developed by Goh et al. focuses explicitly on the early diagnosis of sepsis, as patients who receive treatment promptly experience better outcomes (71). This tool used both structured and unstructured data in the form of clinical notes to predict and diagnose sepsis using machine learning techniques. When compared against clinicians, it was found that there was an increase in early detection of around 32% (71). AI tools have also been used for the early detection of sepsis using real-time data from EHRs (72). A study by Yuan et al. demonstrated that the AI tool using real-time data had an accuracy of over 80% and performed better than the current process (73). Further to diagnosing sepsis, AI tools have been used to help indicate the most appropriate treatment for the individual patient. One study used reinforcement learning to create the 'AI clinician' that aimed to provide the optimal treatment for a specific patient. When validated, results found that if a patient received a treatment that matched the suggestions provided by the AI tool, their mortality was lower (74). Furthermore, Gupta et al. specifically aimed to understand the optimal treatment for sepsis by using human-in-the-loop modelling to indicate what type of fluid should be administered and in what volume. Validation found that the tool reduced mortality risk by 22% and concluded that it could support clinicians in providing precision patient treatment (65).

1.2.4. Real-world applications of AI technology in healthcare

Despite evolving research showing positive outcomes, there remains a broad debate around whether AI tools can perform as well as proposed once applied in the real-world healthcare setting. For example, if an AI tool will have the same results once implemented into clinical practice or if the tool will support the clinicians in the way the developers suggest (75-79). There has been some evidence to suggest that AI tools' performance may decrease when implemented into clinical practice, with one study focusing on the accuracy of machine learning versus clinicians for classifying skin lesions (78). The study found that the AI technology was more accurate than the clinician when using images from the dataset used to train the algorithm. However, when tested using images outwith that training dataset, there was a significant reduction in performance (78). This reduction in performance may be due to several factors, such as the training dataset not being applicable to the real-world setting, resulting in biased outcomes (80). It may also result from developers focusing solely on the technological side of the AI tool development and not understanding how the tool will work within the clinical system where it will be integrated (61, 81, 82).

Previous research has also highlighted that the introduction of automated technology, such as AI, may result in challenges, including overreliance on the new technology for decision making, a loss of user skills and difficulties in determining who (or what) is responsible for a decision (83). Furthermore, AI technology is not set to replace clinicians' but will work alongside them as a decision-support tool (79). Therefore, as the development of new AI technology continues within the healthcare setting, there needs to be an increased understanding of the technologies' effectiveness, any associated challenges, how it will work alongside the stakeholders as another team member and how it will impact the clinical system as a whole. This may involve learning from other sectors that have integrated AI technology into their environment and taking a systems perspective throughout the technology development. This understanding of how AI technology will impact the system and how it will work within the healthcare setting may be achieved by applying the discipline of human factors.

Chapter 2: The discipline of human factors

The purpose of this chapter is to introduce the discipline of human factors used to underpin the research within this thesis. The chapter begins by providing a background on the discipline of human factors (also termed ergonomics), then discusses how research has moved into the healthcare sector, and briefly highlights the current focus within this setting. Finally, the chapter presents an overview of how human factors approaches are important for developing AI technology and how Work System Models could support research and innovation in this area.

2.1. What is human factors?

The discipline of human factors (also termed ergonomics) aims to optimise work system performance and improve human well-being by taking a systems and human-centric design approach (84-86). Human factors is influenced by various other disciplines, including psychology, engineering, computer science, physiology and biomechanics, which results in several definitions that stem from these different disciplines (87). Therefore, for this thesis, the International Ergonomics Association definition of human factors will be used:

"The scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data, and methods to design in order to optimise human well-being and overall system performance" (88)

The human factors discipline aims to take a systems perspective and consider all the components of that system (e.g. people, tasks, tools and technology, organisation, and environment) and how those components interrelate and interact to create an outcome. This systems perspective can potentially improve outcomes related to that system, including safety and effectiveness and human well-being, including experience and satisfaction. The discipline of human factors has shown to be beneficial in several sectors, including but not limited to aviation (89), nuclear (90) and road (91) sectors. In the past, there have been several instances where a lack of consideration and/or knowledge of human factors concepts, approaches and methods has resulted in events that have impacted individuals and, in some cases, large populations which will be discussed in the following section.

2.2. Brief history of human factors

The discipline of human factors became apparent in the 1940s as a result of investigations into a number of aeroplane accidents during the Second World War. These accidents were particularly common with the Boeing B-17 'Flying Fortress, which often crashed despite pilots being highly trained and the aeroplane functioning as normal (92). Initial investigations concluded that these crashes were the result of 'pilot error'. However, in 1943, Alphonse Chapanis joined as the first psychologist in the Army Air Force Aero Medical Lab and discovered that in fact, these crashes may not be due to pilot error but because of the aeroplane design (92). Chapanis''s investigations found that these crashes often resulted from the cockpit's design, including that the switches for the landing gear and flaps were identical and placed close to each other, which often caused the pilot to retract the landing gear, rather than the flaps (92, 93). As a result of these investigations, changes were made to the aircraft, which resulted in these types of events becoming less frequent. After the Second World War, the civilian equipment and transportation sectors were becoming increasingly complex, which resulted in the need for increased safety and better processes (94). To support this, investigations were completed by Paul Fitts and Richard Jones in 1947, where they analysed 460 errors made in operating aircraft controls. This analysis resulted in the development of design measures for the displays and controls of aircraft, and to this day, accidents associated with aircraft design are extremely rare (92).

While the work done during and after the Second World War was not officially termed 'human factors' or 'ergonomics', it is believed to have been the beginnings of the discipline and this work is now considered within this domain (93). It was not until 1949 that the term ergonomics was developed when the 'Ergonomics Research Society' (now the Chartered Institute of Ergonomics and Human Factors) was formed in the UK, which was followed by the Human Factors Society being founded in America in 1957 (95). These societies were the world's first professional human factors body and is still considered one of the main contributors to the development of the discipline.

Since its initial conception, the discipline of human factors has expanded into several different settings, including rail, civilian aviation, and heavy industry (e.g. nuclear and oil and gas). Within those settings, there have been several examples of how not taking a human factors perspective or considering the system as a whole can contribute to adverse events and loss of life. One example is the Chernobyl disaster, which took place in the 1980s (96):

The Chernobyl disaster occurred on the 26th of April 1986 at the Chernobyl nuclear power plant near Pripyat, Ukraine. As a result of a low-power safety test, there was an explosion and a fire, resulting in the destruction of the reactor and the release of a devastating level of radiation into the atmosphere.

A further example of how the lack of consideration for human factors in the design of an aircraft resulted in an adverse event is the Air France 447 crash (97):

The Air France 447 disaster happened in June 2009, when a flight from Brazil to France crashed into the Atlantic Ocean, which resulted in the death of all passengers and crew. It was found that a malfunction of the aircraft's Pitot tubes, used to measure airspeed, was responsible.

Several factors were likely to have resulted in the two events, including a lack of human factors application in the design and use of the system. For example, regarding the Chernobyl accident, a lack of training, combined with the culture within the organisation, resulted in those involved being unprepared for the situation, which in turn resulted in a lack of understanding of roles and limited communication (96). Regarding the Air France 447 disaster, the initial analysis found that a lack of situational awareness of the pilot crew caused the crash. However, further analysis completed in 2015 found that, in fact, the situational awareness may have been lost across the sociotechnical system (between the pilot crew, cockpit and aeroplane system) rather than the pilot crew individually (97).

The benefit and importance of applying human factors related concepts, approaches theories and methods has been increasingly realised since its initial conception. This increased understanding has resulted in the development of several professional bodies, which aim to raise awareness of the discipline and advance the profession across settings. These professional bodies provide a space for human factors professionals to interact and facilitates collaboration between individuals and sectors. An example is the Chartered Institute of Ergonomics and Human Factors (CIEHF), based within the United Kingdom but with members worldwide (98). The CIEHF provides members with the ability to become chartered and provides educational support and resources. Other examples of member bodies within the human factors discipline are the Human Factors and Ergonomics Society based in the United States and the International Ergonomics and Human Factors Association (99, 100)

2.3. Human factors in healthcare

The healthcare sector can be considered a sociotechnical system, which results from the types of components within a system, including the people, the tools and technology they use and the environment in which they work (101, 102). Healthcare can also be seen as complex due to the variety of dynamic and often unpredictable interactions between these components that create different outcomes (101). Furthermore, healthcare is also a complex adaptive system in nature, as the actors (clinicians for example) are flexible and able to react to new situations which in turn influence the actions of other actors (other clinicians or patients, for example) (103). It is believed that the complex sociotechnical nature of healthcare contributes to the slow uptake and application of human factors approaches in the sector, alongside other aspects such as a lack of policy or qualified specialists. (104).

While the human factors discipline was increasing in other settings, it was not until the 1960s that the discipline was initially applied to healthcare. The early applications included Chapanis and Safern, who used the Critical Incident Techniques developed by Flanagan in 1954 to examine medication safety and errors (105, 106). Their work found that several work system factors influenced medication errors, such as failure to complete checking processes and problems with verbal and written communication problems (105). Despite this work highlighting how human factors could be used effectively within healthcare, it was not until the 1990s that the discipline became more apparent in the healthcare sector (107). This resulted from several publications, including the work completed by James Reason in 1995, which examined how healthcare systems need to consider the groups of people involved with a chosen initiative and the organisational factors that influence the design to allow for a system to be safe and effective (108). In addition to the work completed by Reason, the report 'to Err is Human: building a safer health system' published by the Institute of Medicine in 2000 is considered by many to be the main catalyst for introducing the concept of human factors into the healthcare setting. For example, the report identified the strategies needed to solve safety problems within the healthcare system and further highlighted the importance of utilising a human factors approach in all aspects of care (109).

The work completed by Martin Bromiley further showcased the use of human factors approaches in healthcare (110). Martin Bromiley's wife, Elain Bromiley, died during routine surgery in 2005 due to complications with her airways. After multiple attempts to secure her airway using intubation, her oxygen continued to drop, which resulted in her death. It was found that several human factors-related issues resulted in her death. These issues included a lack of communication between medical teams, lack of leadership and role clarity, and task fixation where medical personnel had no understanding how much time has passed (111). As a result of her death, in 2007, Martin Bromiley, who is an airline pilot and therefore had a partial understanding of the discipline, and several others interested in the field set up the Clinical Human Factors Group. The Clinical Human Factors Group is a charity that with the National Health Service (NHS) aims to support adopting human factors approaches and methods in all areas of healthcare (112). Furthermore, the United States Food and Drug Administration updated their regulatory approval guidelines for developing and creating medical devices in 2011, which further encouraged the use of human factors in healthcare (93). These developments set out a clear agenda that there should be an increase in human factors evaluations during any medical device's pre-market phase to test its usability in real-world settings. These guidelines were crucial in defining what assessments should be completed during the final stages of a device's usability testing to help reduce future harm as a result of the medical device (113).

The events and publications above did provide some initial evidence of the benefit of utilising the discipline of human factors in the healthcare sector. However, there are still to this day several argued misconceptions and misuses that have arisen from these early applications. A number of misunderstandings around human factors in healthcare were set out by Russ et al's in 2013 (86) and include:

- Human factors involves addressing problems by teaching individuals how to change their behaviour, while the discipline is actually about addressing these problems by designing a system that is more supportive of the users.
- Human factors focuses solely on individuals, when, in reality, work can range from the individual to the organisational level.
- Human factors is focused on removing human error, when, in fact, the discipline focuses on designing a system that is resilient to unexpected events.

These may result from several factors, including human factors-related activities in healthcare often being completed by those with limited expertise in the discipline (114, 115). To overcome this, work is being done to help ensure that human factors principles are embedded into healthcare education, such as ensuring, teaching staff should have the knowledge and skills to deliver the content (116). Another potential reason is that these misconceptions are the result of research and application of human factors in healthcare often stemming from aviation and other process-orientated industries. While this has supported the understanding of human factors in healthcare, it often results in the application of the discipline mainly focusing on non-technical skills and not considering the complexity of the healthcare system (114, 115). One example of this is the use of checklists, which have been shown to be effective in other sectors, including aviation. While the use of checklists may work for certain tasks within the healthcare sector, they often do not consider the problem needing to be solved (117). This is because checklists may not be flexible enough for the complex adaptive sociotechnical nature of the healthcare setting, where processes and people must be fluid and responsive (118, 119). However, if a checklist is used for an appropriate task and designed correctly using a systems approach in the healthcare setting, it may be of benefit (120).

However, while there are issues with the application of human factors within the healthcare sector, research has highlighted the benefit of the domain, especially for the development of technology. The use of technology in healthcare is increasing, with the advancement in Healthcare 3.0 bringing in the introduction of EHR, e-prescribing and other technologies (Chapter 1, Section 1.1.6). Research has highlighted how the human factors discipline can help support the design and redesign of healthcare technology. An example, is a study completed in 2023 by Marrow et al where user-centred design and approaches, alongside design thinking techniques were used to support the co-design of physical activity technology for adolescents with type 1 diabetes (121). The study was able to highlight key themes that influence experience and engagement with physical activity technology. Results were also able to highlight future design considerations for physical activity technologies, that support adolescents with type 1 diabetes. A further example is the study completed by Aufegger et al. who completed a mixed methods study to understand how an e-prescribing system could be improved within a London teaching hospital (122). The study was conducted with prescribers in a simulation environment where eye-gaze tracking, and participant interviews were completed to understand how the e-prescribing platform could be fully improved. The study provided recommendations for features that may improve the usability and safety of the platform, highlighting the benefit of applying a human factors approach to the design of the healthcare technology (122). However, despite the potential benefits, challenges with the use of automated technology have been suggested. In 1983, Lisanne Bainbridge published the 'Ironies of Automation', which set out potential challenges that could result from the introduction of automated technologies into systems. While not specific to healthcare, these challenges are relevant and include a potential for individuals to become over-reliant on the technology for their decision making. Further, new technology may result in workers experiencing a loss of skills important to their job role, and it being unclear who is responsible for any issues that may arise (83). Another potential challenge for the use of human factors in healthcare is work being completed in silos, with a variety of inconsistent terminologies used (104, 123-125). In some cases, human factors is not explicitly referenced as the relevant discipline, when it is clear an approach related to human factors has been applied.

Overall, a human factors approach can be used within healthcare as a means to better understand the complex sociotechnical nature of the setting. However, despite evidence that the human factors discipline may support healthcare, challenges still exist around the complex sociotechnical nature of healthcare, due to the number of system components that must interact to create a desired outcome.

2.4. Human factors in healthcare AI

The use of AI technology is increasing in healthcare, with research showing its potential effectiveness in supporting clinical decisions (Chapter 1, Section 1.2.1) (126, 127). However, despite the suggested effectiveness, research has also postulated that the AI technology's performance reduces once integrated into a real-world setting. This may be due to several factors, such as the quality of data used to develop the technology and a disproportionate focus on the technological development of AI technology rather than how it may impact the whole system (61, 81, 82). Furthermore, as previously stated, healthcare is a highly complex and adaptive sociotechnical system, and the introduction of new automated technology has been highlighted as bringing new challenges to any system (See section 2.3). As with any automated technology, these challenges are also seen with the introduction of AI technology specifically. For example, research has suggested that AI technology may result in users experiencing automation bias and becoming complacent and reliant on the technology for a decision (81). Specifically regarding AI technology, it is advertised as being able to free up clinician's time, meaning they can spend more time with patients, however it is unclear whether this will be the case in practice (81). Finally, research has also suggested challenges with handover of duties, regarding when clinicians should take over from the AI technology during patient care. Therefore, there is a need to consider these challenges when designing AI technology to ensure they are overcome, and the full potential of the technology is realised (81).

It is also arguably important to consider what aspects are most important to those interacting with AI technology in healthcare. The developers of AI technology should be concerned with all aspects of the technology's development, including the size of the dataset, the sensitivity and specificity of the model, ensuring the data used is not biased towards a certain group, and whether there is a clinical need for the AI technology. However, while developers must be concerned with all aspects, others who interact with the AI technology may not need or have the capacity to be as involved in the finite details. For example, clinicians involved with using the new AI technology may not have the time to understand the details of how the AI technology was developed to ensure this was done to a high standard. However, clinicians need to feel that they can trust the output of the AI technology in order to feel confident in using it, and therefore may wish to have a level of explanation/transferability for how a decision was made that is digestible and easy to understand (37). Similarly with patients, they also may not have the wish to understand the details of any AI technologies development but will still need to have a level of trust in the output to feel confident in the care they are receiving, and may wish to understand how or when AI technology is used in their care (128). While clinicians and patients may not need or have the capacity to understand all aspects of AI technology development, regulation is required to ensure any AI technology integrated into healthcare is developed to a high standard to allow clinicians and others within the setting to trust the output.

By applying the human factors discipline to AI technology research a comprehensive understanding of the whole system may be achieved, helping to overcome potential challenges, understanding what is important to those interacting with the technology, and supporting the development of the technology for a specific system (82). Research has highlighted fundamental human factors principles that could be considered when developing AI technology in healthcare. One of these key principles relates to the human-AI team, and how the technology works alongside those within a healthcare setting (79, 82). AI technology in its current state will not have the capabilities to take over the work completed by clinicians within healthcare settings (79). However, this new technology will have a more active role in patient care when compared to previous technological innovations implemented within the healthcare setting. Therefore, the new technology must be developed and implemented to help ensure it can work as part of a multidisciplinary team and in the context where work takes place (82). To support this, human factors approaches can be deployed to help gain an understanding of the chosen setting and the teamwork already taking place (82). To further ensure sufficient human-AI teaming, the technology also needs to be beneficial to those within the setting, in the form of providing support where support is needed, for example, for time-consuming tasks (administrative tasks) or tasks that may involve several clinicians to produce an outcome (e.g. breast cancer screening) (129). Further, consideration should be given to the future users' needs in the AI technology's design so it is developed for those users and can be easily applied within the setting. By considering those within the multidisciplinary team during the development of AI technology, this may result in an increased willingness to use and integrate the AI technology.

Another key human factors related principle is organisational readiness, which refers to an ‘organisation’s willingness and ability to adapt to change’ (130, 131). Organisational readiness encompasses several factors, such as culture, leadership, knowledge, resources and infrastructure (132). A systems perspective has been shown to be beneficial for understanding organisational readiness, as it can provide an understanding of the components that may make up a system and the interconnectedness between those components (131). Having appropriate organisational readiness is important for using AI technology in healthcare, as it will ensure successful adoption and use (133). However, despite the understood importance of sufficient organisational readiness for healthcare AI technology, there is currently little research in the area (133).

To help ensure the principles above are considered in the development of AI technology for healthcare, human factors approaches can be considered from the outset of AI technology conception and continued throughout its development lifecycle (107). The development life cycle covers three main stages: Design, Implementation and Use with research highlighting that a human factors approach applied at these stages can be beneficial to ensure the technology is developed for the users and their work system (61, 134-136). This lifecycle has been used previously to describe the development process of AI systems in different sectors, including food waste management (137). Within healthcare AI, a white paper created by the Chartered Institute of Ergonomics and Human Factors (CIEHF) suggested that using human factors approaches at these three key stages is important for allowing technology to be developed for the work system (61). Within the lifecycle, Design focuses on developing, testing and evaluating a new technology prototype prior to implementation (138). This stage incorporates user-centred design approaches and is important when developing technology so that the design considers the healthcare system and the users themselves (139-142). Once a prototype of the AI technology has been created and tested, the next stage is Implementation, which is when the technology is integrated into the healthcare setting. Implementation Science research focuses on understanding and promoting the systematic uptake of innovations (e.g. evidence-based practices or technology) to improve the healthcare sector (143). Implementation Science is its own field of research which can be underpinned by human factors and systems concepts, approaches and methods. Implementation is an essential step in the AI technology lifecycle and can include training staff, ensuring the technology works within the clinical processes and understanding any barriers and facilitators that may impact the adoption (144, 145). While there is an evidence base for the importance of correctly implementing technology in general, previous reviews have suggested that for AI technology, this is often overlooked (146). Once implemented into the clinical setting, the Use stage begins where the technology is consistently tested. This testing allows for an understanding of how the technology works in practice, fits within the work system, as well as the stakeholders' perceptions of the technology (147). While the lifecycle can be seen as three main stages, it does not need to be completed in a linear process. For example, it may be the case that once a technology is implemented, an issue may arise, and the prototype will return to the design stage to resolve the issues before full integration. In another example, once a technology is used within practice, there may be a change in requirements in the setting, resulting in the AI-CDS reverting to the implementation stage or even being redesigned altogether (146).

Overall, the discipline of human factors has the potential to support the development of AI technology for the healthcare setting by allowing a systems perspective. By ensuring that human factors approaches are considered throughout the development lifecycle of the AI technology, it will help ensure that key principles such as the human-AI team and organisational readiness are considered. To support human factors approaches being applied throughout the development, a work system model can be applied to ensure that a systems perspective is taken throughout.

2.4.1. Work System Model for healthcare AI

To support the use of human factors research in healthcare, systems models and theories have been developed that consider the components within a system and how they interact to influence an organisational outcome (e.g. those related to the systems performance and human well-being) (148). These systems-based models and theories, include the sociotechnical systems theory which was initially developed to understand the impacts of new innovations on humans and organisation, in industries such as coal mining and weaving (149). This theory has now expanded and can be applied to any sectors to understand the complex nature of work, and the interactions between people and their work system (149).

Within healthcare, Smith and Carayon-Sainfort first discussed the work system as part of the Balance Theory in 1989, which was developed to provide a more realistic and person-centred approach to the design of work systems (150). As part of the Balance Theory, the first Work System Model was created, which is made up of five components which interact to create an outcome: person(s), tools and technology, physical environment, tasks and organisation (See Figure 2.1 for the original Work System Model).

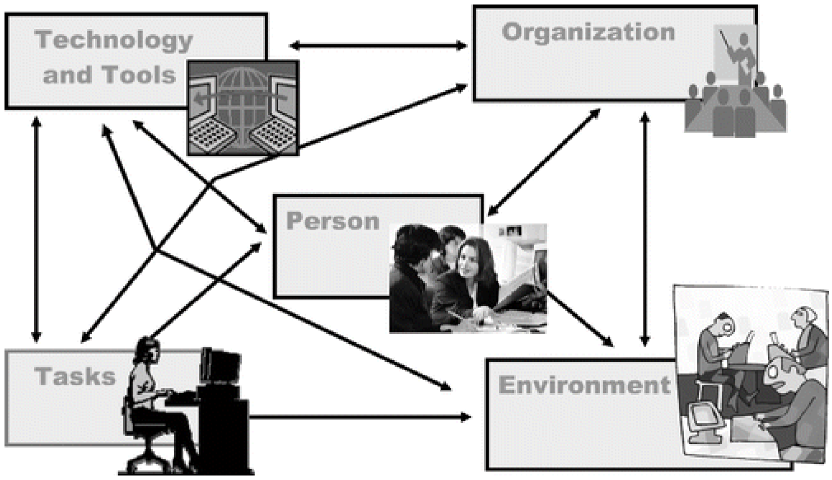

Figure 2.1: The original Work System Model
Taken directly from (151)

A definition of each of the five components within the original work system model can be seen below:

Person: Individual characteristics such as perceptions, skills, and expertise.

Other technologies/tools: Objects, hardware, or software that people use to do work or assist them in doing the work.

Physical environment: The environment that work is completed in, such as the layout, workstation, and noise within the setting.

Tasks: Specific actions taken and the attributes or characteristics of the tasks, such as difficulty, complexity, variety, etc.

Organisation: Structures external to a person, such as time, space, resources, and activity.

Since its development, the Work System Model has been adapted to healthcare and expanded into other human factors models, such as the Systems Engineering Initiative for Patient Safety (SEIPS) model (152-154). The SEIPS model was developed using the work system model and Donabedian's structure-process-outcome (SPO) framework to show the complexities of interactions found in healthcare (152). The model, now on its third interaction, highlights how interacting components within a sociotechnical system result in processes that impact outcomes within that system (152-154). More recently, the Work System Model has been applied to new innovations in healthcare, such as AI technology (155) (Section 2.4.1).

As AI technology has the potential to change the healthcare setting drastically, models and theories that have been developed previously may not be appropriate and may not consider the full work system. To ensure that this systems perspective is taken for healthcare AI, an extended version of the Work System Model was developed in 2022 by Salwei and Carayon (155). This extended Work System Model comprises the five components within the original Work System Model but also contains a sixth component; AI technology (see Figure 2.2). The extended model outlines that AI technology is one distinct component of the work system and that its interactions with the other components within the chosen work system should be considered to ensure it is utilised effectively (155).

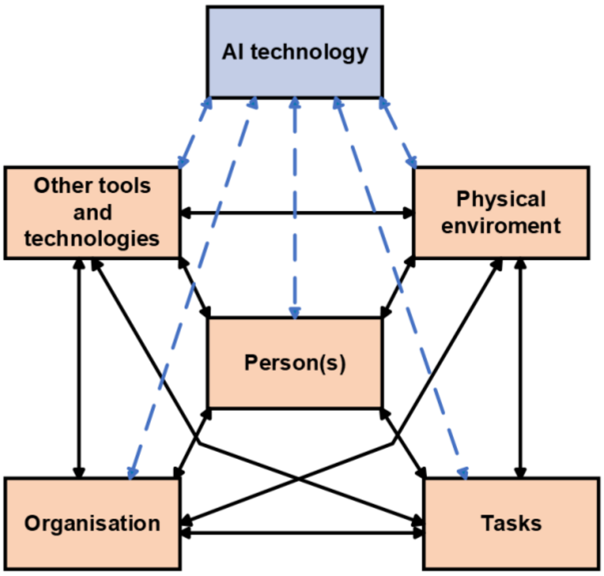

Figure 2.2: The extended version of the Work System Model
Model taken and reproduced from (155)

Within the model, the solid lines represent the interaction between the original components of the work system, and the blue dashed lines represent how AI technology interacts with the original components. The original components retain their existing definitions, except for 'other tools and technology', which only refers to any tools and technology except from the AI technology used within the setting.

Overall, applying human factors approaches from the outset of the development lifecycle of healthcare AI technology will ensure that key principles, such as the human-AI teaming and organisational readiness, are considered. However, to ensure a systems perspective is taken, a work system model that is developed specially for AI technology can be adopted to support those human factors approaches.

Chapter 3: Aims and Objectives

Significant technological advancements have been seen in recent years, with research increasing and strategies being created globally and within Scotland to facilitate integrating these technologies into healthcare (Chapter 1, Section 1.1.3 and 1.1.5). One of the key advancements is the development of Artificial Intelligence (AI) technology, with research highlighting the potential these tools have for supporting the healthcare setting (36, 37, 42). Currently, a key area of healthcare where AI technology has been applied is the critical care setting for diagnosing and treating sepsis (36). Sepsis is a life-threatening disease that requires early diagnosis and treatment with antibiotics and fluids, with previous studies suggesting that this should be specific to the individual (64-66). AI technology has the potential to provide this individual treatment, which is based on patients' specific characteristics. However, despite research suggesting that AI technology can support healthcare with a variety of tasks such as diagnosis and treatment decision, evidence also indicates that this potential may be reduced once any new AI technology is applied in real-world settings (75-79). This may result from several factors, including a lack of understanding of the healthcare-related work systems and the components within that system that interact to create outcomes (61, 81, 82).

The discipline of human factors can be applied to support an understanding of the work systems in healthcare, allowing for the full benefit of AI technology to be realised. The discipline of human factors can be considered *"The scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data, and methods to design in order to optimise human well-being and overall system performance" (88)*, and helps ensure a systems perspective is taken. More recently, research has focused on how human factors approaches may support the development of AI technology for healthcare (126, 127). This increased research has highlighted several human factors principles that must be considered when developing AI technology. This includes considering how AI technology will fit within the multi-disciplinary team and the need for appropriate organisational readiness in healthcare to ensure effective integration (82, 133). To ensure these principles are considered, human factors approaches can be applied early in the development of AI with the support of a work system model (155). This will allow for a system perspective throughout the AI technology development lifecycle, which will help overcome potential issues that may arise when applying the technology in a real-world setting. Therefore, this thesis aims to describe how the discipline of human factors can be applied to support the development of Artificial Intelligence in the healthcare setting. This was achieved by applying the three-stage process outlined in Figure 3.1.

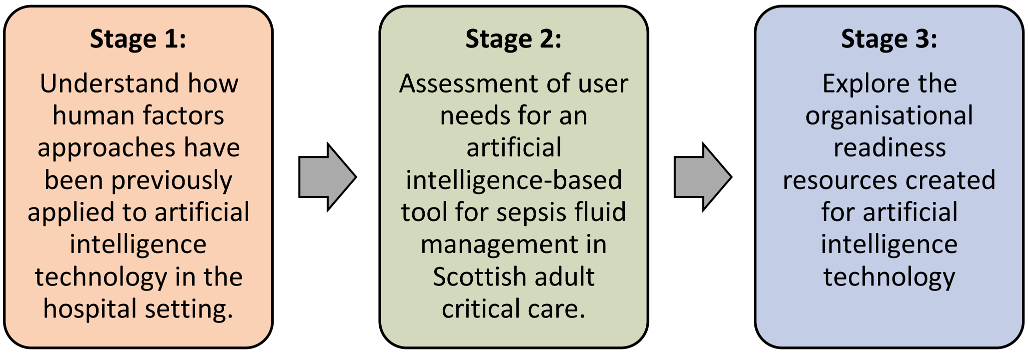

Figure 3.1: Stages of thesis

Stage 1: Understand how human factors approaches have been previously applied to artificial intelligence technology in the hospital setting (Chapter 4).

Aim: Identify where human factors approaches have been used previously for AI-based clinical decision support (AI-CDS) in the hospital setting. Utilising a systematic scoping review, this stage aims to:

- Report on the characteristics of studies that have applied human factors approaches for AI-CDS in hospitals;
- Categorise the human factors approaches that have been applied to hospital AI-CDS.

Stage 2: Assessment of user needs for an artificial intelligence-based tool for sepsis fluid management in Scottish adult critical care (Chapter 5).

Aim: Complete an assessment of user needs for an AI clinical decision tool for sepsis fluid management (AI-SFM tool) in adult critical care. Utilising semi-structured interviews, this stage aims to:

- Approximate potential users' current work system for sepsis fluid management in Scottish adult critical care using an extended Work System Model;
- Describe the user requirements for an AI-SFM tool, informed by their current work system.

Stage 3: Explore the organisational readiness resources created for artificial intelligence technology (Chapter 6).

Aim: Assess the resources developed to measure organisational readiness for AI technology across any setting. Utilising a scoping review of resources, this stage aims to:

- Identify and report on the characteristics of established organisational readiness resources developed for AI technology;
- Compare and contrast the factors within the organisational readiness resources for AI technology using the extended Work System Model.

Chapter 4: Human factors approaches used for artificial intelligence-based clinical decision support technology in hospitals: a systematic scoping review

4.1. Introduction

There has been an increase in the development of artificial intelligence (AI) technology across the healthcare sector (156). Specifically within secondary care, the development of AI technology has mainly focused on clinical decision support, where the technology aims to aid clinicians in making judgements about patient care (51) (see Chapter 1, Section 1.2). The potential benefits of using this type of AI technology have been highlighted in previous research, with studies focusing on skin cancer finding that the decision output from the technology was similar to those made by a clinician (54). However, research has suggested that overall, there has been more focus on the technical aspects of developing AI technology (61, 82). This refers to developers historically focusing solely on the performance of the AI technology rather than how it would interact within the chosen healthcare setting (81). This lack of understanding of how AI technology interacts and fits within the healthcare setting may result in the new technology not being used to its full potential when implemented in real-world settings (61, 82). Therefore, to allow for the full benefit of AI technology to be realised, there may need to be a shift to focusing on the technological development of AI technology in parallel with understanding how any new tool would fit into the work system already in place (61, 82).

Healthcare is considered a complex sociotechnical work system where a number of components interplay to create an outcome (61, 154) (see Chapter 2). A limited understanding of these components and their interaction may result in technology not being utilised to its full potential and reduce its transferability into the clinical setting. Therefore, the development of future AI technology can to take a systems perspective, which considers not only the performance of the technology but also the factors impacting the clinical setting in which the technology will be integrated (37, 129). This systems perspective may be achieved by applying the discipline of human factors, defined as *"The scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data, and methods to design in order to optimise human well-being and overall system performance"* (88) (see Chapter 2). A human factors approach, and method has been applied in healthcare for several years with research gaining momentum within the domain (123-125, 157). Regarding AI technology specifically evidence has suggested that taking a human factors approach throughout the development lifecycle can help ensure it is used effectively in the healthcare sector (82).

The development lifecycle of AI technology can be seen as encompassing three main stages: Design, Implementation and Use (Chapter 2, Section 2.4) (61, 134-136). Design refers to developing, testing and evaluating a new technology prototype before it is implemented into the setting (138). Implementation is an important step in the AI technologies lifecycle and can include ensuring it works within the clinical processes and understanding any barriers and facilitators that may impact its adoption (144, 145). Once implemented into the clinical setting, the technology should be consistently tested, which comes under the stage of Use which refers to testing the AI technology once it is implemented. This continuous testing allows for an understanding of how the technology routinely works in the healthcare setting (147). While the lifecycle can be seen as three main stages, it does not need to be completed in a linear process. By considering a technology's development as a lifecycle and applying the human factors approaches at each stage, future AI technology will take a systems perspective, allowing for an understanding of how the technology will work with the users and their work system.

Previous studies have suggested that the discipline of human factors should be applied at all stages of an AI technologies lifecycle; however, often, this is not done, with research mostly focusing on the technical development of the technology. This may be due to the discipline being in its infancy in healthcare AI technology and often those working in the area having little knowledge of how human factors approaches and methods can be applied, or there being no clear guidance on how the approaches can be applied practically. In order to provide some initial guidance, this chapter aims to complete an in-depth systematic scoping review of the literature that has applied human factors approaches to AI technology, specifically those developed to provide support for clinical decisions in the hospital setting. To the author's knowledge, no such review has been completed previously, and by doing so may provide an evidence base for future researchers and developers on how human factors can be applied at all stages of future AI technologies lifecycle.

4.2. Aims and objectives

The overall aim of this systematic scoping review is to identify where human factors approaches have been used previously for AI-based clinical decision support (AI-CDS) in the hospital setting, with the following objectives:

1. Report on the characteristics of studies that have applied human factors approaches for AI-CDS in hospitals
2. Categorise the human factors approaches that have been applied within the area of hospital AI-CDS.

4.3. Review methods

A scoping review is a tool used to explore and map the current evidence base for a certain topic in a systematic manner. This type of review can help understand a body of evidence and show the current literature volume alongside any emerging topics or evidence (158). A scoping review was chosen over other types of review methods, as it would help answer a broad question (unlike a systematic review, which answers a narrow question) but is still completed in a systematic and iterative manner (unlike other review methods such as literature or narrative review which employs a less systematic approach) (159, 160).

The review utilised a systematic search strategy, selection process and data collection method with the Preferred Reporting Items for Systematic Reviews and Meta-Analysis for Scoping Reviews (PRISMA-ScR) 2020 checklist used as a guide for reporting these methods (161).

4.3.1. Eligibility criteria

4.3.1.1. Inclusion criteria

The study should take a human factors approach

A study was identified as taking a human factors approach if it had applied a method or thinking derived from the discipline of human factors. The studies must have involved technology users (e.g., relevant staff members and patients) to understand their involvement in the technology's lifecycle. Studies did not need to explicitly state that they used 'human factors' or 'ergonomics' approach, as previous research has suggested that often these terms are not always used in studies that adopt a human factors or ergonomic approach. Where studies did not explicitly state the use of a human factors approach, the researcher's subjective yet informed opinion was taken. This is considered common practice in healthcare human factors-related reviews due to the discipline's infancy in this setting (123-125). Therefore, to aide robustness of the review, the following working definition was used to inform the decision: *"The scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data, and methods to design in order to optimise human well-being and overall system performance"* (88). Another researcher was consulted if there was any lack of clarity over whether a study had adopted a human factors approach. Studies that used a combination of human factors approaches alongside other research approaches that were not deemed as human factors or ergonomics were also included in the review.

The study should focus on AI-CDS technology

Studies were included if they focused on AI-CDS, a technology that aids the stakeholder(s) in making a clinical decision based on patients' own characteristics (e.g. blood pressure). AI-CDS technology was chosen as it is considered the most common AI technology developed currently within the healthcare sector (42). The technology had to include the input of more than one patient characteristic, with the output generated by the technology being based on guidelines created from prior knowledge/research or by using software trained to make inferences based on patient data and/or outcomes to be considered AI-CDS technology (51).

The study should be based in a hospital setting

Studies were included if they were based within a hospital setting within either secondary or tertiary care and as either inpatient or outpatient.

The study should be a peer-reviewed primary paper

Studies were included if they were primary research and had gone through the peer review process, including journal articles, conference articles or reports. Conference articles were included as often, within this area of research, papers are published as part of a conference and go through a peer-review process like that of journal articles.

The study should be published in English, from any geographical context and after 2013

Studies were included if they were published in English and from any geographical location. The studies had to be published after 2013, as previous reviews have stated that this is when the AI technology, IBM Watson, was first used in healthcare and showed the potential benefit of using modern AI technology in this setting (49, 162).

4.3.1.2. Exclusion Criteria

Studies that did not focus on the sociotechnical work system of the technology

Studies were excluded if they focused solely on technological effectiveness and not on the relationship between the technology and the wider sociotechnical work system. This included studies that looked at the technology's prediction ability, the ability of the technology to perform better than clinical staff at certain tasks, or the development of the algorithm used for the technology.

Studies that only mention that human factors approaches should be utilised within the introduction or discussion

Studies that only referenced human factors in their introduction and/or discussion but did not include any human factors approaches were excluded. For example, studies that mentioned that future research should utilise human factors or that it is important to include human factors approaches to understand the technology's effectiveness were excluded.

Studies that did not focus on AI-CDS

Studies were excluded if the technology only used a single or no patient characteristics, such as disease type or drug interaction, to help make a clinical decision. Other types of decision support were also excluded, including paper-based guidance, checklists, or colleague advice.

Studies that did not focus on a hospital setting

Studies were excluded if they focused on non-hospital settings, for example, primary care, including: community pharmacy; general practice; care homes and studies completed at the patient's home.

Studies that were not the primary paper or peer-reviewed

Studies were excluded if they were not primary research, including opinion pieces, reviews, and discussion articles. Studies that had not been peer-reviewed were also excluded, along with conference abstracts (often part of a conference proceeding), books, and unpublished literature.

4.3.2. Information sources

The following databases were searched on 14th May 2021 and again on 29th August 2023: Medline; Embase; PsycINFO; and Ergonomics Abstracts and Engineering Village. Medline and Embase were chosen as they were considered prominent healthcare databases. PsycINFO was used to capture psychological science-related papers. Ergonomics Abstracts was searched as a human factors database, and finally, Engineering Village was chosen to cover studies that had applied human factors from an engineering perspective.

Further searches were completed after full-text screening to capture any studies not found in the databases, including hand-searching the references of included studies and using Google Scholar©. An expert in human factors and healthcare AI was also contacted (MS) and asked to send any studies they felt should be included. Studies were included if they had not already been captured in the original searches.

4.3.3. Search strategy

The search strategy was developed by creating key terms and synonyms under three main headings: ‘Hospital’, ‘AI-CDS’ and ‘Human factors’. The search strategy was informed by previously completed reviews (125, 163) and reviewed by a University of Strathclyde librarian and other PhD candidates (AF + CM). Syntaxes were used for each term to allow for word variations and index terms were included for those databases that used them (e.g., MESH for Medline). The search terms were matched across each database for consistency. Between the three main headings and each individual search term the Boolean terms ‘AND’ and ‘OR’ were used appropriately. This allowed for each study to include one or more search term from each main heading. The specific syntaxes used for each database are detailed in Appendix 1. Examples of the search terms are illustrated in Table 4.1, with the full search strategy presented in Appendix 2.

Table 4.1: Examples of the search terms used for each main heading.

Main Heading	Example of search terms
Human factors	‘Human factors research’; ‘Ergonomics’; ‘Sociotechnical’; ‘Safety culture’; ‘User-centred’.
Hospital	‘Hospital’; ‘Hospitalisation’; ‘Secondary care’; ‘Outpatient care’; ‘Critical care’.
AI-CDS	‘Clinical decision support technology’; ‘Artificial intelligence’; ‘Deep learning’; ‘Image processing’; ‘Chatbot’.

AI-CDS = artificial intelligence-based clinical decision support

4.3.4. Selection Process

The software Covidence© (164), a screening and data extraction tool for completing systematic reviews, was used for the full screening process. The researcher completed 100% of the screening and a random 20% of studies were independently screened at both title and abstract and full text stage by another PhD candidate (AF) to ensure consistency. The level of agreement was calculated, with a percentage of 80-89% considered to be good, and 90%+ considered excellent (165). If a good or excellent level of agreement was achieved, then the rest of the screening was conducted by the primary reviewer. If the agreement level was below 80%, a further 10% of studies was screened, and a supervisor (ED) was consulted.

Where studies were not available online for full-text screening, the authors of those studies were contacted twice by email and through ResearchGate© where possible. If the full texts were still unavailable or not received from the authors, they were excluded.

4.3.5. Data charting

A data extraction template was created using Microsoft Excel©, which included: title; author; year published; hospital setting(s); geographical location(s); the people involved with the study; study aim; type of AI-CDS; type of support provided by the AI-CDS; approaches used (some studies utilised several approaches, these were separated) and the specific methods for each approach (for example, specific questionnaires, analysis methods or models). A random 20% of the studies were independently extracted by another PhD candidate (AF) to ensure consistency. If a good (80-89%) or excellent (90%+) percentage of agreement was reached, then the primary reviewer completed the extraction. If the agreement level was below 80%, a further 10% of studies were screened, and a supervisor (ED) was consulted.

4.3.6. Synthesis methods

The synthesis methods used for each objective are as follows:

4.3.6.1. Objective 1: Report on the characteristics of studies that apply human factors approaches for AI-CDS in hospitals.

A PRISMA flow chart was generated to illustrate the screening process used to identify included studies. The characteristics of the included studies (title, author, date published, hospital setting, the staff involved and the verbatim aim of the study) were collated into a table. The date published was then presented as a bar chart and percentages. The hospital setting and staff involved were also presented as percentages.

The type of AI-CDS was deductively aligned under the broad headings of ‘Rules-based’ and ‘Learning-based’ AI-CDS. ‘Rules-based’ refers to technology that aims to imitate the decision-making process of subject matter experts (SME), with the rules often created by those SME and based on best practice and basic data about the patient (51). ‘Learning-based’ is where the software is trained to make inferences in the patient data, with the SME possibly involved in this training (51). These two headings were chosen as they are considered the two main types of AI used within healthcare (51). The support the technology provided, the health condition/task it was designed to support and whether the technology was integrated into the Electronic Health Record (EHR) was presented in tabular form and described.

4.3.6.2. Objective 2: Categorise the human factors approaches that have been applied within the area of hospital AI-CDS.

A content analysis method was used as a guide for the synthesis of the human factors approaches, and is defined as *“any technique for making inferences by objectively and systematically identifying specified characteristics of messages”* (166).

Step 1: A count of the studies that mentioned ‘Human factors’ or ‘Ergonomics’ within the main text was completed, as previous research has suggested that while a human factors approach had been utilised, these specific terms may not always be explicitly stated (123, 124).

Step 2: The researcher completed a deductive content analysis which aligned the human factors approaches under the headings of Design, Implementation, and Use (134). Operational definitions were created for the three headings informed by literature (see Table 4.2 for definitions) (138, 144, 147). A deductive content analysis is a method that uses a pre-determined structure as an analysis matrix (167), and was chosen to demonstrate how human factors can be applied throughout the technology's lifecycle (134). Another PhD candidate (AF) replicated 100% of the deductive content analysis to validate the analysis as validation. Where there was disagreement, KP and AF discussed, and if a consensus could not be reached, a supervisor (ED) was consulted.

Table 4.2: Definition for Design, Implementation and Use.
Definitions adapted from (138, 144, 147)

Heading	Definition
Design	Design refers to developing and evaluating the AI-CDS before it is implemented into practice. This stage starts once an AI concept is decided and ends after a prototype of the technology is ready to be integrated into the clinical setting.
Implementation	Implementation refers to the integration of the AI-CDS prototype into clinical practice. This stage starts after a prototype is created and ends when the technology is used in everyday clinical practice.
Use	Use refers to evaluating the AI-CDS once it is integrated into clinical practice to understand its suitability. This stage starts once the technology is used in everyday practice and should only end if the technology is no longer used.

AI-CDS = artificial intelligence-based clinical decision support

Step 3: Once aligned under the Design, Implementation and Use headings, the human factors approaches from the studies were inductively analysed using Microsoft Excel© (168). The human factors approaches conducted in more than one study (e.g., two studies may state they completed 'usability testing') or those focused on similar approaches were grouped under one appropriate label (169). An example of similar approaches may be 'process mapping' and 'analysis of workflow', which are similar as they both focus on analysing the processes being completed. To validate the analysis, another PhD candidate (AF) replicated 20% of the grouping processes, and where there was disagreement, these were discussed, and if consensus could not be reached, a supervisor (ED) was consulted. Once finalised, labels and definitions were created for each grouping. This was checked by another PhD candidate (AF) to make sure the final groupings were appropriate and that the labels and definitions were suitable (170).

Step 4: Categories within Design, Implementation and Use were created inductively. This aimed to provide further understanding of what the approaches aimed to accomplish with regard to the technology. Another PhD candidate (AF) checked this step to ensure the category was appropriate (170). The final approaches were then presented in tabular form, under the relevant heading and category, alongside a definition of the approach and a study reference.

Step 5: The specific research techniques used in each study (e.g., relevant questionnaires, use of models, frameworks, or other data collection methods) extracted were then presented in tabular form under each approach with reference to the specific heading and category.

4.4. Results

4.4.1. Study selection

From the initial 9,728 studies found in the first search, and the 5,852 studies in the second search, 64 were included in the final review (see Figure 4.1 for the PRISMA flow chart). The percentage of agreement for the title and abstract screening was 94.5% (excellent) for the first search and 98% (excellent) for the second search. For full-text screening, there was an agreement percentage of 91% (excellent) for the first search and 96% (excellent) for the second search.

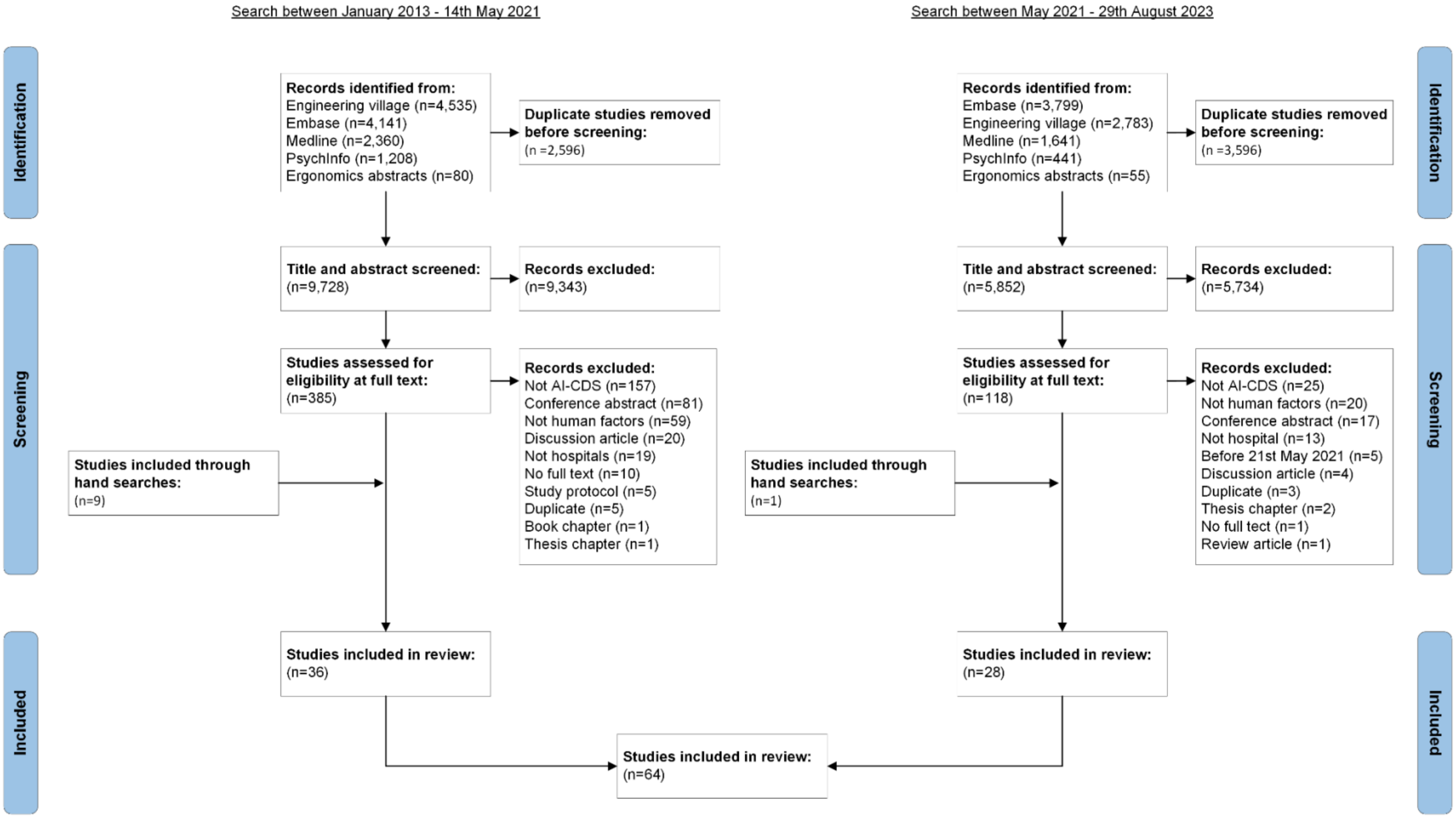

Figure 4.1: PRISMA flow chart showing the number of studies identified at each stage
(AI-CDS = artificial intelligence-based clinical decision support)

4.4.2. *Study Characteristics*

The majority of the 64 included studies were published from 2019 onwards (n=48, 75.0%), with the most studies published in 2022 (n=15, 23.4%). Figure 4.2 shows the number of studies published each year. Over half of the studies were published in North America (n=39, 60.9%), including the United States of America (USA) (n=34) and Canada (n=5). Thirteen studies (20.3%) were published in European countries, including France (n=3), the Netherlands (n=3) the UK (n=2), and Germany (n=2). The remaining 12 (18.8%) studies were published in other international settings, including Taiwan (n=2) and Australia (n=2) and finally two studies had an unclear location. Most studies involved healthcare professionals (HCPs) (n=60, 93.8%), such as physicians, nurses, and pharmacists and 13 (20.3%) included non-HCPs such as clinical lab personnel and managerial staff. Six (9.4%) studies involved patients, with four (6.3%) focusing solely on this group. Twenty-three studies (35.9%) stated a specific department or service where the technology was applied, including the emergency departments (paediatric and general) (n=12), critical care (neonatal and general) (n=9) and dermatology (n=2). The full characteristics of the studies are presented in Table 4.3.

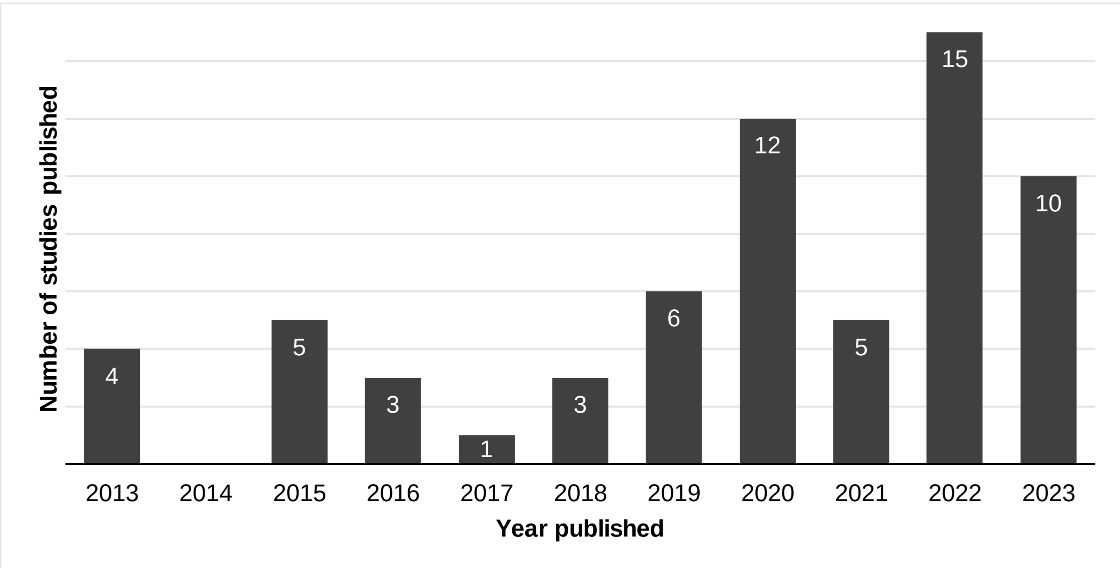

Figure 4.2: Number of studies published in each year (n=64)

Table 4.3: Study characteristics in order of publication year (n=64)

Study	Year	Hospital setting	Participants	Country	Study aim (verbatim)
Ozel et al (171)	2013	Intensive care unit	Physicians	Turkey	The aim of this study is to develop and evaluate a web-based CDSS containing clinical guidelines and protocols that will support intensive care unit providers in making decisions more effectively and quickly.
Portela et al (172)	2013	Intensive care unit	Nurses	Portugal	In this case and with the goal to evaluate the implementation process, an assessment model was applied to a real system called INTCare.
Sheehan et al (173)	2013	Emergency department	Physicians, residents, nurses, other clinicians, and non-clinical staff	USA	We conducted a multi-site cross-sectional qualitative study whose aim was to describe the sociotechnical environment in the emergency department to inform the design of a CDSS intervention to implement the Paediatric Emergency Care Applied Research Network clinical prediction rules for children with minor blunt head trauma.
Yuan et al (174)	2013	Acute care hospital	Nurses	USA	Our objective was to develop a novel CDSS to help frontline nurses better manage critical symptom changes in hospitalized patients, hence reducing preventable failure to rescue cases.
Esmaeilzadeh et al (175)	2015	Public and private hospitals	Physicians	Malaysia	The basic objective of this research is to study the antecedents and outcomes of professional autonomy which is a central construct that affects physicians' intention to adopt clinical decision support systems.
Morrison et al (176)	2015	Hospital	Neurologists and nurses	Unclear	The study presented here is a mixed-methods empirical evaluation of the usability and acceptability of these aspects of Assessment of Motor Dysfunction in Multiple Sclerosis.
Norton et al (177)	2015	Academic medical centre	Surgeons, anaesthesiologists, nurses, and non-clinical staff	USA	We examined providers' perceptions of the Decision Support for Safer Surgery tool which provided preoperative patient-level risk estimates of postoperative adverse events.
Press et al (178)	2015	Emergency department at a tertiary care centre	Physicians and residents	USA	The objective of the study was to conduct usability testing for the integration of the Wells clinical

Study	Year	Hospital setting	Participants	Country	Study aim (verbatim)
					prediction rule into a tertiary care centre's emergency department electronic health record.
Yadav et al (179)	2015	Urban tertiary care teaching hospital	Physicians and non-clinical staff	USA	The objective was to design a paediatric traumatic brain injury electronic clinical decision support (eCDS) tool for trauma resuscitation using a human factors approach. The hypothesis was that clinical experts will rate a usability-enhanced eCDS tool better than the existing tools for user interface design and suitability for clinical use.
Abdel-Rahman et al (180)	2016	Children's hospital	Physicians, nurses, pharmacists, pharmacologists, and non-clinical staff	USA	Development and testing of a unique clinical decision support tool aimed at the clinician and embedded in our Electronic Health Record.
Chang et al (181)	2016	Medical university hospital	Physicians	Taiwan	The purpose of this research is first to propose a set of design guidelines based on cognitive fit design and then to follow the guidelines to design an effective CDSS. We aim to enhance CDSS ease of use and flexibility in supporting physicians making effective diagnoses and providing proper treatment with less cognitive effort and load.
Khan et al (182)	2016	Tertiary academic institution	Emergency medicine physicians	USA	This was a study to conduct a formative assessment of emergency medicine physicians that included focus groups and key informant interviews. The focus of this study was twofold, to determine the general attitude towards CDS tool integration and the ideal integration point into the clinical workflow.
English et al (183)	2017	Clinical pharmacy	Clinical pharmacists	USA	The present study applied a modified version of the Unified Theory of Acceptance and Use of Technology to evaluate the disposition and satisfaction with CDSS among clinical pharmacists who perform surveillance to identify potential medication therapy interventions on patients in the hospital setting.

Study	Year	Hospital setting	Participants	Country	Study aim (verbatim)
Fink et al (184)	2018	University medical centre	Patients	Germany	The objective of this study is to assess patient acceptance and trust in automated melanoma diagnosis with dermatofluoroscopy.
Flohr et al (185)	2018	Intensive care unit	Doctors, nurses, and respiratory therapists	Canada	The aim of this study is to identify requirements for the VitalPAD application and to design and evaluate application components through a participatory design process.
Pertiwi et al (186)	2018	Tertiary hospital	Experts in usability and the Electronic Health Records	Unclear	This article reports on the application of a usability inspection method called heuristic evaluation of a sepsis alert system, designed by a major electronic health record vendor, in use in a tertiary hospital.
Akhloufi et al (187)	2019	University medical centre	Medical and surgical residents, physicians, pharmacists, and non-clinical staff	Netherlands	We have developed a CDSS for empirical antibiotic treatment in hospitalized adult patients. Here we determined in a usability study if the developed CDSS needed changes.
Fico et al (188)	2019	University hospital	Medical doctors, nurses, and non-clinical staff	Spain and Italy	The goal of the project was to develop new computer models and implement them in tools to support the detection and prediction of type 2 diabetes onset and related complications, in different healthcare settings.
Garvin et al (189)	2019	Hospital	Clinicians and non-clinical staff	USA	We used iterative user-centred design and formative evaluation to create Cirrhosis Order Set and Clinical Decision Support, a workflow and decision-support tool to aid in the identification and treatment of patients with cirrhosis.
Ginestra et al (190)	2019	Tertiary teaching hospital	Physicians, advanced practitioners, and registered nurses	USA	This study describes clinician perceptions of our predictive machine learning based early warning system 2.0 deployed prospectively across our healthcare system.
Harte et al (191)	2019	Neonatal intensive care unit	Doctors and nurses	France	In this paper, we present our experience with applying a participatory design-based prototyping method to create user interface concepts for the Digi-Newb system and then testing the prototypes with end-users.

Study	Year	Hospital setting	Participants	Country	Study aim (verbatim)
Sarwar et al (192)	2019	Pathology department	Physicians	Canada	We performed an online survey of pathologist colleagues on topics regarding incorporation of AI into clinical practice, its impact on research, and pathologists' projections for the future of pathology training and teaching.
Abdel-Rahman et al (193)	2020	Standalone paediatric hospital	Physicians, nurses, pharmacists, and pharmacologists	USA	The objective of this paper is to describe the development and usability of this clinical decision support tool for antihemophilic factor dose individualization.
Ahmad et al (194)	2020	Paediatric emergency department	Providers, Emergency Department staff and patients	USA	We created a flexible framework for integrating a clinical decision support into the electronic health record. We provide an overview of the software platform and qualitative user acceptance.
Babione et al (195)	2020	Hospital	Internal medicine and emergency department clinicians, medical students, and non-clinical staff	Canada	This article describes common human centred design methods and case study focusing on a CDSS tool supporting pulmonary embolism diagnosis – an inherently challenging clinical area.
Bailey et al (196)	2020	Tertiary renal services in a teaching hospital	Key clinical and managerial staff, nurses, and patients	UK	Through studying the implementation of acute kidney injury CDSSs, using ethnographic methods, we explored the professional and organisational work surrounding the translation of policy drivers and clinical guidance into routine hospital care.
Bersani et al (197)	2020	Academic acute care hospital	Physicians and nurses	USA	This study was aimed to describe providers' use and perceived usability of the Patient Safety Dashboard and discuss barriers and facilitators to implementation.
Carayon et al (198)	2020	Emergency department	Residents	USA	In this study, we used human factors methods and principles to design a CDS that provides cognitive support to the pulmonary embolism diagnostic decision-making process in the emergency department.
Jutzi et al (199)	2020	Dermatology department	Patients	Germany	We therefore conducted a survey to evaluate the patients' view of artificial intelligence in melanoma

Study	Year	Hospital setting	Participants	Country	Study aim (verbatim)
					diagnostics in Germany, with a particular focus on patients with a history of melanoma.
Nelson et al (200)	2020	Dermatology department	Patients	USA	Our primary aims in this study were to explore how patients conceptualize AI and view the use of direct-to-patient and clinician decision-support AI tools for skin cancer screening. decision-making, and recommendation for or against AI.
Patterson et al (201)	2020	Hospital	Physicians and pharmacists	USA	Our objective is to operationalize a novel antibiotic advisor, called the Personalized Weighted Incidence Syndromic Combination Antibiogram.
Petitgand et al (202)	2020	Emergency department in an academic medical centre	Doctors, nurses, managers, and developers	Canada	This article adopts an interpretative perspective to analyse the implementation of an AI-based decision support system in an emergency department, focusing on actors' representations of the system.
Sandhu et al (203)	2020	Emergency department at a university hospital	Doctors and nurses	USA	This study aims to explore the factors influencing the integration of a machine learning sepsis early warning system (Sepsis Watch) into clinical workflows.
Strohm et al (204)	2020	Radiology department	Radiologists and non-clinical staff	Netherlands	The objective was to identify barriers and facilitators to the implementation of AI applications in clinical radiology in the Netherlands.
*Greenberg et al (205)	2021	Hospital	Physicians from neurosurgery, emergency medicine, critical care and paediatric general surgery and non-clinical staff	USA	To guide these efforts, we evaluated the sociotechnical environment impacting the implementation of electronic CDS, including workflow and communication, institutional culture, and hardware and software infrastructure, among other factors.
Jauk et al (206)	2021	Hospital	Doctors and nurses	Austria	The overall goal of our study was to gain knowledge of the uptake, user acceptance and concerns regarding a machine learning-based prediction application designed to improve patient safety in a clinical setting.
Jia et al (207)	2021	Hospital	Front-line staff	UK	We developed and applied a novel methodology that incorporates safety engineering processes to support

Study	Year	Hospital setting	Participants	Country	Study aim (verbatim)
					development and refinement of the clinical workflow and the machine learning model.
*Salwei et al (208)	2021	Emergency department	Physicians	USA	In this study, we applied our proposed definition of workflow integration to understand the barriers and facilitators to workflow integration of a human factors-based CDS used in the emergency department of a large academic health system.
*Sarti et al (209)	2021	Intensive care unit	Respiratory therapists	Canada	Although spontaneous breathing trials are standard of care to extubation readiness, no tool exists that optimises prediction and standardises assessment. In this study, we evaluated the feasibility and clinical impressions of Extubation Advisor, a comprehensive clinical extubation decision support tool
*Choudhury (210)	2022	University hospital	Physicians, residents and nurses	USA	We specifically aimed to understand how the perception of AI, risk, and expectancy influences clinicians' intention to use Blood Utilisation Calculator.
*Choudhury et al (211)	2022	University hospital	Clinicians	USA	This study aims to explore how clinicians perceived this AI-based decision support system and, consequently, understand the factors hindering Blood Utilisation Calculator use.
*Daniel et al (212)	2022	Private non-profit hospital	Nurses, pharmacists and non-clinical staff	France	We aimed at developing and implementing a chatbot to answer questions from hospital caregivers about drugs and pharmacy organization 24 hours a day and to evaluate this tool.
*Fujimori et al (213)	2022	Community tertiary care hospital	Physicians and residents	Japan	We aimed to evaluate the acceptance, barriers, and facilitators to implementing AI-based CDSSs in the emergency care setting through the opinions of physicians on our newly developed, real-time AI-based CDSS, which alerts emergency department physicians by predicting aortic dissection based on numeric and text information from medical charts, by using the Unified Theory of Acceptance and Use of Technology and the Consolidated Framework for Implementation Research frameworks.

Study	Year	Hospital setting	Participants	Country	Study aim (verbatim)
*Greenberg et al (214)	2022	Hospital	Emergency medicine and neurosurgery physicians	USA	Our objective was to evaluate the acceptability and usability of an electronic CDS tool for managing children with minor head trauma and intracranial injuries.
*Kehoe et al (215)	2022	Intensive care unit	Nurses	USA	The goals of the exercise were twofold: 1) to assess if the display output of the graphic user interface was confusing such that it may cause patient management error (i.e., dangerously confusing); and 2) whether the CDSS was perceived as useful to clinicians.
*Rabinovich et al (216)	2022	Emergency department in a university hospital	Radiology residents and emergency physicians	Argentina	In this study, we evaluated the TRx application integrated in the Electronic Health Records and the Radiology Information System of our centre. Our objective was to find patterns in perceptions that were common across users, and identify which factors are implied in the positive uptake of an AI-system for medical imaging, stratifying the results by users' specialties.
*Salwei et al (217)	2022	Emergency department	Physicians	USA	To evaluate the usability and use of human factors–based CDS implemented in the emergency department.
*Salwei et al (218)	2022	Emergency department	Physicians	USA	To identify and describe the usability barriers and facilitators of a human factors and ergonomics-based CDS prior to implementation in the emergency department.
*Sax et al (219)	2022	Emergency department	Providers	USA	To achieve this goal, we conducted semi-structured interviews and surveys with front-line emergency department physicians and used a mixed-methods analysis approach to better understand barriers and opportunities regarding optimal implementation of the tool and paired clinical decision support.
*Schwartz et al (220)	2022	Hospital	Physicians, physician assistants and nurse practitioners	USA	The aim of this study was to explore the phenomenon of clinician trust in predictive CDSSs for in-hospital deterioration by confirming and characterizing factors known to influence trust (understandability and

Study	Year	Hospital setting	Participants	Country	Study aim (verbatim)
					accuracy), uncovering and describing other influencing factors, and comparing nurses' and prescribing providers' trust in predictive CDSSs.
*Silvestri et al (221)	2022	Large academic medical centre	Practicing bedside nurse, advanced practice providers and physicians	USA	We aimed to identify perceptions of predictive information in sepsis CDS systems based on clinicians' past experiences, explore clinicians' perceptions of a hypothetical sepsis CDS system, and identify the characteristics of a CDS system that would be helpful in promoting timely recognition and management of suspected sepsis in a multidisciplinary, team-based clinical setting.
*Stacy et al (222)	2022	Hospital	Cardiology and internal medicine attendings, fellows and residents	USA	We qualitatively evaluated a novel, AI-based CDSS for atrial fibrillation rhythm management called QRhythm, which uses both supervised and reinforcement learning to recommend either a rate control or one of 3 types of rhythm control strategies—external cardioversion, antiarrhythmic medication, or ablation—based on individual patient characteristics.
*Tsai et al (223)	2022	Emergency department	Physicians and nurses	Taiwan	Therefore, the purpose of this study is to systematically share the successful experience of Chi Mei Medical Center in developing this emergency department AI dashboard, and to serve as an important reference for the development of AI in other hospitals by providing the overall AI infrastructure and software operation mode.
*Zhai et al (224)	2022	Tertiary hospital setting	Nurses	China	CDSSs have been increasingly introduced to health care settings; however, their adoption is far from ideal. Guided by the FITT framework, this study aims to explore barriers and facilitators to the implementation of a CDSS from the perspective of nurses.
*Abraham et al (225)	2023	Perioperative setting	Anaesthesiologists, surgeons, certified registered nurse anaesthetists,	USA	Our study objectives were threefold: (1) evaluate whether machine learning (ML)-generated postoperative predictions are concordant with clinician-generated risk rankings for acute kidney

Study	Year	Hospital setting	Participants	Country	Study aim (verbatim)
			registered nurses, and critical care physicians		injury, delirium, pneumonia, deep vein thrombosis, and pulmonary embolism, and establish their associated risk factors; (2) ascertain clinician end-user suggestions to improve adoption of ML-generated risks and their integration into the perioperative workflow; and (3) develop a user-friendly visualization format for a tool to display ML-generated risks and risk factors to support postoperative care planning, for example, within the context of operating room-intensive care unit handoffs.
*Au et al (226)	2023	Tertiary healthcare network	Patients	Australia	Our study aims to investigate whether a novel AI chatbot is an acceptable tool to provide health information to patients with decompensated Cirrhosis.
*Besculides et al (227)	2023	Hospital	Registered dietitians	USA	This study aims to evaluate the implementation of an ML tool, Malnutrition Universal Screening Tool (MUST)–Plus, that predicts hospital patients at high risk for malnutrition and identify best implementation practices applicable to this and other machine learning-based CDSS.
*Hua et al (228)	2023	Hospital	Radiologists	Australia	This study adopts a multi-stage approach to ensure a systematic and comprehensive evaluation of qXR.
*Marcilly et al (229)	2023	Hospital pharmacy	Pharmacists	France	To evaluate the usability and perceived usefulness of a CDSS for medication review by hospital-based pharmacists and to draw up guidelines on improving its usability.
*Meidani et al (230)	2023	Teaching hospital	Anaesthesiology residents and intensive care fellows	Iran	Since usability is considered a significant success factor for CDSSs, this study seeks to assess the usability of an electronic medical records-embedded CDSS for arterial blood gas interpretation and ordering
*Mlodzinski et al (231)	2023	Critical care	Physicians	USA	This study presents the development and early evaluation of a clinical decision support tool that uses a predictive model to help providers reduce low-yield, repetitive laboratory testing in hospitalized patients.

Study	Year	Hospital setting	Participants	Country	Study aim (verbatim)
*Rabbani et al (232)	2023	Academic medical centre	Physicians	USA	This study presents the development and early evaluation of a clinical decision support tool that uses a predictive model to help providers reduce low-yield, repetitive laboratory testing in hospitalized patients.
*van der Meijden et al (233)	2023	Academic intensive care unit	Physicians	Netherlands	We aimed to investigate physicians' perspectives and their current decision-making behaviour before implementing a discharge AI-CDS tool for predicting readmission and mortality risk after intensive care unit discharge.
*Wong et al (234)	2023	Intensive care unit	Physicians and radiologists	USA	To integrate and evaluate an AI system that assists in checking endotracheal tube placement on chest x-rays in clinical practice.

*Studies included during second search (29th August 2023)
CDS(S) = clinical decision support (system), AI = artificial intelligence

4.4.3. Characteristics of the AI-CDS

See Table 4.4 for a full account of the characteristics of all the types of AI-CDS identified in this review.

4.4.3.1. Learning-based AI-CDS (n=35)

Thirty-five studies (54.7%) explored learning-based AI-CDS, where the technology is trained to make inferences from patient data. In those 35 studies, various clinical decision support was described, with the most common being supporting the assessment of risk (n=7, 20.0%), general prediction (n=7, 20.0%) and diagnostics (n=5, 14.3%). This support was provided for various conditions and tasks, the most common being sepsis (n=4, 11.4%), skin cancer (n=3, 8.6%), and blood transfusion (n=2, 5.7%). Of the 35 studies that explored learning-based AI, the technology was integrated into the EHR in 22 (62.9%) studies.

4.4.3.2. Rules-based AI-CDS (n=29)

Twenty-nine studies (45.3%) focused on rules-based AI-CDS, where the technology was created using rules developed by subject matter experts. Of those 29 studies, there was a wide variety of clinical decision support described, with the most common being diagnostic/decision support (n=13, 44.8%), prediction (n=3, 10.3%), antibiotic treatment advice/ordering (n=2, 6.9%), risk calculation (n=2, 6.9%), and management of critical system changes (n=2, 6.9%). This support was provided for various conditions and tasks, with the most common being pulmonary embolism (n=7, 24.1%) and sepsis (n=4, 13.8%). Of the 29 studies that adopted rules-based AI, the majority were integrated in the EHR (n=20, 69.0%).

Table 4.4: Characteristics of the learning-based and rules-based AI-CDS in the included studies (n=64)

Study	Type of support	Condition/task being supported	Integrated into EHR
Learning- based AI			
Abdel-Rahman et al (180)	Therapeutic drug monitoring	Busulfan Pharmacokinetics	✓
Abdel-Rahman et al (193)	Dosing support	Antihemophilic factor	✓
*Abraham et al (225)	Preoperative risk support	Acute kidney injury, delirium, pneumonia, deep vein thrombosis and pulmonary embolism	✓
*Au et al (226)	Advice and support	Decompensated chronic liver disease	×
*Besculides et al (227)	Risk prediction	Malnutrition	✓
*Choudhury (210)	Utilisation calculator	Blood transfusion	✓
*Choudhury et al (211)	Utilisation calculator	Blood transfusion	✓
*Daniel (212)	Advice and support	Not specified	×
Fico et al (188)	Risk assessment	Type 2 diabetes	×
Fink et al (184)	Diagnostic support	Skin cancer	×
Flohr et al (185)	Monitoring and communication	Patient safety	×
*Fujimori et al (213)	Prediction	Aortic dissection	✓
Ginestra et al (190)	Early warning system	Sepsis	✓
*Greenberg et al (205)	Risk prediction	Children with mild traumatic brain injuries and intracranial injuries	✓
*Greenberg et al (214)	Risk prediction	Children with mild traumatic brain injuries and intracranial injuries	✓
*Hua et al (228)	Radiological detection	Tuberculosis	×
Jauk et al (206)	Prediction	Delirium	✓
Jia et al (207)	Monitoring for sudden changes in vasopressor dose	Sepsis	×
Jutzi et al (199)	Diagnostic support	Skin cancer	×
*Mlodzinski et al (231)	Prediction	Intubation patients	×
Morrison et al (176)	Assessment of motor function	Multiple sclerosis	×
Nelson et al (200)	Screening	Skin cancer	×
Petitgand et al (202)	Risk assessment	Admissions	✓
Portela et al (172)	Prediction	Organ failure and patient outcomes	✓
*Rabinovich et al (216)	Interpretation	Chest x-rays	✓
Sandhu et al (203)	Early warning system	Sepsis	✓

Study	Type of support	Condition/task being supported	Integrated into EHR
Sarwar et al (192)	Diagnostic support	Pathology	×
*Sax et al (219)	Risk stratification	Acute heart failure	✓
*Schwartz et al (220)	Prediction	Hospital deterioration	✓
*Silvestri et al (221)	Recognition and management	Sepsis	✓
*Stacy et al (222)	Decision support	Arterial fibrillation rhythm management	✓
Strohm et al (204)	Diagnostic support	Radiology	×
*Tsai et al (223)	Real-time prediction	Patient prognosis	✓
*van der Meijden et al (233)	Prediction	Discharge	✓
*Wong et al (234)	Checking support	Endotracheal tube placement	✓
Rules-based AI			
Ahmad et al (194)	Diagnostic support	Sexually transmitted infections	✓
Akhloufi et al (187)	Antibiotic treatment advice	Pneumonia, sepsis, urinary tract infections, meningitis, and secondary peritonitis.	✓
Babione et al (195)	Diagnostic support	Pulmonary embolism	×
Bailey et al (196)	Detection, alteration, and response	Acute kidney injury	✓
Bersani et al (197)	Compliance with safety practices	Patient safety	✓
Carayon et al (198)	Diagnostics decision making	Pulmonary embolism	✓
Chang et al (181)	Decision support	Stroke	✓
English et al (183)	Real-time pharmacy surveillance	Not specified	✓
Esmaeilzadeh et al (175)	Case-specific advice	Not specified	✓
Garvin et al (189)	Workflow support tool	Chronic liver disease and cirrhosis	✓
Hatre et al (191)	Risk calculator	Sepsis	×
*Kehoe et al (215)	Prediction	Patients on vasopressors	×
Khan et al (182)	Diagnostic support	Pulmonary embolism	✓
*Marcilly et al (229)	Medication review	Not specified	✓
*Meidani et al (230)	Interpretation and ordering	Arterial blood gas	×
Norton et al (177)	Risk calculator	Pre-surgery	×
Ozel et al (171)	Decision support	Sepsis and other conditions found in intensive care	×
Patterson et al (201)	Ordering of antibiotic medication	Antibiotic stewardship	×
Pertiwi et al (186)	Diagnostic support	Sepsis	✓

Study	Type of support	Condition/task being supported	Integrated into EHR
Press et al (178)	Prediction	Pulmonary embolism	✓
*Rabbani et al (232)	Prediction	Laboratory testing	✓
*Salwei et al (208)	Diagnostic decision making	Pulmonary embolism	✓
*Salwei et al (217)	Diagnostic decision making	Pulmonary embolism	✓
*Salwei et al (218)	Diagnostic decision making	Pulmonary embolism	✓
*Sarti et al (209)	Decision support	Extubating patient	×
Sheehan et al (173)	Diagnostic support	Blunt head trauma	✓
Yadav et al (179)	Management of critical symptom changes	Trauma resuscitation	✓
Yuan et al (174)	Management of critical symptom changes	Reduce preventable failure to rescue cases	×
*Zhai et al (224)	Decision support	Nursing tasks	✓

*Studies included during second search
AI = artificial intelligence

4.4.4. Human factors approach

The results found that 20 (31.3%) of the 64 included studies explicitly mentioned that they used human factors and ergonomics approaches in their study (see Table 4.5). Of the remaining 44 studies, six (13.6%) either referenced human factors/ergonomics in the main written text (introduction or discussion), had a reference referring to human factors/ergonomics, involved a human factors expert as an author, or had published the study in a human factors journal. Of the 64 studies included, only one (1.6%) applied a human factors approach across all three stages of the lifecycle (193), and one applied a human factors approach at two stages of the lifecycle (180) (see Table 4.5).

Table 4.5: Studies' reference to and use of human factors approaches at Design, Implementation and Use (n=64)

Title	Design	Implementation	Use	Explicitly used human factors approach?
Abdel-Rahman et al (180)	✓		✓	
Abdel-Rahman et al (193)	✓	✓	✓	
*Abraham et al (225)	✓			
Ahmad et al (194)			✓	
Akhloufi et al (187)			✓	
*Au et al (226)	✓			
Babione et al (195)	✓			✓
Bailey et al (196)		✓		
Bersani et al (197)			✓	✓
*Besculides et al (227)			✓	
Carayon et al (198)	✓			✓
Chang et al (181)	✓			
*Choudhury (210)			✓	✓
*Choudhury et al (211)			✓	✓
*Daniel et al (212)	✓			
English et al (183)			✓	
Esmaeilzadeh et al (175)		✓		
Fico et al (188)	✓			
Fink et al (184)			✓	
Flohr et al (185)	✓			✓
*Fujimori et al (213)		✓		
Garvin et al (189)	✓			✓
Ginestra et al (190)			✓	
*Greenberg et al (205)		✓		
*Greenberg et al (214)	✓			
Harte et al (191)	✓			✓
*Hua et al (228)			✓	✓
Jauk et al (206)			✓	
Jia et al (207)	✓			✓
Jutzi et al (199)			✓	
*Kehoe et al (215)	✓			
Khan et al (182)	✓			
*Marcilly et al (229)			✓	
*Meidani et al (230)			✓	
*Mlodzinski et al (231)		✓		
Morrison et al (176)			✓	✓
Nelson et al (200)			✓	
Norton et al (177)			✓	
Ozel et al (171)	✓			
Patterson et al (201)	✓			✓
Pertiwi et al (186)			✓	
Petitgand et al (202)		✓		
Portela et al (172)			✓	
Press et al (178)			✓	✓
*Rabbani et al (232)	✓			
*Rabinovich et al (216)			✓	
*Salwei et al (208)			✓	✓

Title	Design	Implementation	Use	Explicitly used human factors approach?
*Salwei et al (235)			✓	✓
*Salwei et al (218)		✓		✓
Sandhu et al (203)		✓		
*Sarti et al (209)		✓		
Sarwar et al (192)		✓		
*Sax et al (219)		✓		
*Schwartz et al (220)			✓	✓
*Silvestri et al (221)	✓			✓
Sheehan et al (173)	✓			
*Stacy et al (222)	✓			
Strohm et al (204)		✓		
*Tsai et al (223)			✓	
*Van der Meijden et al (233)	✓			✓
*Wong et al (234)			✓	
Yadav et al (179)	✓			✓
Yuan et al (174)	✓			
*Zhai et al (224)		✓		

*Studies included during second search

4.4.4.1. Design

Twenty-five studies (39.1%) used a human factors approach to explore the Design stage of AI-CDS development (see Table 4.5). Design was divided into three main categories: ‘Pre-development Analysis’, ‘Development of a Prototype’ and ‘Prototype Testing’. ‘Pre-development Analysis’ refers to testing that should be completed before the technology prototype is created. There were 18 (72.0%) of these studies which focused on pre-development analysis, adopting four main approaches, with the most common being *Assessment of user needs* (n=10, 55.6%) and *Analysis of clinical workflow* (n=10, 55.6%). Thirteen (52.0%) studies focused on the ‘Development of a Prototype’, which refers studies that used the approaches from the ‘Pre-development Analysis’ stage to create a mock-up of the AI-CDS for testing. One approach was used under this category: *Developed based on pre-development analysis* (n=13, 100%). The last category under Design was ‘Prototype testing’, which was the approach taken by 17 (68.0%) studies. ‘Prototype testing’ refers to when an AI-CDS prototype is tested prior to implementation. There were two main approaches used, the most common being *Usability testing of prototype* (n=16, 94.1%). Table 4.6 presents the approaches, their definitions, and the associated studies.

4.4.4.2. Implementation

Fourteen (21.8%) studies focused on Implementation (see Table 4.5) and there were three main categories: ‘Pre-implementation Testing’, ‘Implementation Process’ and ‘Post-implementation Testing’. Eleven (78.6%) of these studies completed ‘Pre-implementation testing’ which refers to when the factors that may influence AI-CDS integration are assessed. There was one approach under this category used in all of these which was *Factors influencing implementation* (n=11, 100%). The second category was ‘Implementation process’, which refers to the process of integrating the AI-CDS into the system and was completed by one (7.1%) study. There was one approach used within this category– *Iterative implementation* (n=1, 100%). Three (21.3%) of the studies focusing on implementation completed an approach within the category of ‘Post-implementation Testing’, where the AI-CDS integration is assessed. There were two approaches found in this category, with the most common being, *Analysis of perceptions towards implementation* (n=2, 66.7%), followed by *Understanding impact of implementation* (n=1, 33.3%). Table 4.6 presents the human factors approaches, their definitions, and the associated studies.

4.4.4.3. Use

Twenty-eight (43.8%) studies explored Use of the AI-CDS (see Table 4.5) for which there were two main categories: ‘Testing in Practice’ and ‘Stakeholder Perceptions’. ‘Testing in Practice’ refers to assessing and evaluating the technologies fit in the clinical setting and was completed by 18 (64.3%) of these studies. There was one approach within this category used by all 18 studies looking at Testing in Practice- *Usability testing of the AI-CDS* (n=18, 100.0%). The second category under Use was ‘Understanding Stakeholder’s Perceptions’, which refers to where studies aimed to understand the thoughts of those using the technology in practice was completed by 12 (42.9%) of the studies exploring Use. There were two approaches within this category, with the most common being, *Testing stakeholders’ perceptions towards the AI-CDS* (n=8, 66.7%) followed by *Understanding stakeholders’ acceptance of the AI-CDS* (n=5, 41.7%). Table 4.6 presents the human factors approaches, their definitions, and the associated studies.

Table 4.6: Categorisation of human factors approaches (n=64)

DESIGN		
Human factors approach	**Definition**	**Specific study**
Pre-development analysis		
Assessment of user needs	Assessing what future stakeholders require from the technology, including their attitudes, barriers/facilitators to its use, and any further perceptions.	(171, 174, 180, 185, 188, 191, 198) *(212, 221, 233)
Analysis of clinical workflow	Understanding the workflow and processes already used in the clinical workflow. This includes how the technology may impact the system and any influencing factors.	(173, 180-182, 185, 188, 189, 193, 198, 207)
Evaluation of current technology and/or prototypes	Reviewing the technology already integrated into practice to help with the design of the technology, including the usability, the workflow, and any current issues.	(179, 195, 201)
Hazard and safety analysis	Analysis of system to identify any safety requirements or hazards.	(207)
Development of a prototype		
Developed based on pre-development analysis	Creation of the initial AI-CDS prototype, including mock ups, workflow pathways, and wireframes.	(171, 174, 179-182, 185, 189, 191, 193, 195, 198) *(212)
Prototype testing		
Usability testing of prototype	Where the prototype is tested by users to assess if it is fit for purpose, including areas such as satisfaction, confidence, heuristic evaluation, and workflow testing.	(171, 174, 179, 185, 188, 189, 191, 195, 198) *(212, 214, 215, 222, 225, 226, 232)
Understanding prototypes impact on cognition	Understanding how the prototype will impact stakeholders' cognitive effort, load, and their overall workload.	(181, 198)

IMPLEMENTATION		
Human factors approach	**Definition**	**Specific study**
Pre-implementation testing		
Understanding factors that may influence implementation	Understanding variables that may influence the integration of the AI-CDS into practice, including any barriers and facilitators.	(175, 202-204) *(205, 209, 213, 218, 219, 224, 231)
Implementation process		
Iterative integration of the AI-CDS	Where the implementation of the AI-CDS is broken down into stages.	(193)
Post-implementation testing		
Analysis of stakeholders' perceptions towards implementation	Gauging stakeholders' thoughts, feelings, and attitudes towards the implementation of AI-CDS.	(192) *(209)
Understanding impact of implementation	Understanding where the implementation of the AI-CDS may influence practice.	(196)

USE		
Human factors approach	**Definition**	**Specific study**
Testing in practice		
Usability testing of the AI-CDS	Where the AI-CDS is tested by users to assess if it is fit for purpose, including areas such as satisfaction, confidence, heuristics evaluation and workflow testing.	(176, 178, 180, 183, 186, 187, 193, 194, 197) *(208, 216, 223, 227-230, 234, 235)
Understanding stakeholders' perspectives		
Testing stakeholders' perceptions towards the AI-CDS	Understanding stakeholders' perceptions towards the AI-CDS, including their trust and the perceived worth of it in practice.	(177, 184, 190, 194, 199, 200) *(211, 220)
Understanding stakeholders' acceptance of the AI-CDS	Gauging whether the stakeholders welcome the use of AI-CDS in practice.	(172, 176, 184, 206) *(210)

*Studies included during second search (May 2021 – August 2023)
AI-CDS = artificial intelligence clinical decision support

4.4.5. Research techniques associated with the human factors approaches

In this review, research techniques refer to the data collection methods, models, frameworks or theories applied to conduct the human factors approach used in the studies. The research techniques associated with each approach were extracted and can be seen in Table 4.7. Overall, the most common technique used across all three stages of the AI-CDS life cycle was interviews, utilised across eight approaches and within 24 (37.5%) studies. In addition, three other techniques were used across all three life cycle stages: interviews, self-development questionnaires, and a version of the Unified Theory of Acceptance and Use of Technology Model. However, across two stages of the lifecycle (e.g. Design and Use), there were many commonalities, including ethnographical methods (Implementation and Use) and think aloud Methods (Design and Use). Within each lifecycle stage, there were also commonalities; for example, within Design, interviews were used during four approaches, and focus groups were used in two approaches. In studies that applied an approach under the Use stage, interviews and self-developed questionnaires were used across three approaches. Lastly, during the Implementation stage, self-developed questionnaires and ethnographic methods were utilised for two approaches.

In terms of the specific type of techniques, there was a mix of different data collection methods, including qualitative (interviews, observations, and think-aloud methods) and quantitative (self-developed questionnaire and computer system usability questionnaire) methods used. There were 12 models, theories or frameworks applied to underpin the approach or for analysis. There were five frameworks used, with the most common being the Non-adoption, Abandonment, Scale-up, Spread and Sustainability framework which was used for two approaches (*Understanding factors that may influence implementation* and *Usability testing of the AI-CDS*). Regarding models, four were applied, with the most common being the Technology Acceptance Model, which was used for two approaches (*Usability testing of the AI-CDS* and *Understanding stakeholders' acceptance of the AI-CDS*). Finally, three theories were used, with the most common being the Unified Theory of Acceptance and Use of Technology which was used across all three stage of the AI lifecycle (*Usability testing of prototype*, *Understanding factors that may influence implementation* and *Usability testing of the AI-CDS*).

Some individual studies used multiple techniques to explore different approaches. For example, Fico et al. (188), within one approach (*Usability testing of prototype*), used a combination of the Systems Usability Scale, an analytical hieratical process, and an Attrakdiff questionnaire. Further, Abdel-Raham et al., in two studies (180, 193), utilised process charts, task decomposition, task flow diagrams, and use case scenarios for the *Analysis of the Clinical workflow* approach. Lastly, Sandhu et al. (203) employed three techniques for an implementation approach (*Understanding factors that may influence implementation*): interviews, grounded theory, and the Situational Awareness Model. Finally, some studies used the same method for two different approaches; for example, Fink et al. (184) used the trust in medicine technology questionnaire for the *Testing stakeholders' perceptions towards the AI-CDS* and *Understanding stakeholders' acceptance of the AI-CDS* approaches.

Table 4.7: Associated techniques used for each approach (n=64)[2]

DESIGN The design and evaluation of the AI-CDS before it is implemented into practice.		
Human factors approach	**Technique used**	
Pre-development analysis		
Analysis of clinical workflow	Focus groups (173, 182, 198) Observations (173, 185) Process charts (180, 193) Task decomposition (180, 193) Task flow diagrams (180, 193) Use case scenarios (180, 193)	Interviews (181) *(221) Cognitive walkthrough *(221) Running lean Canvas (188) Self-developed questionnaire *(233) Vignettes *(221) Workshops (189)
Assessment of user needs	Analytic Hierarchic Process (188) Focus groups (188) Interviews (174) Observations (185)	Self-developed questionnaire (171) *(212) UFurT (User, Function, Representation and Task analyses) (174)
Evaluation of current technology and/or prototypes	Useability heuristic (195, 201) Interviews (195, 201) Self-developed questionnaire (179)	Think aloud methods (195) Walkthrough interview (201) Hierarchal Task Analysis (179)
Hazard and safety analysis	Bowtie analysis (207)	
Development of prototype		
Developed based on pre-development analysis	Interactive participatory design (185) Parallel design (191)	Storyboard simulation (189)
Prototype testing		
Usability testing of prototype	Interviews (185, 189, 195) *(214, 215, 225, 232) System Usability Scale (171, 188, 189, 191) *(232) Self-developed questionnaire *(212, 214, 222, 226) Think aloud methods (191, 195) *(214)	Attrakdiff questionnaire (188) Electronic Health Record Usability Scale (189) NASA Task Load Index (174) The Patient Experience with Treatment and Self-Management questionnaire (226) Participatory methods (198) Star-life life cycle (179)

	Cognitive walkthrough (191) *(225) Nielsen’s 10 usability heuristic (179, 191) After-Scenario Questionnaire (191) Analytic Hieratical Process (188)	Unified Theory of Acceptance and Use of Technology *(226) Use case (174)
Understanding prototypes impact on cognition	ELECTRE I method (181) NASA task load questionnaire (198)	Self-developed questionnaire (181)
IMPLEMENTATION Refers to the process and perceptions of integrating the technology into practice.		
Human factors approach	**Techniques used**	
Pre-implementation testing		
Understanding factors that may influence implementation	Interviews (203, 204) *(209, 213, 218, 219, 224) Self-developed questionnaire (175) *(219, 231) Consolidated Framework for Implementation Research *(213) Ethnographical methods (202) FITT framework *(224) Focus groups *(205) Grounded theory (203)	Observations (224) Non-adoption, Abandonment, Scale-up, Spread and Sustainability framework (204) Scapin and Bastien usability criteria *(218) Situational awareness model (203) Unified Theory of Acceptance and Use of Technology *(213) Vignettes *(213)
Implementation process		
Iterative integration of the AI-CDS	Agile development principles (193)	
Post-implementation testing		
Analysis of stakeholders’ perceptions towards implementation	Self-developed questionnaire (192)	
Understanding impact of implementation	Ethnographical methods (196)	
USE Refers to testing the utilisation of the technology once implemented into practice.		
Human factors approach	**Techniques used**	
Testing in practice		
Usability testing of the AI-CDS	Interviews (176) *(208, 227-229) Think aloud methods (178, 187, 193) Post-Study System Usability Questionnaire (180, 193) System Usability Scale *(228, 230) Self-developed questionnaire (176, 194) *(234, 235) Structured cognitive walkthrough (180, 193)	Near-live clinical simulation (178) Nielsen’s 10 usability heuristic (186) Non-adoption, Abandonment, Scale-up, Spread and Sustainability *(227) Observations (197) Schneiderman’s 8 golden rules (186) Technology Acceptance Model *(216)

	Unified Theory of Acceptance and Use of Technology (183) *(229) Computer System Usability Questionnaire (198) Health Information Technology Usability Evaluation Scale (197) NASA Task Load Index *(228)	Theoretical framework of acceptability *(228) Unified Theory of Acceptance and Use of Technology 2 *(210) User Action Framework with Neilson's severity rating of usability problems (187) Usefulness, satisfaction and ease of use questionnaire *(229)
Understanding stakeholders' perspectives		
Testing stakeholders' perceptions towards the AI-CDS	Self-developed questionnaire (177, 190, 199) Computer trust conceptual model *(220) Diffusion of innovation theory (177)	Grounded theory (200) Interviews (200) *(211) Trust in Medicine Technology questionnaire (184)
Understanding stakeholders' acceptance of the AI-CDS	Delphi methodology (172) Interviews (176) Self-developed questionnaire (176) Technology Acceptance Model (206)	Technology Acceptance Model 3 (172) Trust in Medicine Technology questionnaire (184)

[2]Presented by most common method, then in alphabetical order.
*Studies included during second search (May 2021- August 2023)
Techniques in italics are considered models, theories or frameworks
AI-CDS = artificial intelligence clinical decision support

4.5. Discussion

This systematic scoping review aimed to synthesise previous research on the applied human factors approaches for hospital AI-CDS. It is hoped that these results can provide evidence and cohesion for how the discipline of human factors can be applied to future AI technology development which has been previously stated as a challenge in this area of research (37, 125). Overall, there were 64 studies included in this review, with the majority published from 2019 onward (n=48, Figure 4.2). Most studies included HCP (n=60), such as doctors and nurses, 13 studies included non-HCP such as clinical lab personal and managerial staff and six studies included patients (Table 4.3). Studies were categorised into the type of AI-CDS they explored, which were either learning-based (n=35) or rules-based (n=29) AI (Table 4.4). Of the 64 studies included, 42 explored AI-CDS which was integrated into the EHR (Table 4.4) and only 20 mentioned 'human factors' or 'ergonomics' in their full text despite applying a human factors approach.

The results were structured to create an initial evidence base of how previous studies have applied human factors approaches during an AI-CDS's development lifecycle (Design, Implementation and Use) and the techniques used for each approach (e.g. data collection methods, frameworks, models or theories). Only two studies applied a human factors approach at more than one stage of the AI lifecycle: one study at all three stages (193) and one at two stages (180) (Table 4.5). There were 25 studies exploring the Design stage, utilising seven individual human factors approaches including Usability testing of prototype (n=16) and Assessment of user needs (n=10) (Table 4.6). Under the Implementation stage there were 14 studies, which contained four approaches, including Factors influencing implementation (n=11) and Understanding impact of AI-CDS (n=1) (Table 4.6). Finally, under the Use stage there was 28 studies that utilised three human factors approaches, including Usability testing of the AI-CDS (n=18) and Understanding stakeholders' acceptance of the AI-CDS (n=5) (Table 4.6). The techniques used (e.g. data collection methods, frameworks models or theories) for the human factor's approaches were also extracted. The most common research technique used were interviews, which was used for eight approaches, and in 24 different studies. Some studies used multiple qualitative and quantitative data collection methods for a single human factors approach and overall, there were a number of frameworks (n=5), models (n=4) and theories (n=3) used to underpin the approach or for data analysis (Table 4.7). The following discussion aims to provide a commentary on these results, including study characteristics and the human factors approaches and methods used for each stage of the AI-CDS lifecycle (Design, Implementation and Use). The strengths and limitations of the review will then be discussed, along with ideas for future research and finally, conclusions from the review will be drawn.

4.5.1. Study characteristics

Overall, there were 64 studies included in this review, which is in line with previous literature that suggests the use of human factors in healthcare is in its infancy, resulting in a limited number of published studies (123-125). Of those 64 studies, the majority were published after 2019, possibly due to the use of AI-CDS and knowledge of how the discipline of human factors can be applied increasing in recent years (Figure 4.2) (156, 157). This increase in studies after 2019 has been seen in other published reviews, for example, Mollmann et al's review focusing on the ethical concerns of applying AI in the digital health field (236). There was a variety of hospital staff involved in the studies found within the current review, with most studies involving clinicians (n=60), including doctors and nurses (Table 4.3). There was a small number of studies that included non-clinical staff (n=13). While this was expected, as clinicians will be the primary group interacting with the AI-CDS, the evidence does suggest that to take a systems perspective, there should be involvement from all those who will be affected by the technology, including non-clinical staff (154, 157). Based on the evidence, it may be that gaining an understanding of the clinical environment before utilising any human factors approaches would be beneficial, to allow for the inclusion of the relevant personnel. Furthermore, only a small proportion of studies in this review included patients (n=6), and only two involved them alongside healthcare professionals as participants (Table 4.3). AI-CDS may result in increased person-centred care and precision medicine, where the technology for example will guide a specific patient's treatment. This may result in increased patient involvement in care decision and therefore, the patients themselves may potentially benefit from being involved in the design of future AI technology. It may also be that the AI technology being developed would benefit from increased patient involvement, as the technology will be created alongside the user it will impact and therefore be increasingly human-centric (128, 154, 237).

Regarding the type of AI-CDS explored in the included studies, these were split into two categories: rules-based and learning-based (Table 4.4). Most studies focused on exploring learning-based AI-CDS (n=35), which relates to technology trained to make inferences from patient data. This finding was not unexpected, as the development of learning-based technology has increased in recent years. In contrast, practices for developing rules-based AI-CDS are more established (51, 238). Therefore, it is a positive that the number of studies focusing on learning-based AI-CDS has increased. Overall, the type of support provided by the AI-CDS described in the current review focused on diagnosis and general decision support, with the most common conditions or tasks supported by the technology being pulmonary embolism, sepsis, and cancer (Table 4.4). These findings are in line with previous research, which suggests that AI-CDS in its current state focuses more on diagnosis and is best developed for specific tasks or conditions, for example, the diagnosis of breast cancer or the use of autonomous infusion pumps in critical care (129, 239, 240). AI-CDS designed with a focused purpose may in theory, result in a more accurate output, potentially due to the types of rules created or the availability of training datasets (241). However, some studies showed that AI-CDS can be designed for multiple conditions and broader areas such as monitoring, communication, nursing, and patient safety. For example, Abraham et al. (225) created an AI-CDS that provided preoperative risk support for several conditions, such as acute kidney injury, delirium and pulmonary embolism, and the AI-CDS developed by Bersani et al (197) focused on increasing compliance with safety procedures. Therefore, as AI-CDS continues to develop, so will the technologies' abilities, which may result in new human factors applications and challenges. Therefore, the human factors approaches identified in this review may need to be updated or adapted in the future to consider changes in AI technology development.

The majority of studies (n=42, Table 4.4) stated that the AI-CDS had been integrated into the EHR, where it received patient-level data and was part of the hospital electronic platform. Previous research has suggested that when a technology is not integrated into the current clinical platforms, it will not be utilised effectively (238). Integration into electronic platforms may also be prevalent due to the high task load already seen in healthcare, and therefore users are less likely to use a separate system for a single task or condition (238). However, some studies did not integrate the AI-CDS (n= 22), therefore a separate, un-integrated AI-CDS may be perceived as more suitable for that specific setting. For example, in cases where the healthcare settings lacks organisational readiness and perhaps uses a multitude of platforms already that are not interoperable, meaning integration may not always be possible or be the most useable option (133, 242). Therefore, it may be that when developing an AI-CDS for the healthcare setting in general, efforts could be made to increase organisational readiness and understand whether users wish for the AI technology to be integrated or not to allow it to be utilised effectively.

4.5.2. Human factors approaches

This review provides evidence that human factors approaches can be applied at the three key stages (Design, Implementation and Use) of an AI-CDS's development (Table 4.5). This application is in line with previous research which recommends that future AI technology should take a systems perspective throughout its development (61) as has been seen previously for other healthcare technologies, including redesigning electronic systems (163). Interestingly, only one study applied human factors approaches at all three stages of the AI-CDS's lifecycle (76), and another applied them at both the Design and Use stage (63). Both studies were conducted by the same first author but focused on different AI-CDS technologies, with the most recent (2020) applying human factors across the three stages of the lifecycle. The focus on only one stage of the AI lifecycle may be due to publication bias, where individual published studies focus solely on a single stage of the AI lifecycle but is actually part of a larger project that consider all three stages. Therefore, more guidance on how human factors approaches can be applied at more than one stage of the AI-CDS lifecycle could be necessary and that when a single publication is part of a larger project this is made clear to the reader (123, 125, 135, 243).

4.5.3. Design

The initial stage of the AI-CDS's lifecycle is Design, where technology is developed and a prototype is evaluated before it is implemented into practice (Table 4.6). Overall, 25 studies applied a human factors approach to explore the Design stage of the AI-CDS lifecycle. Furthermore, the literature suggests that if the design of new technology is not considered from a human factors perspective, it may result in a system that is difficult to use and inadequate for the setting and user (244). Therefore, it is positive to see that a number of studies within the current review applied a human factors approach at the Design stage. Specifically, the results of this review suggest that the human factors approaches used at the Design stage can be completed in a linear sequence, beginning with pre-development analysis before a prototype is created, creating that prototype, and then evaluating the prototype before it is implemented into practice. This linear sequence for designing technology has previously been seen in the literature within “user-centred design,” which is derived from the discipline of human factors (141, 245). In a review by Holden et al, the human factors approaches that may be beneficial within the pharmacy setting were discussed, including user-centred design (85). The review suggested that user-centred design could incorporate several human factors approaches completed in a linear process, including understanding users and system needs through various methods, forming an interactive prototype for the targeted users which is then evaluated. The human factors approaches suggested in Holden et al’s review are similar to those found in the current review, however, interestingly, the terminology used for the individual approaches are different (85). This variation in terminology within the human factors discipline is common and can be shown in other studies focusing on design of healthcare technology. Another example of this varied terminology is found in Ghazali et al’s review focusing on user-centred design practices in healthcare, where they suggested that user-centred design incorporates three main phases: analysis, design, and implementation (“implementation” here refers to evaluating the proposed design) (246). Overall, despite the varied terminology used, previous literature alongside the results from the current review would suggest that the design phase is important for the development of AI-CDS and can be completed in a linear sequence, allowing for a systems perspective that considers the future users, setting and workflow it will be integrated into.

4.5.4. Implementation

The next stage of the lifecycle was Implementation (Table 4.6), which is defined as integrating the AI-CDS prototype into the clinical environment, starting from understanding any barriers to that integration and ending once it is used in routine practice. Overall, fewer studies (n=14) applied a human factors approach to explore Implementation, which was expected as previous research has suggested this stage of a technology’s development is often not considered (123, 134, 144, 146, 163). A scoping review by Gama et al. focused on the implementation frameworks currently used to integrate AI and suggested that implementing AI technology into the healthcare setting is a complex process involving many stakeholders, organisations and system regulators (146). This level of complexity may be the cause of the limited application of human factors at the implementation stage, despite previous research on decision support interventions suggesting that there needs to be a focus on integrating the technology effectively (244). However, there is evidence that research on implementation is starting to increase with the creation of frameworks to help this process, such as the Behaviour and Acceptance Framework which combines several implementation frameworks to support the integration of clinical decision support systems (247).

Despite the limited application, the human factors approaches found in the current review were in line with previous research that has focused on the implementation of other digital innovations (248, 249). For example, a previous study completed in 2015 by Lugtenberg et al focused on understanding the factors that may influence integration for a computerised decision support intervention in primary care (249). Lugtenberg et al, found that there was several barriers that affected the integration of the decision support tool and concluded that in the future the technology should be implemented alongside the end-user (249). Further studies have focused on understanding stakeholder perceptions of healthcare technology implementation, which is in line with an approach found in the current review. One study completed in Zimbabwe focused on health information technology and found that in some cases there was negative perceptions and resistance towards this type of technology, and concluded that there needs to be engagement with staff from early on in the development so they have ownership of the system (250). While the number of studies in the current review that applied a human factors approach at the Implementation stage is limited, it is positive to see that the way in which they were applied is in line with previous research focusing on healthcare technology.

4.5.5. Use

The final stage of the AI-CDS lifecycle was Use (n=28) (Table 4.6), which referred to evaluating the technology once it is integrated into clinical practice to understand its suitability. Previous research has suggested that once a technology has been used in practice, it should be continuously tested (251). This continuous testing should then create evidence for how the new technology impacts on both clinical staff and patients, showing the benefit (125, 252). This type of evaluation and monitoring can be important to make sure any challenges around applying AI technology are considered (244). The human factors approaches found at the Use stage were in line with previous literature focused on healthcare technology. In the current review the most common approach undertaken at this stage was usability testing, which can help understand whether the technology fits within the system once it has been used for a period of time (134, 253). The prevalence of usability testing found in the current review is positive as research has emphasised the importance of technology being usable in the clinical setting (85, 254). Previous research has applied usability testing to several healthcare technologies, including a web-based COVID-19 self-triage platform, where they determined that the participants found the website easy to use (255). A further study focused on the usability of a chatbot for mental health care using the System Usability Scale and found that the participants enjoyed using the chatbot and that it was easy to use but that there were areas that needed major improvements (256). A further human factors approach set out in the current review related to understanding user's perceptions of the technology, such as their attitudes and acceptance towards the AI-CDS. This type of testing has been seen previously for new technology in healthcare, for example for barcode scanning technology in community pharmacy where participants perceptions and acceptance of the technology was examined using the Technology Acceptance Model (145). Overall, the human factors approaches identified at the Use stage were expected and in line with previous literature, which may indicate that human factors approaches and techniques can be applied across different types of technologies and is flexible in nature (257).

4.5.6. Research techniques associated with human factors approaches

Overall, there was large number of research techniques associated with the human factors approaches at each stage of the AI-CDS's life cycle (Table 4.7). Some of these techniques were related strongly to the discipline of human factors, such as Hierarchal Task Analysis and the System Usability Scale. However, in some cases more generic qualitative and quantitative data collection methods were applied, such as interviews and questionnaires. This is in line with previous reviews which have suggested that many techniques can be applied to complete a human factors approach (123). For example, one review focusing on human factors use for the redesign of healthcare systems found that techniques often included observations, interviews, surveys and reviews of secondary data (163). These techniques, alongside others such as use-case scenarios, were also found in a further review on how human factors can be used for pharmacy research (85). Some studies within the current review applied several techniques for a single approach, such as Abdel-Raham et al. in 2016 and 2020 who applied four techniques to *Analyse the clinical workflow* (180, 193). Additionally, several techniques were used across multiple different approaches and life cycle stages, for example interviews were used across all three stages of the lifecycle, but also for several different approaches within a single stage. The use of a large number of techniques has been commended in previously published reviews as it can lead to a better understanding and analysis of the work system within which the technology or innovation will be used (123, 258).

Interestingly, the current review found 12 studies that used a model, theory or framework as part of the techniques, which is in line with a previous review completed by Weir et al, which looked at human factors use in the pharmacy dispensing process. Weir et al found that 31.3% (n=32) of the studies applied a model, theory or framework (123). While it is not necessary to apply a model or framework to a human factors approach, previous research has suggested that the application of these models, theories and/or frameworks allows for a full understanding of the technology or setting (248). For example, one review aimed to understand the factors that influence the integration of guideline-based clinical decision support. As part of their results, they mapped the extracted factors onto the Human, Organisation and Technology-fit model and concluded that future research should utilise sociotechnical frameworks and models to guide research around technology implementation (248). Furthermore, there are also benefits of applying models and frameworks to the Design or Use stages of the AI-CDS lifecycle, by allowing an understanding of the full sociotechnical work system that the innovation is being designed for or used in. Overall, it is positive to see that some included studies used a model, theory, or framework, due to the associated benefits. In the future, researchers and developers may consider whether applying a model, theory or framework would be of benefit to their human factors approach.

4.5.7. Strengths and limitations

To the authors' knowledge, this is the first review focusing on how human factors approaches have been applied to hospital AI-CDS. Therefore, it is hoped that this review will add to the evidence based on how human factors can be applied to the development of AI technology at all stages. Furthermore, while this review focuses specifically on AI-CDS within the hospital setting, there may be some transferability of the findings to other AI technology in other healthcare setting due to the flexibility and adaptability of the discipline (257).

The review was limited to the English language, which may have resulted in some studies not being included. However, it was found that 21 (32.8%) of the included studies came from countries where English is not a first language, indicating that there was international representation. The review was also limited to studies completed from 2013 onwards, which was based on previous reviews and evidence suggesting that this was the year when AI technology was first used within healthcare (49, 162). While some relevant studies may have been published before 2013, this review found that most studies were published after 2019 suggesting that expanding the time scale would not have resulted in the inclusion of many additional studies. Furthermore, some studies may not have been included as they were not published in a peer-reviewed journal or as a conference paper. However, limiting to peer-reviewed publications is typical for this type of review, as it allows for the assurance of scientific quality (163).

Previous research has suggested that a human factors approach can often be applied but that studies will not state specifically the terms 'human factors' or 'ergonomics' anywhere in the text (123-125). Therefore, this review included studies that used a human factors approach regardless of whether the authors included these terms. This allowed for the inclusion of relevant studies that adopted human factors approaches that otherwise would have been missed simply because it was not stated that they used a human factors approach. However, this resulted in the primary reviewer in some cases using their judgement when deciding if the study used a human factors approach. This practice is in line with previously completed reviews in this area, but may have resulted in studies being included that other researchers would believe did not utilise a human factors approach (123, 125). To help mitigate against this, several steps were taken. Firstly, another reviewer (AF) with knowledge of the discipline validated 20% of the screening and 100% of the extraction. Secondly, a framework of the technology's lifecycle was used, which contained three headings taken from the AI technologies lifecycle framework (Design, Implementation and Use) (Table 4.2). These three headings were each given an operational definition which helped distinguish between the different lifecycle stages. While the operational definitions were created for the study, they were created using previous literature and the researcher's own knowledge of the area; therefore, it is believed to have minimal impact on the accuracy of how the human factors approaches were identified from the literature and categorised under the three headings.

The human factors approaches used within each study were placed under the AI technologies lifecycle framework, which was taken from the literature (138, 144, 147). The human factors approaches under each heading were then inductively grouped by similarities, and each new approach was given a name, for example, ‘process mapping’ and ‘analysis of workflow’ which are considered similar. These human factors approaches were then further grouped to create meaningful categories. As this analysis was inductive, it may have resulted in groupings that were based on the researcher’s own judgement and knowledge. However, as the discipline of human factors has varied terminology, inductively grouping and naming the human factors approaches based on the included studies allowed the results to be independent of previous research and more inclusive.

4.5.8. Future directions and recommendations

The use of human factors for the development of AI technology in healthcare is in its infancy, resulting in only a limited number of studies emerging from this review (n=64). Therefore, it is recommended that the review is repeated in the future to allow for the inclusion of new publications. Further, the results in the current review suggest that more studies focus on task/condition-restricted technology. However, evidence suggests this will change with the future development of AI technology. Therefore, by repeating the current review it may also allow for an understanding of the changes in the type of AI-CDS used within healthcare.

The results of this review add to the growing evidence on how the discipline of human factors can be applied to AI technology development. Furthermore, categorising the human factors approaches used previously for AI-CDS may support future researchers and developers when deciding how the discipline of human factors could be applied to their work and increase awareness of the discipline of human factors in general. For example, the results show how human factors approaches can be used before developing a prototype (pre-development analysis), allowing the technologies development to consider the sociotechnical system from the outset. Further to this, it was found that the human factors approaches identified aligned with previous applications of human factors approaches (e.g. user-centred design processes). Understanding how the human factors approaches in this review are similar to other human factors-based frameworks or processes would be an interesting area for future work.

4.5.9. Conclusions

To the authors knowledge this is the first comprehensive scoping review of how human factors approaches have been applied to AI-CDS in the hospital setting. The results have been structured to provide an initial evidence base of how published studies have previously applied human factors approaches throughout the AI technology development lifecycle. Overall, the results found that there was a large number of human factors approaches and techniques that can be utilised across the AI lifecycle of Design, Implementation and Use. The majority of the human factor's approaches were under the headings of Design and Use, with less focusing on Implementation. Further to this, often studies focused on one stage of the AI lifecycle but may have applied multiple human factors approaches and techniques under that single stage. If the application of these human factors approaches is continued, then future AI technology may be increasingly human-centric in its development and effectively and safely utilised in practice. The results found in this study may be of benefit to AI developers and researchers to help them in deciding how human factors approaches can be applied to this new technology. It may also be useful for those working in healthcare, as it could highlight key approaches that could be conducted in their healthcare setting prior to an AI technology being integrated.

Chapter 5: Assessing the needs of clinicians working in adult critical care in Scotland for a sepsis fluid management Artificial Intelligence tool.

5.1. Introduction

Sepsis occurs as a result of an adverse response to an infection and can result in life-threatening organ dysfunction and, consequently, severe complications or death (64-66). When sepsis is diagnosed, or clinicians suspects the condition is present, treatment must start as soon as possible to prevent the infection from becoming severe or life-threatening (64). Treatment includes antibiotic and fluid administration, which are considered the cornerstones of sepsis management by international guidelines (64, 65). While it is universally accepted that fluids in sepsis treatment are necessary, the fluid volume that should be administered is widely debated. Previous research has suggested that giving a patient either insufficient or excessive fluids can harm their survival and recovery (70). Therefore, an individualised volume tailored to a patient's physiological characteristics is recommended (70). However, this individualised or precision medicine fluid decision may be difficult and time-consuming for clinicians to calculate, due to the vast amount of data required (See Chapter 1, Section 1.2.3 for further information on sepsis). Therefore, AI tools could provide a solution to support clinicians in calculating fluid volume for patients with sepsis and could do so by incorporating the current evidence-based clinical guidelines and the patient’s characteristics.

As previously discussed in Chapter 1 (Section 1.2), AI technology comprises innovations that aim to imitate human functionality by making decisions. For sepsis, AI-based diagnosis and treatment tools are evolving, with individual tools showing positive outcomes (36). For example, several AI tools have been developed to support the early diagnosis of sepsis, with the studies finding the decisions calculated by the technology to be comparable and perceived positively when compared with the clinician’s decision-making (71, 72). Further to diagnosis, AI tools used to indicate the most appropriate and optimal treatment for the individual sepsis patient have also produced positive results once developed (65, 74) (See Chapter 1, Section 1.2.3). However, despite evolving research showing encouraging outcomes, there remains a broad debate around whether AI technology, in reality, can improve how care is delivered or if the tools can actually provide the support proposed by developers (75-77, 79, 259). Furthermore, some evidence has suggested that the performance of the AI tool may not be as effective once implemented into the healthcare setting (259). This poor performance, once implemented, may result from developers focusing solely on the technological aspects of the AI tool and not on how the tool will interact with the work system it will be integrated within (61, 81, 82) (see Chapter 1, Section 1.2.4). Therefore, while AI tools can potentially transform the management of sepsis within the hospital setting, more focus needs to be given to how these tools could integrate and interact within work systems, which may be achieved by applying the discipline of human factors (See Chapter 2 for an overview of human factors).

A systematic scoping review completed as part of this PhD (Chapter 4) aimed to understand how human factors approaches had been previously applied to AI-based clinical decision support technology (AI-CDS) across the development lifecycle. Results found that several studies have previously applied a human factors approach to AI technology for sepsis, including for monitoring, risk calculation and diagnosis/decision support (171, 186, 190, 191, 203, 207). The human factors approaches applied to sepsis AI-CDS tools were used across several stages of the technology development lifecycle, including for understanding factors that may influence the implementation and usability testing of the AI tool once adopted into practice (186, 203). Several approaches were also grouped under the heading of 'pre-development analysis' within the Design stage of the lifecycle (Table 4.6, Section 4.4 in Chapter 4). 'Pre-development analysis' refers to the approaches conducted before a prototype has been developed, which aligns with previous research, which stipulates that for the full benefit of AI technology to be known, human factors approaches should be applied from the outset of development (239). Four approaches were grouped under 'pre-development analysis', including *analysis of clinical workflow, evaluation of current technology and/or prototypes, hazard and safety analysis*, and lastly, *assessment of user needs.*

Assessment of user needs refers to understanding what future stakeholders require to use the AI technology within their current work systems, such as any barriers to its use, overall attitudes, and any other perceptions. Two studies found in Chapter 4's review specifically focused on completing an assessment of user needs for a sepsis AI tool for risk calculation and general decision support. Firstly, Harte et al. (2019) created a rules-based AI tool for diagnosing sepsis in the neonatal intensive care unit, using participatory design (191). Their study focused on creating a prototype for the AI tool using the results from a user requirement analysis. Use cases of the AI tool were designed for the study to provide context and understand the needs of future users of that technology (191). Secondly, Ozel et al. (2013) aimed to develop algorithmic rules that supported sepsis and other conditions diagnosis in the intensive care unit and aligned with the needs and preferences of those working in the setting (171). These studies illustrate the importance of understanding users' needs to support the initial design of an AI-CDS tool, including those developed for sepsis. Therefore, this study aims to apply this assessment of user needs approach to the development of an artificial intelligence (AI) based clinical decision tool for sepsis fluid management (AI-SFM tool). This human factors approach should help to ensure that the new technology is person-centred in its development and created for those users and their work systems.

5.2. Aims and objectives

This study aimed to complete an assessment of user needs for an AI-SFM tool in Scottish adult critical care. The following objectives were used to complete the aim:

- Use a human factors model to approximate clinicians' current work system concerning sepsis fluid management.
- Use a human factors model to describe the user's needs within their current work system for the AI-SFM tool, including any suggestions, barriers, and changes.

5.3. Methods

The study was completed and reported in line with the Consolidated criteria for Reporting Qualitative research Checklist (see Appendix 3) (260).

5.3.1. Study design

A qualitative methodology was used for this study in the form of semi-structured interviews, which could be conducted in-person, over video conferencing software or on the phone, as per the participant's preference. Semi-structured interviews involve the researcher asking a participant a number of questions that are predetermined but open-ended with scope for additional questions or probing (168). The use of interview methods was considered relevant for the study as the aim was to understand and explore participants' needs for an AI-SFM tool (unlike surveys, questionnaires or focus group methods, which would not capture all the detail required such as an individual experience or perceptions) (261). This aligns with previous research exploring participants' attitudes, preferences and perceived barriers to the use of an AI tool for sepsis diagnosis (171). The Strathclyde Institute of Pharmacy and Biomedical Science’s Ethics Committee granted ethical approval for this study in October 2022.

5.3.2. Development of research materials

The research materials developed for this study were:

- Contextual vignette
- Semi-structured interview schedule
- Participant information sheet, consent form and demographic questionnaire
- Research advert.

5.3.2.1. Contextual vignette

Vignettes are short descriptions of a situation or topic, which can be used to give a participant context or prompt a response during data collection (262). For this study, a vignette was created to give the participants a conceptual understanding of how the AI-SFM tool could be applied in practice once developed. The AI-SFM tool is being developed by a PhD candidate (CM) who is part of the Human Centric AI in Healthcare doctoral school and is currently in the conceptual phase. The vignette was created in collaboration with the AI algorithm developer (CM) and was designed to be both informative and visually interesting to support engagement with the research.

To ensure content validity, the vignette was sent to a human factors expert and two clinicians with knowledge of sepsis fluid management in critical care. They were asked to complete the Content Validity Index (CVI), a standard approach for looking at the validity of qualitative methods, which has been shown in previous studies to be helpful when assessing vignettes (263). The CVI was comprised of three areas: Clarity, Relevance and Importance and was rated using a 4-point Likert scale. The CVI (see Table 5.1) was sent to the clinicians and human factors expert to complete once they had seen the vignette, and they were also given the opportunity to provide further comments. If the comments resulted in substantial changes to the vignette or the CVI scores were two or lower on average for each area, resulting in changes being made to the vignette, it would undergo a second round of validation with the same clinicians and human factors expert (263, 264). However, this second round was unnecessary as the comments resulted in no substantial changes, and the CVI scores were two or higher on average for each area. The finalised vignette can be seen in Appendix 4.

Table 5.1: Content Validity Index
Adapted from (263)

Dimension	Question example	Rating			
		1	**2**	**3**	**4**
Clarity	Is the content clear to understand?	Unclear	Somewhat clear	Clear	Very clear
Relevance	Is it relevant for clinical practice?	Not relevant	Somewhat relevant	Relevant	Very relevant
Importance	Is it important for clinical practice?	Not important	Somewhat important	Important	Very important

5.3.2.2. Semi-structured interview schedule

Previous research has suggested that a sociotechnical perspective should be taken when understanding user needs for AI-based technology (265). This allows for consideration of the whole work system into which the new technology will be implemented and increases acceptance and use within the healthcare setting (265). To ensure a sociotechnical perspective is taken, a model or theory can be used to underpin the approach, which previous research has highlighted as a benefit (248). Several models/theories were applied in studies found in Chapter 4's scoping review, including the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology. However, while this highlights that models/theories can be used to underpin human factors related approaches, these models are not appropriate for understanding user needs, as they focus on later stages of the AI lifecycle. Further to Chapter 4's scoping review, other models/theories have been developed that can help underpin a human factors approach, including the SEIPS model (see Chapter 2, Section 2.4.1).

While the SEIPS model would have provided a useful underpinning for the interview schedule, it does not consider AI technology as a separate component. As previously discussed in Chapter 2 (Section 2.4.1) AI technology has the potential to dramatically change how work is done, which may result in previously established models, such as SEIPS, not being appropriate. Therefore, it was felt that an extended version of the Work System Model would be better placed to highlight the interactions that AI technology may have with the rest of the work system where it would be integrated (155) (Figure 5.1).

The original Work System Model comprises five components: tools and technology; physical environment; person(s); organisation; and tasks (151). These components then interact to create the work system and should be considered in unison (151). In 2022, Salwei and Carayon extended this model and applied it to the context of healthcare AI technology (155). The model suggests that AI technology is only one component of the work system and that once the technology is implemented, it will impact all other components and change their interactions (155). Therefore, it is vital to consider the user needs across the whole work system, including the new AI technology, as a separate sixth component. Within this model, the solid arrows show an interaction between the original components. The dashed arrows show how the AI technology would interact with these components once integrated.

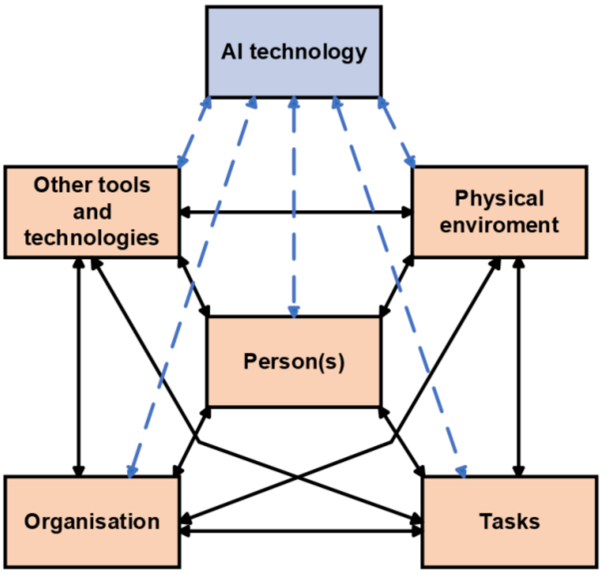

Figure 5.1: Extended version of the Work System Model
Model taken and reproduced from (155)

Evidence suggests that the current work system and the users' needs within that work system should be understood when developing a new AI for the healthcare setting. Therefore, two main areas were covered under each of the components (155):

1. Understand the users' current work system, which includes what they use or do in practice, as well as their perceptions of the AI technology.

2. Understand what participants would require within their current work system to use the AI-SFM tool, including any suggestions for, or barriers to, its use.

Where appropriate, the definitions of the six work system components and knowledge gained from a previously completed review (Chapter 4) were used to create prompts within the interview schedule to elicit further information from the participants. A description of the components used in the semi-structured interview schedule are presented in Table 5.2.

Table 5.2: Sections in the semi-structured interview
Adapted from (155)

Work system component	Description for study
AI technology	The AI technology that is being created for the healthcare setting.
Other tools and technology	Objects, hardware or software (other than the AI itself) that people use to do work or assist them in doing the work.
Person	Individual characteristics such as perceptions, skills and expertise.
Tasks	Specific actions taken and the attributes or characteristics of the tasks such as difficulty, complexity, variety etc.
Organisation	Structures that are external to a person such as time, space, resources, and activity.
Physical environment	The environment that the participants work in, such as the layout, workstation, and noise.

AI = artificial intelligence

The semi-structured interview schedule underwent face and content validity. Face validity aimed to establish whether the questions measure what they intended to and can be used as an initial assessment of content, language and grammar (266). This can be done before content validity by experts or lay people (266). Two colleagues within the Pharmacoepidemiology & Healthcare Research Group conducted face validity, where they were asked to read over the schedule and provide comments on any suggested changes. Once face validity was established, the interview schedule underwent content validity, which aimed to measure each item for relevance in the chosen setting (266). To ensure the interview schedule was valid for the setting, it was sent to two clinicians with knowledge of sepsis fluid management in critical care and one human factors expert with experience in taking a sociotechnical approach. They were asked to complete the CVI (see Table 5.1) for the overall schedule and comment on any potential changes (263). If the comments resulted in substantial changes or the CVI scores were two or lower on average for each area, it would undergo a second round of validation with the same clinicians and human factors expert (263, 264). However, this second round was unnecessary because the comments resulted in no substantial changes, and the average CVI scores were two or higher for each area. The final interview schedule can be seen in Appendix 5.

5.3.2.3. Participant information sheet, consent form and demographics questionnaire

These materials were created to provide information to participants and gain their consent before completing an interview. The University of Strathclyde's template participant information sheet and consent form were adapted for the current study. A short demographics questionnaire was created to gain information from the participants, including gender, job role, health board, how long they have been in their current position, how long they have worked for the NHS, how long they have worked in critical care, their experience of working with AI and how they heard about the study. These materials underwent face validity with supervisors (MB and ED) and another PhD candidate on the research team (AF) with qualitative experience and human factors research knowledge. The finalised materials can be seen in Appendix 6.

5.3.2.4. Recruitment advert

An advert was created for the study to recruit participants through social media platforms and over email. The University of Strathclyde guidelines on creating a recruitment advert were used to inform the development and colour selection (267). The advert underwent face validity with supervisors (MB and ED) and another PhD candidate on the research team (AF). The final research advert can be seen in Appendix 7.

5.3.3. Piloting

Piloting was completed to test and rehearse the interview schedule before data collection began. The researcher recruited two pilot participants (a pharmacist and an advanced critical care practitioner (ACCP) as these were target participant groups) who were led through the entire interview process to gauge whether the interview schedule provided the necessary data to meet the study aims (268). How long the interview took to complete was also recorded. After the pilot interviews, the pilot participants were asked to provide any feedback on the interview schedule. One of the interview transcripts was then sent to a supervisor (ED) to check for any other issues with the schedule and provide feedback on the researcher's interview skills. As no significant changes were required, the data from the pilot participants were used in the main sample.

5.3.4. Sample strategy

A convenience sampling approach was taken, where participants who volunteered to participate were included (269). The researcher strived to balance the number of participants across the variables of job role (physician, pharmacist, ACCP and nurse), location (health board) and the number of years qualified. These variables were chosen as there may be differences in user needs between the groups, and therefore, balanced representation was attempted. If the participant sample became unbalanced for a specific variable, the researcher purposely aimed to recruit from an underrepresented group to establish balance.

For qualitative research, the sample size is varied and determined by several factors related to the study itself (261). The initial analysis sample size for the current study was 10 participants (270). After 10 interviews, the researcher continued to interview until three subsequent consecutive interviews produced no new themes or concepts. This would indicate that data saturation had been reached, and recruitment would be stopped (270-272).

5.3.5. Recruitment strategy

Recruitment was completed through several concurrent strategies:

- The advert was posted on social media sites like Twitter© (now *X©)* and LinkedIn©, which included the researcher's email address. When the advert was posted on social media, relevant groups and individuals were tagged to the post and asked to retweet/forward the advert. The advert was re-posted once a week for five weeks and pinned to the top of the researcher's Twitter© (now *X©)* feed.
- Existing contacts of the researcher were contacted and asked to circulate the advert through various means, such as special interest groups, societies, and newsletters.
- Snowball sampling also took place, where participants were asked to forward the study advert to potential participants or groups, such as colleagues, etc.

Regardless of the recruitment route, if an individual showed interest in taking part, they were asked to contact the researcher by email as per the advert, who then sent a link to a survey created on a secure University-endorsed survey platform (Qualtrics©), which included a digital version of the participant information sheet, consent form and a short demographic questionnaire to be completed before the interview. Via email, a convenient time was chosen for the participant, and they were given the option to complete the interview in person, over video conferencing software or on the telephone.

5.3.6. Data collection

Once a date and time had been selected, the researcher sent out an electronic calendar invite, and the participant was informed that the vignette (used for contextual aid during the interview) would be sent the day before their interview. When the vignette was sent to the participants, they were asked to read it before the interview. At the same time, they were sent a reminder to read the participant information sheet, sign the consent form and complete the demographic questionnaire if they had not done so already. Before the interview, the researcher checked that these had been completed before proceeding. During the interview, the following steps were taken:

Step 1: The researcher reaffirmed that the participant was happy to participate, knowing they could stop the interview at any point and would remain anonymous throughout the study. They were then asked if they had any questions before the recording was started. After any questions were answered, the researcher moved on to step 2.

Step 2: Before the interview, the researcher checked that the participant had read the participant information sheet, signed the consent form, and completed the demographics questionnaire. If they had, audio and video recording started, and the researcher moved on to the next step. If they had not, the researcher asked if the participant could read the participant information sheet, provide verbal or written consent, and complete the demographics questionnaire during the interview. The recording was completed on two devices: MS Teams© and a dictaphone as a backup

Step 3: The participant was then asked if they had read through the vignette and understood how the AI technology could be used within the critical care context. If yes, the researcher moved on to the next step. If no, they were asked to read the vignette at that time (if in person, a paper copy would be provided; if using video conferencing software, it was shared on screen; if over the phone, then they were asked if they could read it currently on their screen or have it read to them if not). The researcher provided more clarity if they had questions about the vignette.

Step 4: The researcher completed the interview as per the schedule (Appendix 5) while making fieldnotes where appropriate. Prompts were used where appropriate to elicit further information. Once the interview was over, the researcher moved on to step 5.

Step 5: The researcher stopped audio and video recording, asked the participant if they had any further questions, and thanked them for participating. They were then asked if they would be interested in taking part in any future research and if they would be able to help snowball recruit.

5.3.7. Data management

Participants were pseudo-anonymised, so they were not identifiable, and all data was stored on a secure remote University server and accessed via a password-protected computer. During all interviews, dictaphones were used to record the interview. In addition, for those who completed the interview using video conferencing software, the interview was audio and video recorded using the facility available on the MS Teams© . However, only the audio was used for analysis. Once the interview had been completed, the audio/video recording (either from the dictaphone if in-person or from the online platform if done via videoconferencing) was saved immediately onto a password-protected University system (OneDrive©). The dictaphone was stored in a locked cabinet on university premises or kept in person until the audio was deleted. The audio was deleted from the dictaphone once transcribed and validated. Only the researcher, another PhD candidate (AF) and the supervisory team (MB and ED) were able to access the dictaphone and any raw data. The data underwent intelligent verbatim transcription. Where interviews had been completed on video conferencing software, the audio transcription automatically generated was used (MS Teams©), and then edited to ensure accuracy. To further ensure accuracy, a random 20% of the transcripts were validated by another PhD candidate on the research team (AF) (Table 5.3, Step 1).

5.3.8. Data Analysis

A modified framework approach was used to analyse and structure the data (273). The steps used for this approach can be seen in Table 5.3.

Table 5.3: Stages of the framework analysis used for study

Stage	Description
Stage 1: Transcription	The data underwent intelligent verbatim transcription. Where interviews had been completed on video conferencing software, the audio transcription that is automatically generated was used, and then edited to ensure accuracy. To further ensure accuracy, a random 20% of the transcripts was validated by another PhD candidate on the research team (AF).
Stage 2: Familiarisation	Familiarisation of the data was completed by listening to the audio-recordings and reading the transcripts and fieldnotes.
Stage 3: Initial coding	Initially 20% of the transcripts (n=4) were coded. The four transcripts chosen were considered conceptually rich and had representation from a consultant, trainee doctor, advanced critical care practitioner, and pharmacist. These four transcripts, using NVivo 2020©, were first deductively aligned with the high-level components from the extended Work System Model. NVivo 2020© is data analysis tool, which helps manage and analyse qualitative data (274). Data under each component then underwent inductive analysis to create codes within the components. Codes were created by going through the data systematically and identifying areas that were relevant to the research question. These codes were then given a name and a short description to help identify what the codes was discussing. This was done separately by the researcher and a supervisor (ED) to ensure accuracy.
Stage 4: Developing a framework	Once the four initial transcripts were coded, the researcher and a supervisor (ED) met to discuss and create the framework that would be applied to the remaining transcripts. Where there was disagreement, another PhD candidate on the research team (AF) was consulted.
Stage 5: Applying the framework	The framework was then applied to the remaining transcripts. If any changes or additions were made to the framework, a supervisor (ED) was informed to check that these were appropriate.
Stage 6: Interpreting the data	Once all transcripts were placed within the framework, the researcher completed a thematic analysis to understand the connections and patterns within each component's code. This was done by looking at the codes under each high-level component and developing headings for those that discuss similar topics and looking for relationships between those headings to find themes. The researcher discussed this process with a supervisor (ED), and another PhD candidate (AF) throughout. Analytical memos were used to help understand the data connections. The themes were then refined, checked to ensure consistency and given a distinct name.
Stage 7: Write up	The final framework was then written up using a variety of methods, including prose, tables and figures.

5.4. Results

5.4.1. Participant demographics

In total, 20 participants working within the Scottish adult critical care setting participated in an interview (see Table 5.4 for participant demographics) between December 2022 and February 2023 over Teams©. Most participants were female (n=11, 55.0%) and worked within the NHS Greater Glasgow and Clyde (GGC) health board (n=10, 50.0%). Eight of the 14 Scottish NHS regional health boards (57.1%) and one special health board (7.1%) were represented, with a mix of rural and urban locations. There was a good mix of job roles, with most participants being trainee doctors (n=6, 30.0%) followed by pharmacists (n=5, 25.0%), advanced critical care practitioners (ACCPs) (n=4, 20.0%), consultants (n=4, 20.0%) and a nurse (n=1, 5.0%). Participants had worked in the NHS for a median of 12.5 years (IQR 7.8, 20.3) and specifically in the adult critical care setting for nine years (IQR 4.3,15.3). Participants had been in their current role, for example, as a ACCP for a median of four years (IQR 3-6.7).

Table 5.4: Participant demographics (n=20)

		n (%)
Gender (n,%)	Female	11 (55.0%)
	Male	9 (45.0%)
Job role (n,%)	Trainee doctor	6 (30.0%)
	Pharmacist	5 (25.0%)
	Advanced critical care practitioner	4 (20.0%)
	Consultant	4 (20.0%)
	Nurse	1 (5.0%)
NHS Scotland Health board (n,%)	Greater Glasgow and Clyde	10 (50.0%)
	Lothian	2 (10.0%)
	Tayside	2 (10.0%)
	Ayrshire and Arran	1 (5.0%)
	Golden Jubilee National Hospital*	1 (5.0%)
	Fife	1 (5.0%)
	Forth Valley	1 (5.0%)
	Highland	1 (5.0%)
	Lanarkshire	1 (5.0%)
		Median (IQR)
Years' experience (Median, IQR)	Working in the NHS	12.5 (7.8, 20.3)
	Working in adult critical care	9 (4.3, 15.3)
	Working in current role (e.g., as a consultant)	4 (3, 6.7)

*Golden Jubilee National Hospital is a special health board
NHS = National Health Service, IQR = Interquartile range, N = number

5.4.2. Summary of all components and associated sub-themes

The interview data underwent a framework analysis under the six main headings of the extended Work System Model (See Table 5.2). The most prominent sub-themes will be discussed; a summary can be seen in Figure 5.2.

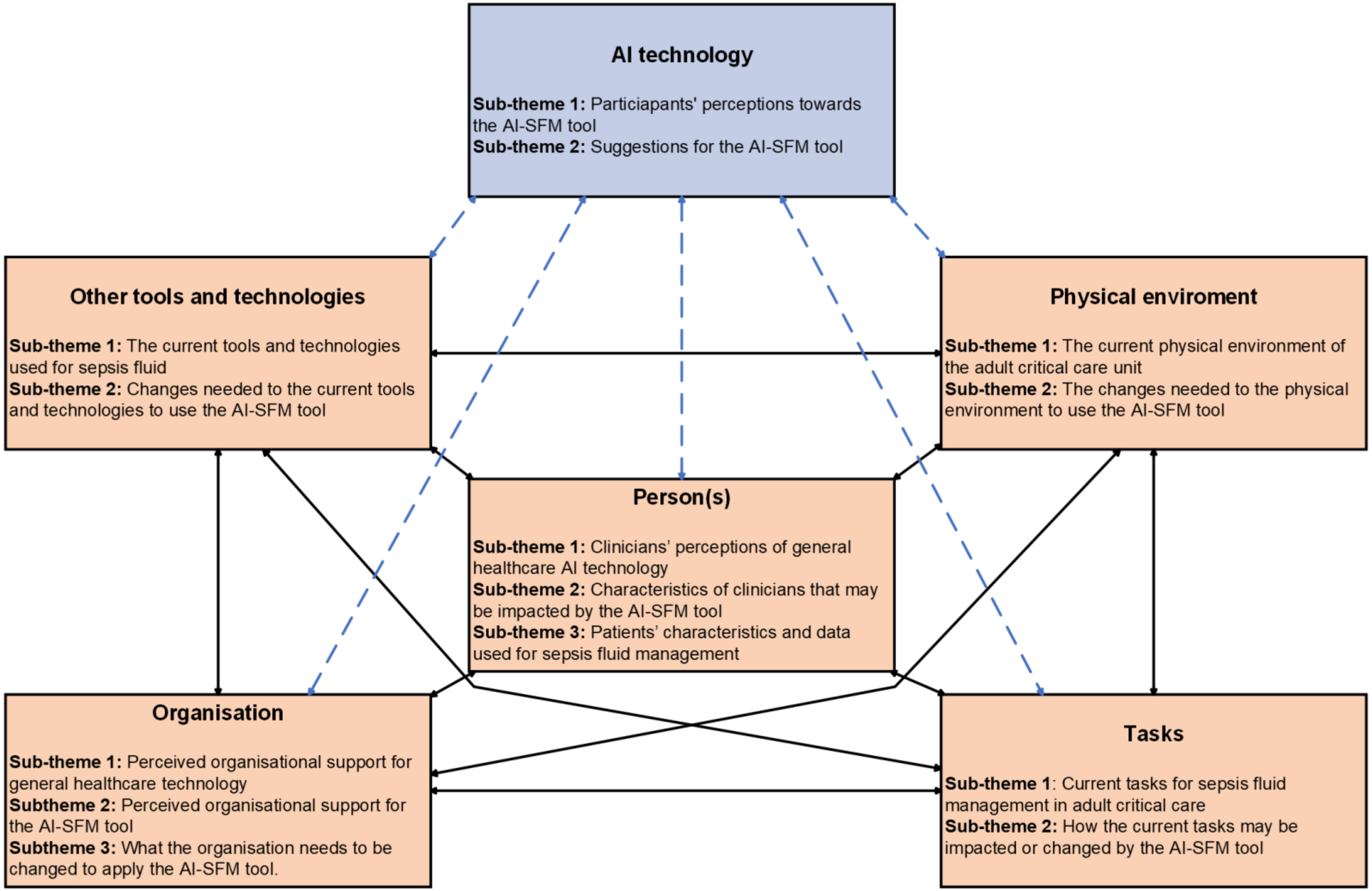

Figure 5.2: Sub-themes under each of the six components of the extended Work System Model
AI-SFM = artificial intelligence sepsis fluid management, AI= artificial intelligence

5.4.3. Component 1: Person(s)

This study defined person(s) as ‘individual characteristics such as perceptions, skills and expertise’. Three main sub-themes were found under the person(s) component: *clinician’s perceptions of general healthcare AI*; *characteristics of clinicians that may be impacted by the AI-SFM tool;* and *patient characteristics used for sepsis fluid management*. A summary of these sub-themes with descriptions can be seen in Table 5.5.

Table 5.5: Summary the of sub-themes under person(s)

Sub-theme	Description of sub-theme
Sub-theme 1: Clinicians’ perception of general healthcare AI technology	How clinicians perceive general healthcare AI, such as their attitude towards the technology, reasons for that attitude and any concerns with its use.
Sub-theme 2: Characteristics of clinicians that may be impacted by the AI-SFM tool	How clinicians may be impacted by the AI-SFM tool in terms of their personal characteristics, including their knowledge, confidence, and IT skills.
Sub-theme 3: Patients’ characteristics and data used for sepsis fluid management	The patient characteristics that are considered during sepsis fluid management decisions, including physiological data, results from patient examinations, demographics, and medical history.

AI= artificial intelligence, AI-SFM =artificial intelligence sepsis fluid management, IT= information technology

5.4.3.1. Sub-theme 1: Clinicians’ perceptions of general healthcare AI technology

i) Attitude toward general healthcare AI technology

Overall, clinicians had a positive attitude towards the use of healthcare AI technology, and it was seen as *“… a very exciting and interesting section of medicine”* (P18, trainee doctor) with a lot of potential within healthcare. Participants thought the use of AI would be beneficial in certain situations, including as a decision aid to guide treatments or to help increase consistency in practice. It was suggested that participants would be willing to use AI technology if given the opportunity, and one participant was surprised it was not already used:

“I'm slightly surprised, I suppose that it hasn't arrived in practice to some extent already, but I suspect it's just because the software is not quite where we need to be yet” (P4, pharmacist)

Participants also provided reasons for their positive attitudes (see Table 5.6), grouped under benefits related to the clinician and benefits related to the patient.

Table 5.6: Reason for participants positive attitude towards healthcare AI

Reason for positive attitude	Description	Illustrative quote
Benefits to clinicians		
Standardisation	Healthcare AI technology could increase standardisation across patient care.	*"I think it could also help to, with… making tasks more standardised." (P1, pharmacist)*
Time saving	Healthcare AI technology may save clinicians time in the future.	*"…potentially cut down a lot of time that we that might have been used to, you know, decipher something that the AI can do quite quickly" (P9, trainee doctor)*
Alleviate risk	If AI technology were used in the right way, then it would help alleviate risks in healthcare, such as errors.	*"I think that it's something that if used in the right way, could help to alleviate risk in the healthcare system" (P1, pharmacist)*
Removes cognitive burden	AI technology may help remove some cognitive burden in complex decision-making tasks.	*"So I'm in favour of anything that can sort of offload bits of the cognitive burden of complex decision making tasks" (P14, trainee doctor)*
Useful decision aid	AI technology would be able to support decision-making within healthcare.	*"…it's becoming more recognised that it can be useful to help with clinical decisions" (P19, trainee doctor)*
AI holds more information	AI technology would have the capacity to hold more information than humans.	*"The human brain does not have the capacity to hold as much information as AI could potentially use and process…" (P18, trainee doctor)*
Benefits to patients		
Patient care	AI technology could give clinicians more information on the patient.	*"I think any tool that helps you understand what's happening with your patient is a good thing" (P2, ACCP)*
Remote patients can be helped	AI technology may support patients who are remote or not near a particular hospital.	*"If you were looking at it from a patient who is remote and isn't near a particular hospital or a clinician or something, then yes, I could see the benefit of that." (P17, pharmacist)*
Individualises care	AI technology may provide patients with individualised decisions based on their data rather than population-level data.	*"…feeding objective information back in AI system and using machine learning or neural networks to try and better understand what that information means and apply to the next patient" (P15, consultant)*

AI= artificial intelligence, ACCP= advanced critical care practitioner

ii) *Concerns with healthcare AI technology*

Despite general positive attitudes, some participants had concerns about certain aspects of using general healthcare AI technology. One of the main concerns was that "*AI is not going to be able to examine a patient"* (P17, pharmacist) and, therefore, not take into account how the patient looks or feels. Another participant stated they were unsure how information gained from examining the patient would be fed into any new AI technology. A further concern was around safety, such as potential issues with the quality of information being inputted into the healthcare AI technology:

"…if you put nonsense into it, you're going to get nonsense out. And that potentially, if it's something that's driving decisions around patient care that is potentially quite harmful…" (P8, trainee doctor)

Other concerns related to the potential for clinicians to rely too heavily on technology for a decision resulting in them no longer using their clinical judgement and whether the AI technology would be trusted and accepted in practice: *"People will either believe it or not believe it and it won't necessarily be to do with how accurate it is"* (P3, consultant). Further concerns related to misconceptions around the use of AI technology within healthcare and that *"…medics are maybe thinking that it's gonna replace them or something…"* (P19, trainee doctor). Finally, there were concerns that *"…it might not be very accurate"* (P12, consultant) as AI technology may miss important data and have an incorrect output, which may impact how comfortable clinicians are in using it.

5.4.3.2. Sub-theme 2: Characteristics of clinicians that may be impacted by the AI-SFM tool

i) <u>Knowledge</u>

Most participants expressed little or no knowledge of AI technology. Participants suggested that increasing clinicians' knowledge of general AI technology and the tool itself would be required to use the AI-SFM tool in the future. It was indicated that it would be useful to have an increased understanding of how any new healthcare AI works, for example, how the AI gains the information and how it was developed:

"...it is important to have a basic understanding of how these decision tools are made… so that you can understand their limitations because no matter how clever they sound… it depends what you put into them." (P3, consultant)

Participants suggested this knowledge could be increased through several means, such as tailored education or training (see section 5.4.8.3) or the clinician increasing their knowledge individually. However, some participants felt that they would not need to increase their understanding of AI technology as the interface of any new tool should be easy to use without needing any extra knowledge.

ii) <u>Confidence</u>

Participants felt that they would be confident in using healthcare AI technology and the AI-SFM tool specifically. Some suggested this may be because their current job role was technologically focused, and they had personal experience using technology:

"I think that just now I'm okay, but that's probably because of personal experience of using technology outwith the workplace." (P1, pharmacist)

Furthermore, one participant stated they would have to be confident in a piece of technology in order to use it. However, some participants suggested that their confidence level would depend on how user-friendly and simple the AI-SFM tool was, as this would: "…*help with confidence, would help with usability and it would make people more likely to use it."* (P6, ACCP). Participants also felt that even if they were not currently confident, being given the correct training before using the AI-SFM tool would allow them to feel confident in using the tool (see section 6.4.8.3).

iii) <u>IT skills</u>

A large number of participants indicated that they currently had good IT skills, which would allow them to use the AI-SFM tool easily. It was also suggested by a number of participants that some other staff working within adult critical care currently struggle with the technology used, with one participant stating that in general:

"We need more IT literacy and that might just mean a clinician with a bit of an interest in it, or it might mean easy access to someone from an IT standpoint, who could help us troubleshoot things" (P8, trainee doctor).

However, some participants believed that they would need to improve their IT skills if the AI-SFM tool was complex and that their current IT skills would only be sufficient if the AI-SFM tool was: *"… really simple and accessible and easy to use…if it's none of those things then people aren't going to use it."* (P12, consultant).

5.4.3.3. Sub-theme 3: Patients' characteristics and data required for sepsis fluid management

Participants suggested several characteristics of patients with sepsis, such as their signs and symptoms, demographics, and medical history, that healthcare professionals consider when deciding how much fluid patients should be provided within adult critical care. A summary of the patient characteristics can be seen in Table 5.7.

Table 5.7: Summary of the patient characteristics considered during sepsis fluid management decisions reported by participants

Characteristic	Description
Patient demographics	Such as age, weight, gender and comorbidities.
Medical history	Clinical history, such as previous conditions, may impact how they handle fluids (e.g. cardiac history), previous and current length of stay, and their patient journey.
Patient's signs and symptoms	Observations of patient charts, how the patient looks and feels (e.g. do they look fluid-depleted, are they cool to the touch and their colouring), and physical assessments such as passive leg raises.
Physiological data	Data taken from monitors or lab results.

Participants felt that patient demographics and medical history allow for a good understanding of the patient as a whole, and are generally easily accessible in adult critical care, for example, on the computer platform within the care unit:

"Patient demographics so their age, weight so on in ICU we've got a computer system which will have all that information in so it's usually quite easy to find a weight… The history, the computer system we use is also really good for that because again, you can see their past medical history as well" (P18, trainee doctor)

One of the key aspects of patient examination discussed by participants was the look and feel of the patient, such as how cool they are to the touch, their colouring and whether they looked 'dry'. Participants were clear that the look and feel of a patient was an important factor when deciding on fluids for patients with sepsis. These examinations are often done at the patient's bedside. Some participants reported that when teaching medical students, they encourage them to *"shake {the patient's} hands because you get a huge amount of information"* (P6, ACCP). Participants also provided the key physiological data that they used during sepsis fluid management decisions, which can be seen in Figure 5.3 as a word cloud, with the most pertinent data in the largest fonts.

Figure 5.3: The physiological data used for sepsis fluid management

Blood pressure was cited as being used by most participants (n=16, 80.0%), followed by heart rate (n=11, 55.0%) and urine output (n=9, 45.0%). Several physiological data points were only mentioned by one participant each, which included: other medicines patients were on and the source of the infection.

5.4.4. Component 2: AI technology

AI technology for this study was defined as the tool that is being created for the hospital setting, which was the sepsis fluid management AI tool for adult critical care patients (AI-SFM tool). Two main sub-themes were found, *Clinicians' perception of AI-SFM tool* and *suggestions for the AI-SFM tool.* A summary and description of these sub-themes can be seen in Table 5.8.

Table 5.8: Summary of sub-themes under AI technology

Sub-theme	Description
Sub-theme 1: Participants' perception towards the AI-SFM tool	How clinicians perceive the AI-SFM tool, such as their attitudes, its perceived usefulness, reasons for that usefulness and any concerns.
Sub-theme 2: Suggestions for the AI-SFM tool	Participants provided suggestions for the AI-SFM tools design, such as the development and the output.

AI-SFM =artificial intelligence sepsis fluid management

5.4.4.1. Participants' perception towards the AI-SFM tool

i) <u>Attitude and the perceived usefulness of AI-SFM tool</u>

Participants generally had a positive attitude towards the AI-SFM tool: *"I found it very interesting…I think that it's something I could see being used within critical care"* (P1 pharmacist). However, some suggested that while the concept showed promise, they would want to know more about the AI-SFM tool before forming a final opinion. Despite the generally positive attitudes, participants expressed mixed feelings about the AI-SFM tool's usefulness, with the majority saying I they would find it useful. However, some participants suggested that it might not be useful for them due to their length of time in the role meaning they would not need the support from the AI-SFM tool. Other participants, specifically pharmacists felt that they were less involved with sepsis fluid management currently, and therefore the AI-SFM tool would be less useful but that *"… potentially in the future it could be useful"* (P20, pharmacist). Furthermore, some felt that this AI-SFM tool would be useful for newer staff as these colleagues often have less experience with fluid volume decisions. There was a mixed response when participants were asked whether the AI-SFM tool would be useful for their patients, with most feeling that it would be:

"… very useful, so we are always cautious in patients that have got like say cardiac issues or renal failure, liver failure. So I do think it would be helpful in those patients where you think. Is 250mls a bit too much?" (P2, ACCP)

Participants also provided reasons for the potential usefulness of the AI-SFM tool, which were grouped under benefits related to the clinician, the patient and sepsis management and can be seen in Table 5.9.

Table 5.9: Participants perceived reasons for the usefulness of the AI-SFM tool

Reason for usefulness	Description	Illustrative quote
Benefits to clinicians		
Increases confidence	It was felt that the AI-SFM tool would help increase clinicians' confidence in decision-making.	"…It'll give you that bit more confidence that you know when you're a few hours in and you've been, you've given this person, you know, you're now starting to doubt yourself" (P10, consultant)
Reduce workload and cognitive burden	The AI-SFM tool may provide support, allowing for reduced workload and cognitive burden.	"…but if it was something that helped to kind of cognitively offload busy doctors, then great." (P14, trainee doctor)
Provide clinicians with more information	The AI-SFM tool could provide the clinicians with more information on the patient to help with fluid decisions.	"So, I think just having you a bit of extra information would be helpful because we do tend to use a standard 250mls as our fluid bolus and then we see what happens…" (P2, ACCP)
Increase ease of task	The AI-SFM tool may make the task of fluid decisions easier.	"Yeah, very supportive in our unit kind of thing if it makes it easier, you know definitely." (P7, ACCP)
Time saving	The AI-SFM tool may have the ability to save the clinician's time.	"… if you've got something that's a bit more easy to use, I think if anything, it would potentially save time." (P1, pharmacist)
A useful learning tool	The AI-SFM tool could be used as a learning tool for clinicians.	"Sort of self-learning going on with this thing because this person is now realising what data this AI is needing in order to make the kind of decision" (P10, consultant)
Provide a back-up	The AI-SFM tool could be helpful as a backup for decision-making.	"…having something that's going to be like that, that's OK like that's a good idea. You should do that rather than just guessing" (P11, ACCP)
Benefits to patients		
Improve patient care	The AI-SFM tool could potentially improve patients' care within adult critical care.	"...anything that can sort of manage risk and improve patient care I think would be great." (P1, pharmacist)
Increase patient safety	The AI-SFM tool may increase the safety of patients.	"…overall for patient safety…it would be beneficial… to use this tool" (P18, trainee doctor)
Individualise patient care	The AI-SFM tool would be able to provide the patient with an individualised amount of fluid based on their characteristics.	"…it would be good to have a kind of patient individualized guided assessment from the AI and then we could agree or disagree…" (P2, ACCP)
Minimise intervention on patients	The AI-SFM tool has the potential to reduce the intervention on patients.	"…minimise intervention with the patient it would be good for the patient as well" (P5, trainee doctor)

Reason for usefulness	Description	Illustrative quote
Benefit for sepsis management		
Helps with complexity	The AI-SFM tool has the potential to reduce some of the complexity surrounding fluid volume decisions.	"…fluid management I think is an awful lot more complex than we used to think … having something that can take into account massive datasets, huge variability {would be useful}" (P8, trainee doctor)
Removes variation	The AI-SFM tool could standardise practice and remove the variation within the setting.	"…there's variation in practise of what people give. I think if there was a tool there to help with a certain number to give that would be very useful" (P19, trainee doctor)
Alleviates risk	The AI-SFM tool may be able to alleviate risks, such as fluid errors.	"I think that anything that minimises the risk of error within the healthcare system is massively useful, especially right now in a system that is very pressurised from the COVID backlog" (P1, pharmacist)
Cost benefit	There may be a cost benefit seen when using the AI-SFM tool.	"…could be a cost benefit at which the AI could also help with." (P7, ACCP)

AI-SFM =artificial intelligence sepsis fluid management, ACCP= advanced critical care practitioner *ii) Concerns with the AI-SFM tool*

Participants raised some concerns about using the AI-SFM tools in adult critical care. The most discussed concerns can be seen in Figure 5.4, which include the quality of the type of data inputted; the complexity of sepsis; the potential for conflict; and the potential lack of impact on clinical practice.

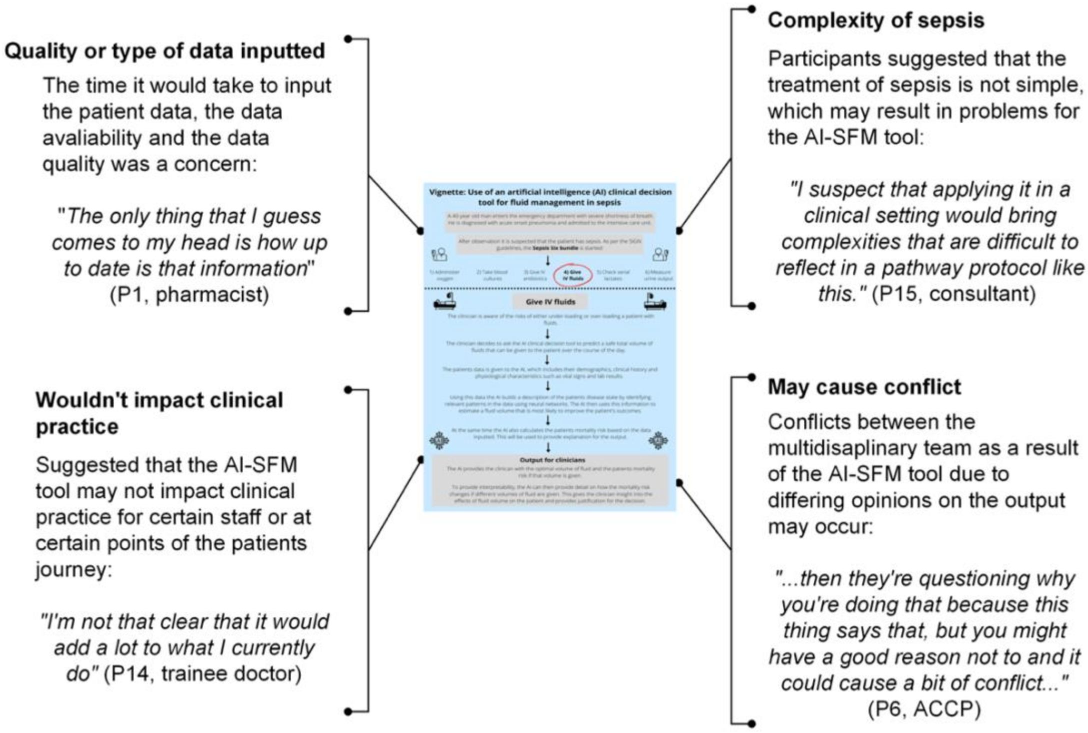

Figure 5.4: Participant's concerns around the use of the AI-SFM tool
AI-SFM =artificial intelligence sepsis fluid management, ACCP= advanced critical care practitioner

Less frequency discussed concerns raised by participants include the accuracy of the AI-SFM tool's output and over-reliance on the tool for decision-making.

5.4.4.2. Suggestions for the AI-SFM tool

Participants were asked what they felt should be changed about the AI-SFM tool provided in the vignette to be able to use the technology in adult critical care. The suggestions for the AI-SFM tool made by participants can be seen in Figure 5.5.

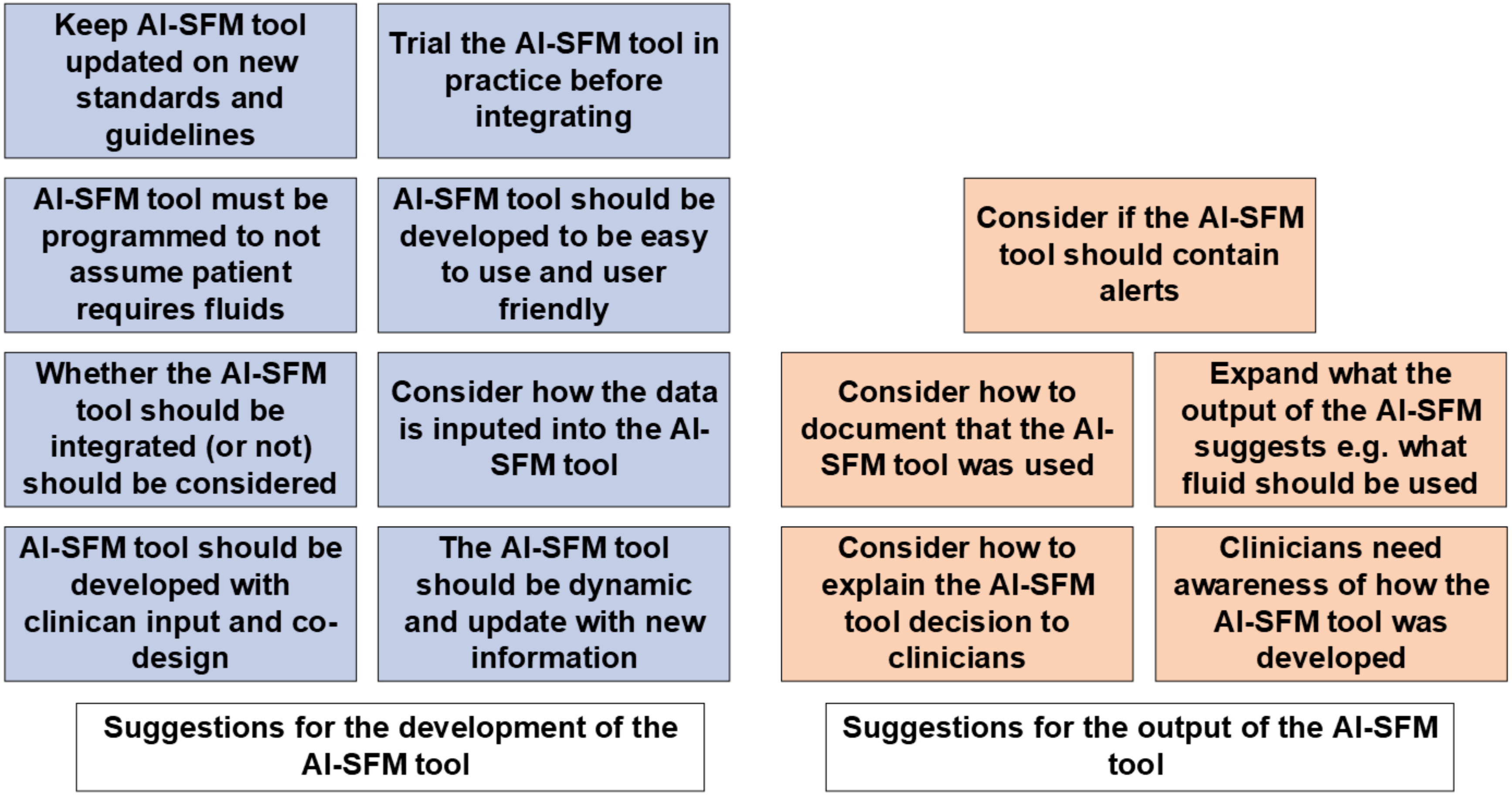

Figure 5.5: Participant's suggestions for the AI-SFM tool
AI-SFM = artificial intelligence sepsis fluid management

i) *Suggestions for the development of the AI-SFM tool*

One of the key suggestions for developing the AI-SFM tool was whether it should be integrated into the current computer platforms or separated into an app or web page. Most participants indicated that they would prefer the AI-SFM tool to be integrated into their current computer platforms, as it may make it easier and more time-efficient to view all patient data together.

> *"With sepsis in particular…you have to be managing in a timely manner so integrated I always find works better in terms of entry to the system, but also being able to interpret that information in line with the other things that you're doing at the same time"* (P1, pharmacist)

Some suggested that having the AI-SFM tool in a separate app would also be suitable, as participants stated they currently use apps in adult critical care. Participants suggested, however, that this may cause issues with the AI-SFM tool's usability, so they suggested that the tool would be best placed within the current apps used within adult critical care, as opposed to a separate app: *"we do have a critical care app… it would be good to have it in our app"* (P2, ACCP). Furthermore, participants indicated that they would not mind if the AI-SFM tool was integrated or independent, with some stating that a hybrid platform would be best as they could pull information across but also have it *"…available on your handheld device…"* (P6, ACCP).

Another area of importance discussed by participants was whether the patient data inputted into the AI-SFM tool should be automatically pulled from an electronic health record (EHR) or manually inputted by the clinician. In general, the participants felt that either the AI-SFM tool should automatically fill in the data from the EHR or have a hybrid platform which allows for automatically pulled data to be manually changed and added to:

> *"…interrogate where that data as come from… and see, right okay, actually that's not representative, that's not what the patients actual blood pressure was for instance I think is important"* (P8, trainee doctor)

Despite most participants suggesting an automatic or hybrid data input platform, some indicated that a fully manual platform would also work for the AI-SFM tool, as they currently have this for other electronic calculators. Finally, participants also indicated what data should be inputted into the AI-SFM tool to arrive at the correct fluid decision.

There were two main types of data that participants felt would be useful to include in the AI-SFM tool: record-based, which refers to patient information that can be accessed over paper or electronic-based health records and real-time data, which is patient information that will be collected at the point of using the AI-SFM tool. A summary of these two main data types can be seen in Figure 5.6.

Record-based data	Real-time data
• Medical history • Patients other medication • The volume of fluid the patient has already received e.g. in surgery or accident and emergency	• How the patient looks and feels • Patient monitoring • Fluid phase patient is in, e.g. resuscitation, replacement or maintenance

Figure 5.6: Participant-reported patient data that should be inputted into AI-SFM tool

ii) *<u>Suggestions for the output generated by the AI-SFM tool</u>*

Explainability was one of the key areas where participants provided suggestions for the AI-SFM tools output. Explainability refers to the way the AI-SFM tool shows the clinicians how and why it came to that fluid volume decision. Many participants suggest that the level of explanation provided by the AI-SFM tool in the contextual vignette was suitable. However, some participants felt they would need further explanation. Suggestions provided by the participants on how to increase the explainability included being able to interrogate the AI-SFM tool to understand how it arrives at that decision, adding a link to where the clinician could access more information, and providing a calculation for how much fluid had already been given to the patient alongside the new fluid volume. Participants also indicated the type of information they would want to see from the AI-SFM tools output, as seen in Table 5.10.

Table 5.10: Suggested types of output from the AI-SFM tool suggested by participants

Type of information	Description	Illustrative quote
Patient trends	Provide an output showing the patient's data trends, such as glucose and salt levels.	"…maybe it would look at the trends as well. Maybe you would keep putting in what's happening to the patient when it would constantly work it out." (P20, pharmacist)
Fluid volume range	Show the higher and lower range of fluid volume that the patient could be given.	"So that would be quite helpful if there was a range of. So if you went for that lower volume, that would be this. If you went for this volume with that and if you went for a bigger volume, it would be that" (P16, pharmacist)
Mortality if volume not given	State the mortality risk if clinicians do not provide the suggested fluid volume.	"…if they're giving risks of mortality with certain amounts of fluid, I wonder equally would that be good to balance with like risk of mortality if you don't give them any fluid" (P18, trainee doctor)
Factors used to make decision	Show the patient factors that resulted in the suggested decision.	"Do you need to give fluid because you're intravascularly dry and then you're gonna give all this fluid and you've still got a low albumin…So suppose you are going to have to look at your biochemical markers." (P17, pharmacist)
Fluid phase	Provide information on the patient's fluid phase (e.g., resuscitation, maintenance, or replacement.)	"You know, so is it so? Is it things like, are you are you in their resuscitation phase, are you in your maintenance phase? So what phase are you in your fluid replacement?" (P17, pharmacist)

Participants also suggested that there may be issues with using mortality as a means of explanation within the AI-SFM tool due to possible misinterpretation as mortality is not commonly used to make decisions:

"Giving someone a mortality… I sometimes worry about that…and then giving them sort of ideas of mortality based on, well, if you give a little bit less or a little bit more, this is how it will change…" (P10, consultant)

However, some participants did suggest that a mortality calculation could be useful. Further to explainability, when asked if they would want alerts from the AI-SFM tool, there was a mixed response from participants, with most suggesting they would want alerts for certain aspects such as reaching a threshold for fluids or *"that this patient will be dry in the next one or two hour"* (P5, trainee doctor). However, some participants stated that they would not want any alerts from the AI-SFM tool as this may result in alert fatigue. Finally, participants suggested expanding the AI-SFM tool to include other aspects of sepsis management by creating a patient management plan that includes the fluid type, whether the patient would need antibiotics alongside fluids, or their target blood pressure.

5.4.5. Component 3: Other tools and technologies

Other tools and technologies for this study were defined as objects or techniques (other than the AI itself) that people use for work or assist them in doing that work. Two main sub-themes were found: *The current tools and technologies used for sepsis fluid management;* and *changes needed to the current tools and technologies to use the AI-SFM tool.* A summary and description of these sub-themes can be seen in Table 5.11.

Table 5.11: Summary of other tools and technologies' sub-theme

Sub-theme	Description
Sub-theme 1: The current tools and technologies used for sepsis fluid	What participants reported as the current tools and technologies they use for sepsis fluid management. This also includes any concerns or challenges they experience with these tools and technologies.
Sub-theme 2: Changes needed to the current tools and technologies to use the AI-SFM tool	When participants have suggested any changes needed to the current tools and technologies to be able to use the AI-SFM tool.

AI-SFM =artificial intelligence sepsis fluid management

5.4.5.1. The current tools and technologies used for sepsis fluid management

i) *<u>What are the current tools and technologies used for sepsis fluid management</u>*

The current tools and technologies used by participants during sepsis fluid management can be seen in Figure 5.7.

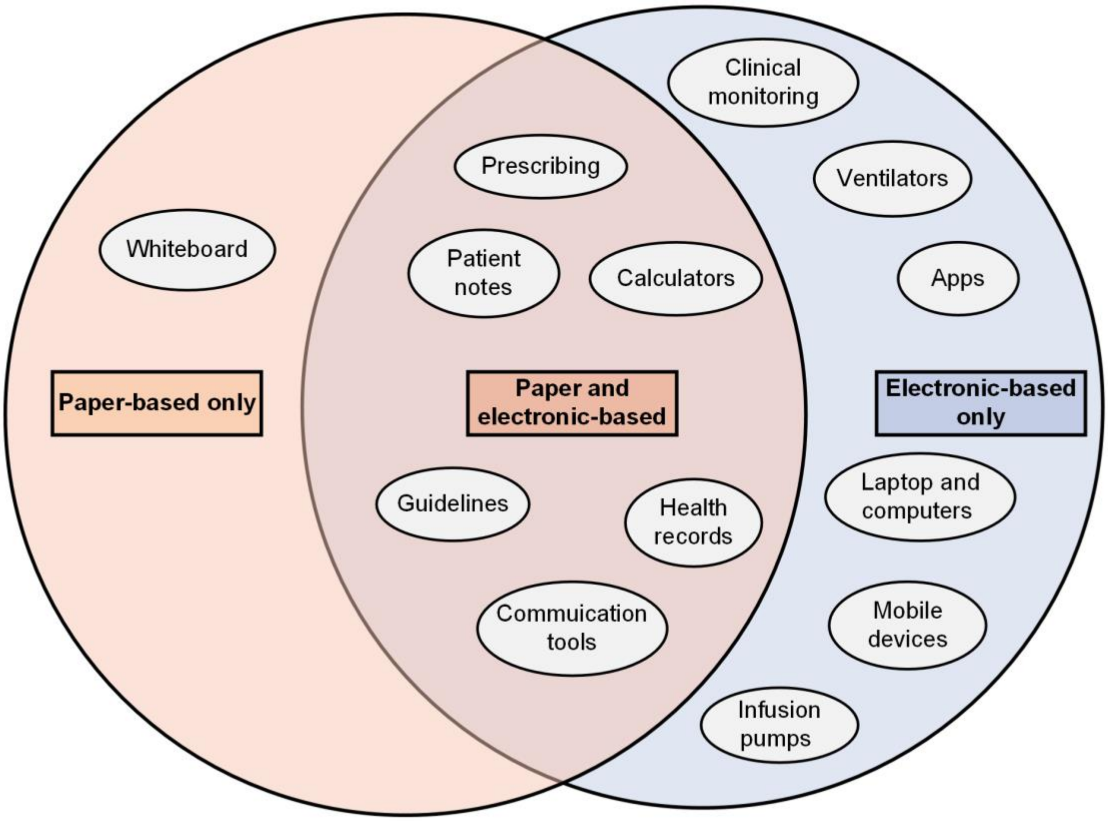

Figure 5.7: Tools and technologies participants indicated are used for sepsis fluid management

Participants suggested prescribing for sepsis fluid management in adult critical care could be done using paper charts or electronic platforms such as Careview© or Clinical Information System (CIS) ©. However, these electronic prescribing platforms were often only used within adult critical care, so for clinicians to find previous patient information, they would have to link with other platforms such as Hospital Electronic Prescribing and Medicine Administration (HEPMA) ©. Similarly, patient notes could be completed using paper charts at the end of the patient bed or on electronic platforms such as Careview©. Whiteboards were the only purely paper-based tool suggested by participants and were indicated to be used to show the patient's fluid goals while in adult critical care.

Participants indicated that the tools and technologies were linked in some cases but could also be accessed separately and were therefore kept separate. For example, if an adult critical care unit used an electronic platform, these could be accessed using computers and laptops, or via guidelines, or calculators. However, guidelines and calculators could also be accessed through apps and paper printouts. Another example was communication tools which included technology such as pagers and MS Teams©, which could be accessed via apps or mobile devices.

Specifically, at the bedside, some participants described their equipment, which included computers or laptops, infusion pumps, ventilators, and monitoring equipment. The tools and technologies used for sepsis fluid management in adult critical care often differed depending on the health board or hospital where the participant worked. Participants stated that some adult critical care units were fully electronic, with the fluids prescribed and tracked on a computer-based platform. However, some participants said the adult critical care unit was fully paper-based, for example, using a large chart at the end of the patient's bed to track and record fluids. There was some indication that these paper-based process would be changing soon or that they were aiming for an electronic platform in the future:

"so the hospital records at the moment are paper, but that's what we're aiming for is to get everything electronic…" (P20, pharmacist)

Some participants stated they use a hybrid system for fluid management, where it is only the fluid management of sepsis is completed on paper:

"…we don't prescribe fluids on the online system, and we have certain items that we still prescribe out with our electronic systems." (P1, pharmacist)

ii) *<u>Challenges of the current tools and technologies</u>*

Participants discussed several challenges with the current tools and technologies used for sepsis fluid management in adult critical care. One challenge included using a mix of electronic and paper-based tools and technologies. This may be due to the adult critical care being electronic-based, with the rest of the hospital using a mix of paper and electronic:

"…there's some areas that are like… one third care view, a third the electronic online system, HEPMA and then the other third is paper charts." (P13, nurse)

This can also be the result of different health boards having paper-based hospitals, which results in other adult critical care units not having access to a patient's notes or history. This mix of paper and electronic tools and technologies can result in issues, which include the time it takes to find patient information and information management:

"…with paper, obviously you have to transcribe that all by hand, which is time consuming, prone to errors, wasteful and in the case of some of my colleagues, occasionally illegible." (P8, trainee doctor)

Another challenge was the varied use of electronic tools and technologies used in adult critical care. Participants suggested that many computer platforms are used in Scottish healthcare, and often, they do not interface with each other, which is "*all very confusing"* (P18, trainee doctor) and does not allow for the easy transfer of patient information. Participants stated that they would like more standardised technology: *"…{if} we were all in one system throughout the whole hospital, that would be much better."* (P16, pharmacist). Participants also reported that computers within the units are often outdated and using them is time-consuming and difficult.

5.4.5.2. Changes needed to the tools and technologies to use the AI-SFM tool

Participants provided suggestions for the changes needed to their current tools and technologies to be able to use the AI-SFM tool. These changes included hospital infrastructure, the adaptation of the current tools and technologies and additional tools and technology needed. A summary of the three areas can be seen in Table 5.12.

Table 5.12: Changes needed to current tools and technology to use the AI-SFM tool reported by participants

Suggested area of change	Description	Illustrative quote
Hospital IT infrastructure	To use the AI-SFM tool, hospitals would need to have electronic platforms. Alongside this, the participants suggested the IT platforms already used would need to be upgraded, as currently, they are slow, or the internet connection does not work on specific devices. These changes would be less pertinent if the AI-SFM tool were an app.	*"...we would need to move to a fully electronic system across the hospital, if not the country..."* (P3, consultant).
Adapt current tools and technology	Participants indicated that the current tools and technologies would need to be adapted to use the AI-SFM tool (e.g. include a new section on the recent patient notes) and to know which platform it would be integrated into. Several participants suggested that the Careview© would be easy to adapt.	*"...they can add parts on to that and so it could become a part of the care view... it wouldn't be a big issue to do so."* (P11, ACCP)
Additional tools and technology needed	Additional tools and technologies within adult critical care would be required to use the AI-SFM tool, such as more computers or wiring. Implementing the use of the AI-SFM tool would result in new guidelines or protocols being required.	*"Would it need extra wiring? An extra bit of you know kit at each of the bed spaces"* (P7, ACCP)

AI-SFM =artificial intelligence sepsis fluid management, IT= information technology,

5.4.6. Component 4: Physical environment

The physical environment was defined for this study as where the participants work, such as the layout, other stakeholders in the environment, the workstation, and the noise levels. Two main sub-themes were found under the physical environment component: *The current physical environment of the adult critical care unit* and the *changes needed to the physical environment to use the AI-SFM tool.* A summary and description of these sub-themes can be seen in Table 5.13.

Table 5.13: Summary of sub-themes under physical environment

Sub-theme	Description
Sub-theme 1: The current physical environment of the adult critical care unit	The participant's description of the physical layout of the adult critical care unit and the people (e.g. colleagues, patients and visitors) that are within the adult critical care unit. This also includes any challenges the participants suggest regarding the layout and people within adult critical care.
Sub-theme 2: The changes needed to the physical environment to use the AI-SFM tool	When participants have suggested any changes needed to the current physical environment to be able to use the AI-SFM tool.

AI-SFM =artificial intelligence sepsis fluid management

5.4.6.1. Sub-theme 1: The current physical environment of the adult critical care unit

This sub-theme is made up of three main areas: *i)* the layout of adult critical care, *ii)* the stakeholders within the adult critical care unit and *iii)* the challenges associated with the physical environment of adult critical care.

i) *<u>The layout of adult critical care</u>*

Participants provided some general descriptions of the adult critical care unit, with some stating that the unit was made up of two areas – the intensive care unit (ICU) and the high dependency unit (HDU), which, while under the umbrella of adult critical care, can be in different areas of the hospital. However, some suggested they had merged their HDU and ICU and that in some hospitals, there were several units, *"well, in my critical care unit, we've got a very big unit, so we've got two HDUs and three ICUs"* (P17, pharmacist). When participants mentioned the location of the adult critical care units within the hospital, it was said to be on the ground floor, with one participant mentioning that they had a separate unit for COVID-19 patients.

Participants suggested a mix of patient beds in open spaces and single-side rooms. There was a clear variation in the number of bed spaces each adult critical care unit had, ranging from eight to 19 per unit, which could be expanded if necessary "*for pandemics or winter pressures"* (P10, consultant). Participants also mentioned areas where staff complete their work, as seen in Figure 5.8.

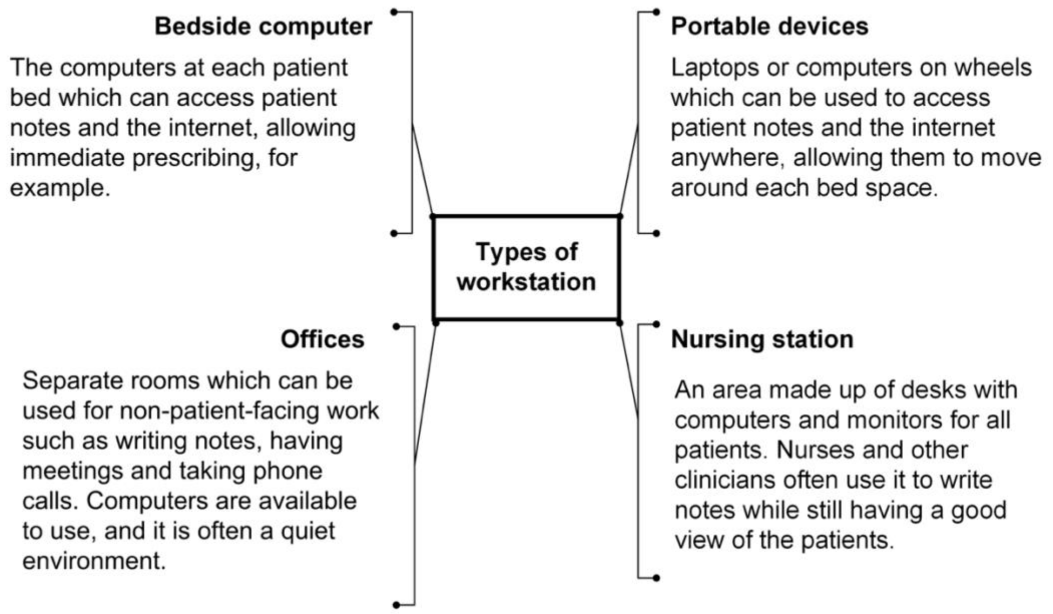

Figure 5.8: Types of workstations used in adult critical care

ii) *<u>The people within adult critical care</u>*

Participants mentioned several people who tended to work in the adult critical care unit, including staff members, patients, and visitors. The staff members were split into their job role and can be seen in Figure 5.9.

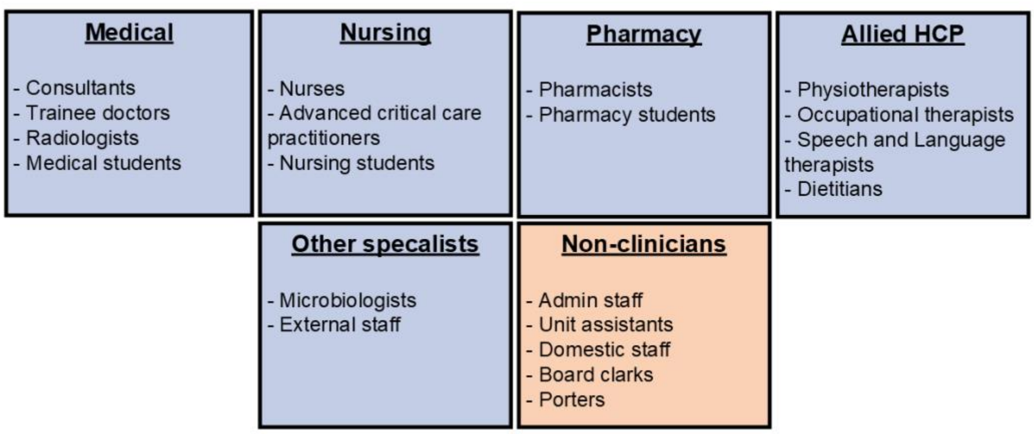

Figure 5.9: Stakeholders working within the adult critical care unit
HCP = healthcare professional

Participants stated that, in general, the unit had to follow a specific ratio of staff to patients, especially for nursing staff:

“Right for every ventilated patient, it should be one nurse to one patient for every high dependency level 2 patient, it should be one nurse to two patients.” (P17, pharmacist)

However, some suggested that there are variable numbers of staff for certain job roles, such as trainee doctors and that issues such as sickness and staff turnover could impact how many staff there were on specific days. There was also a suggested difference reported in the staff numbers over the weekend and at night when the numbers may be reduced, resulting in the adult critical care unit becoming a busier and sometimes more challenging place to work. Further to staff members, the number of patients within the adult critical care unit also varied and was dependent on several factors such as bed availability, the geographical location of the hospital, and staffing levels due to needing a certain staff-to-patient ratio and the time of the year.

iii) *The challenges associated with the physical environment of adult critical care*

Participants suggested challenges associated with the physical layout and stakeholders within adult critical care unit, as seen in Table 5.14.

Table 5.14: Challenges associated with the physical environment of adult critical care units

Challenge	Description	Illustrative quotes
Challenges with layout		
Noise levels	Adult critical care is generally a noisy environment due to machines and the number of staff on the unit. The noise level was also impacted by what was happening in the unit, such as the admissions of new patients or alarms going off.	“Yes, very noisy, a lot of beeping, the machines make a lot of noise, so it's not quite at any point in time, even during the night, is very loud.” (P4, pharmacist)
Lighting	Adult critical care is often a dark environment, with little to no natural light, as there are no windows.	“There’s not a lot of natural daylight. That's a problem in a lot of ICU and it's something that's increasingly being addressed with new builds and renovations, and it's still something that we find is a bit of a pest” (P8, trainee doctor)
Visibility	Visibility within adult critical care can be poor, for example, due to the room's shape, pillars in between bed spaces, or separate patient rooms.	“The horseshoe-shaped {unit} so you're not always visible to your colleagues and particularly inside rooms as well. I think for me that's a big you know a big design issue is that you know if something's going wrong and I'm stuck in the corner of that horseshoe” (P13, nurse)
Clutter	Clutter in terms of equipment and information, such as patient notes and computers, was seen as a challenge as it could impact the speed at which a patient can be cared for and create a ‘chaotic’ environment.	“It's often quite cluttered because of the amount of equipment we have…But for instance, if I need to perform a practical procedure on a patient, I often have to move other equipment out of the way, step over cables and it can be physically not disastrous, but irksome to do certain things.” (P8, trainee doctor)
Age of unit	When the adult critical care unit was built, it impacted how easy it was to work there due to the layout and how easy it was to integrate new equipment.	“Newer ICU's are better than older ones because the building standards have changed and there's no way of trying to integrate equipment into the environment in a less intrusive way.” (P8, trainee doctor)
Environmental challenges for clinicians		
Vulnerable nature of setting	The emotions experienced by patients and family members within adult critical care were expressed as a challenge, as staff must be conscious of what is happening around them.	“It can be quite an emotional environment sometimes erm I guess you have to be cautious that there could be people experiencing you know trauma or particularly difficult periods of their life” (P1, pharmacist)
Busy environment	Adult critical care was said to be a very busy place due to the number of staff, visitors and patients and could also be very cluttered, which may result in a high cognitive load for clinicians.	“So the physical environments, cluttered and noisy and busy with a lot of potential distractions, and that creates quite a high cognitive load” (P8, trainee doctor)

5.4.6.2. Sub-theme 2: The changes needed to the physical environment to use the AI-SFM tool

Where participants suggested changes, it was indicated that the layout of the adult critical care unit may need to be modified. Some felt that more space at the bedside would be necessary if additional computers were needed to use the AI-SFM tool:

> *"I think to fit that additional clinical IT, it would be a bit of a squeeze. It could be done, but ideally, we'd like a brand new unit"* (P8, trainee doctor)

Several participants, who often came from paper-based adult critical care units, suggested that their adult critical care units may need upgrading or rebuilding to use the AI-SFM tool due to the potential need for computers or other electronic equipment. Further to space changes, participants also stated that the noise levels might need to be lowered to ensure any alerts are heard or *"…to make sure that the results of the AI are communicated well"* (P7, ACCP). However, it was felt that the need for any changes would greatly depend on the AI-SFM tool itself; for example, if data had to be manually inputted and took up a lot of time, they would need increased staff. Further, it was felt that if the AI-SFM tool were within an app, then any space issues would not be as impactful, or if the AI-SFM tool gave no alerts or alarms, then the noise level currently would be fine.

Despite this, most participants felt no changes to their physical environment were necessary to use the AI-SFM tool in the future. This was mostly due to participants believing that their physical environment would be suitable and that the AI-SFM tool would integrate well:

> *"…as I say, each bed space has a computer and we've got plenty of access to computers at the nurse's station and our office, so I don't. I don't really think so, no, I think we've got plenty of IT kit around"* (P19, trainee doctor)

It was also felt that aspects such as the ratio of staff to patients would not be impacted by the AI-SFM tool, nor could it be changed.

5.4.7. Component 5: Tasks

Tasks for this study were defined as the specific actions taken and the attributes or characteristics of those actions, such as difficulty, complexity, variety etc. Two main sub-themes were found: *current tasks for sepsis fluid management in adult critical care* and *changes to the current tasks to use the AI-SFM tool.* A summary and description of these sub-themes can be seen in Table 5.15.

Table 5.15: Summary of sub-themes under Tasks

Sub-theme	Description
Sub-theme 1: Current tasks for sepsis fluid management in adult critical care	The tasks the participants reported currently take place for sepsis fluid management and any perceived challenges with those tasks.
Sub-theme 2: How the current tasks may be impacted or changed by the AI-SFM tool	How the participants perceive their current tasks will be impacted or need to change by applying the AI-SFM tool.

AI-SFM =artificial intelligence sepsis fluid management

5.4.7.1. Sub-theme 1: Current tasks for sepsis fluid management in adult critical care

The tasks reported by participants for sepsis fluid management were synthesised, and a visual representation was developed based on the output (see Figure 5.10 and further description in Table 5.16). Inductive analysis suggested five main tasks for sepsis fluid management could be taken, with several corresponding sub-tasks. Participants indicated that there might be variations in where a clinician starts the task process depending on whether the patient was already within the critical care unit when first suspected of having sepsis or within another department, such as accident and emergency. The analysis also suggested that the process of sepsis fluid management within adult critical care could be repeated as necessary, depending on the patient's status during monitoring.

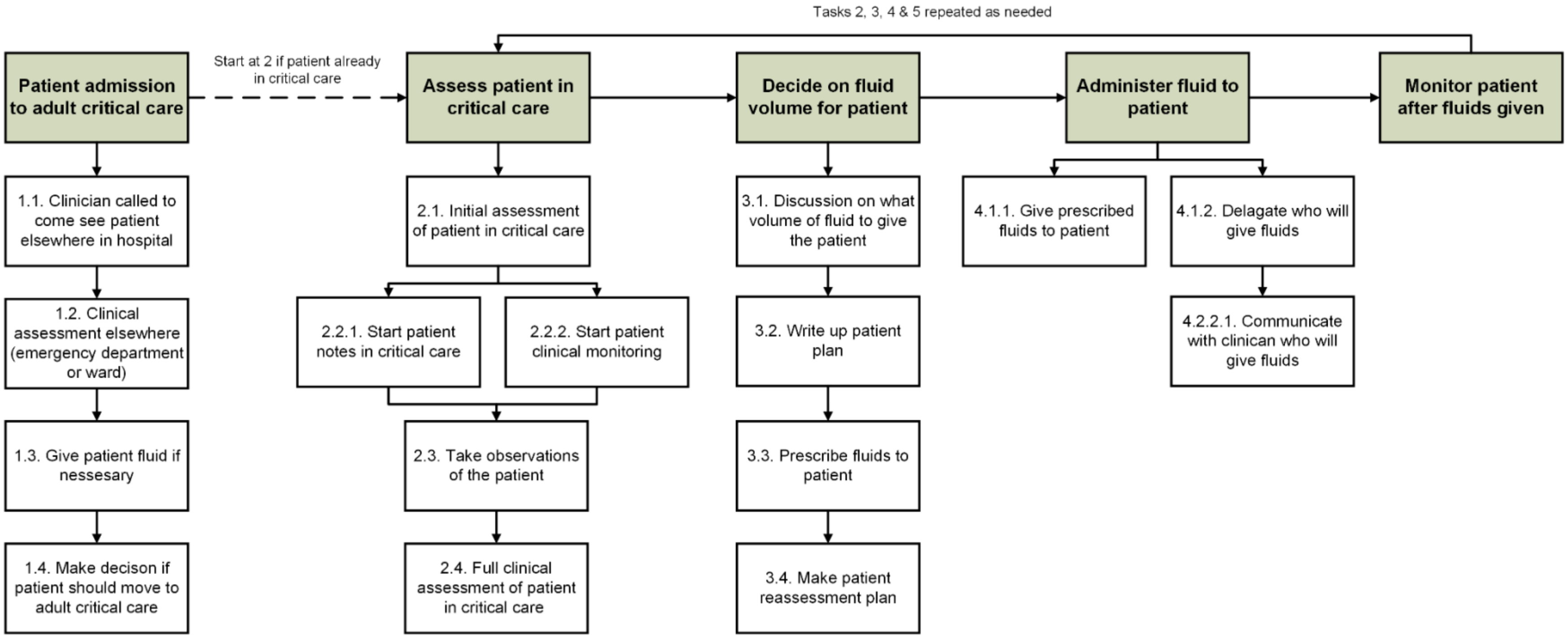

Figure 5.10: Synthesis of tasks reported by participants for sepsis fluid management in adult critical care

Table 5.16: Description of participant-reported tasks for sepsis fluid management report by participants

Task		Description	Participant(s) Number of who reported the task/sub-task	Illustrative quote
Patient admission to adult critical care				
1.1.	Clinician called to come see patient elsewhere in hospital	Clinicians in critical are often asked to see a patient in the emergency department or ward who has suspected or diagnosed sepsis.	P5, P14 (Trainee doctors)	*"And so generally we would be referred someone from either a ward or a or from the emergency department and who has a suspected diagnosis of sepsis or sometimes a confirmed diagnosis of sepsis" (P14, trainee doctor)*
1.2.	Clinical assessment elsewhere (emergency department or ward)	The clinician would then conduct a clinical assessment of the patient where they are to understand their current situation.	P14, P19 (Trainee doctors)	*"My first step would be to go and assess the patient where they are and find out what they've had already in terms of fluid or any vasoactive medications and you know, particularly in terms of antibiotics and actual management of the sepsis." (P14, trainee doctor)*
1.3.	Give patient fluid if necessary	If the patient needs fluids, for example, if they have just arrived at the hospital, then they will be given those fluids.	P3 (Consultant) P19 (Trainee doctor)	*"So if they come into A and E would probably, what I tend to do is give a bag or half a bag of fluid and assess the response." (P3, consultant)*
1.4.	Make decision if patient should move to adult critical care	Clinicians should then monitor how the patient responds to fluids, such as their blood pressure, and based on this, decide if they need to move to adult critical care.	P14, P19 (Trainee doctors)	*"Seeing if there responding to fluids and then if that's not going well, or the pressure coming up… then that's kind of when we think we need to get them to crit care get them started on some vasoactive medicine to try and help that." (P19, trainee doctor)*
Assess patient in critical care				
2.1.	Initial assessment of patient in critical care	Clinicians may clinically assess the patient just as they enter adult critical care, maybe before they are given a bed.	P2 (ACCP)	*"So, the patient would come to us. Straight away, before they're probably even in bed, we would have a look at their monitoring and assess their MAP {mean arterial pressure}" (P2, ACCP)*

Task		Description	Participant(s) Number of who reported the task/sub-task	Illustrative quote
2.2.1.	Start patient notes in critical care	Clinicians will then start the patient notes and input the level of fluid already given.	P2 (ACCP)	*"We would start their careview {electronic patient notes}. We would document how much fluid we'd give, so we would start on the careview and the careview would start to add up {fluids}" (P2, ACCP)*
2.2.2.	Start patient clinical monitoring	Clinicians would start electronically monitoring the patient.	P2 (ACCP)	*"But in our unit year, we're quite quick to put on the LIDCO monitoring." (P2, ACCP)*
2.3.	Take observations of the patient	The patients' observations would then be taken, such as their blood, lactate, and gases.	P13 (Nurse)	*"Like check their lactate. You would always take a gas when you come in like we always do a full set of bloods like our routine or practice is the guidelines" (P13, nurse)*
2.4.	Full clinical assessment of patient in critical care	Complete a clinical assessment of the patient such a look at clinical parameters, patient history and observations.	P1, P4, P17 (Pharmacists) P2, P6, P7, P11 (ACCPs) P5, P8, P9, P18, P19 (Trainee doctors) P10, P12, P15 (Consultants) P13 (Nurse)	*"So, suppose assess the patient clinically, assess their observations and the lab results that are available at that time." (P15, consultant)*
Decision on fluid volume for patient				
3.1.	Discussion on what volume of fluid to give the patient	Discuss with the multidisciplinary team the fluids volume such as the balance aim.	P1 (Pharmacist)	*"I would then be having a discussion with my colleagues to know sort of what we're aiming for…different outputs for different patients, depending what balance they're looking for" (P1, pharmacist)*
3.2.	Write up patient plan	A patient plan would be written up, such as their targets.	P2 (ACCP)	*"We would write on the whiteboard, the plan, so their admission plan, their targets" (P2, ACCP)*
3.3.	Prescribe fluids to patient	The volume and type of fluids would then be prescribed to the patient.	P2 (ACCP) P5, P8, P9, P19 (Trainee doctors)	*"So, when we would prescribe it, so would prescribe the background crystalloid and the Hartmans bolus" (P2, ACCP)*
3.4.	Make patient reassessment plan	A plan would be made for patient reassessment, such as blood pressure level.	P15 (Consultant)	*"Make some kind of plan for reassessment and some indication of what would be the trigger for giving further fluids" (P15, consultant)*

Task		Description	Participant(s) Number of who reported the task/sub-task	Illustrative quote
Administer fluid to patient				
4.1.1.	Give prescribed fluid to patient	The patient is then given the fluids that were prescribed, while watching how the patient responds.	P2, P6, P11 (ACCPs) P8, P9 (Trainee doctors) P12 (Consultant) P13 (Nurse)	*"But I think we are very slow and steady with it. We give small boluses and reassess the situation rather than just pummelling in like two or three litres of fluid at the time" (P11, ACCP)*
4.1.2.	Delegate who will give fluids	Clinician delegates who will be give the patient the fluids.	P7 (ACCP)	*"Or I can be delegated to the nurse that's looking after the patient" (P7, ACCP)*
4.2.2.1.	Communicate with clinician who will give fluids	Clinician will communicate with whoever is giving the fluids.	P5, P8 (Trainee doctors) P6, P7 (ACCPs)	*I'm gonna tell the nurse {that I} have done it and ask them to give it." (P8, trainee doctor)*
Monitor patient after fluid given				

ACCP = Advanced critical care practitioner

The participants were asked if they used guidelines to help inform the tasks completed for sepsis fluid management, to which there were mixed views. Participants suggested they often only use their clinical judgement and experience for each patient rather than a strict protocol:

> *"…just based on experience and actually thinking back to different trusts {health boards} that I've worked in… I don't think there's a protocol at all"* (P9, trainee doctor)

Where guidelines were used, they were either external guidelines, such as National Institute for Health and Care Excellence guidelines, managing sepsis guidelines (e.g. Sepsis Six bundle), the literature evidence base, or those developed internally. This lack of guidance on how to complete the tasks of sepsis fluid management was seen as a key challenge, as it results in a lack of standardisation of the process. Another key sepsis fluid management task was communicating with others in adult critical care. This communication was suggested to be done through several modes, as seen in Figure 5.11.

Internal meetings

- Wardrounds
- Discussions with colleagues
- Handover meetings
- Multidisciplinary team meetings

External meetings

- General critical care national meetings
- Job role specific national meeting (e.g. Scottish Advanced Critical Care Practitioners Network)

Figure 5.11: Modes of communication used in adult critical care reported by participants

5.4.7.2. Sub-theme 2: How the current tasks may be impacted or changed by the AI-SFM tool

Participants had mixed views on whether the AI-SFM tool would impact their workload and tasks, with some suggesting that it would work well with what they currently do, and that it would hopefully streamline the process of sepsis fluid management and reduce the number of tasks they do currently by, *"helping me offload some of the calculations and thinking"* (P9, trainee doctor). Despite this, some suggested that there may be an initial increase in workload when implementing the AI-SFM tool into adult critical care, but that the longer-term impacts of the AI-SFM tool could depend on several factors. These factors included how labour-intensive the AI-SFM tool was. For example, if data had to be manually inputted, time would be taken to enter the patient's results or clinical history. One participant also suggested:

“If there were more errors being made because the AI is being misinterpreted or the AI was leaving people down an incorrect management pathway, that would definitely make a difference” (P4, pharmacist)

On the other hand, it was also suggested that if the AI-SFM tool were an app, there would be less impact on clinicians' workload. It was further indicated that participants would want to know how the AI-SFM tool would fit in with their current processes before integrating it into clinical practice, including any paperwork that could accompany its use. Participants also indicated specific changes to their current tasks, including that the AI-SFM tool may be best placed after initial fluids are given when clinicians start to think about the patient's long-term care.

5.4.8. Component 6: Organisation

The organisation was defined in this study as structures that are external to a person, such as time, space, resources, and activity. There were three main sub-themes under organisation: *perceived organisational support for general healthcare technology; perceived organisational support for the AI-SFM tool;* and *what within the organisation needs to be changed to apply the AI-SFM tool.* A summary and description of these sub-themes can be seen in Table 5.17.

Table 5.17: Summary and description of sub-themes under organisation

Sub-theme	Description
Sub-theme 1: Perceived organisational support for general healthcare technology	The participant’s perceptions of how supportive the current organisation (at the health board, hospital and department levels) is of general healthcare technology.
Sub-theme 2: Perceived organisational support for the AI-SFM too	The participant's perceptions of the current organisation's support (at a health board, hospital and department level) for the AI-SFM tool.
Sub-theme 3: Organisational changes needed to apply the AI-SFM tool	How the participants perceive the organisation will need to change to apply the AI-SFM tool in practice.

AI-SFM =artificial intelligence sepsis fluid management

5.4.8.1. *Sub-theme 1: Perceived organisational support for general healthcare technology*

Participants suggested that at a healthboard level, there is support for the use of healthcare technology and that any discussions about future technology were often positive. This perception was due to their increased use of technology in recent years, including apps, and electronic prescribing. Despite this, some participants mentioned that their health board was only *"supportive in principle"* (P4, pharmacist), as when asked to provide practical support they were unwilling to do so. Other participants suggested that their healthboard was not supportive of investing in technology, and if an IT issue was brought up, they were uninterested or did not want to fix it. Participants suggested that at a hospital level, there was similar support for general healthcare technology as there was at a health board level, with the hospitals often following their lead regarding innovations:

> *"…when you get down to hospital level potentially people can say all these right things, but when it actually comes down to delivering it then it can be a bit different."* (P16, pharmacist)

It was also suggested that the age of the hospital also impacted the support for healthcare technology.

In terms of departmental level, most participants suggested that there is often a push for the application of new technology. However, participants also mentioned that while those working in adult critical care are often supportive, there would need to be evidence that any proposed new healthcare technology was worth implementing. In contrast, some participants felt that while the department was supportive, this was often limited by support from those at a hospital or health board level.

5.4.8.2. *Sub-theme 2: Perceived organisational support for the AI-SFM tool*

Participants suggested that at both a health board and hospital level, they expected support for the AI-SFM tool would be high if it were to be implemented into practice in the future. Despite this, it was suggested that in certain health boards or hospitals, there might be limited support for using the AI-SFM tool due to an unwillingness to invest in new technology. However, there was a suggestion that while the support of the health board would be important, participants felt this would be limited to the procurement and purchasing of the technology and that any subsequent support for using the AI-SFM tool would need to come from the department into which it was being integrated. When asked if there would be support at the departmental level, participants suggested that they would support the implementation of the AI-SFM tool as they are often *"…open to new approaches or new technologies*" (P20, pharmacist). This potential level of support was due to several reasons, including that staff who work in adult critical care were often already interested in the use of technology and, therefore, a current priority for them in their everyday practice. It was also suggested that in some cases, the use of AI technology is already discussed within the department:

"I think that we've had different talks about research, and like I said, one which particularly included a bit about the use of AI" (P18, trainee doctor)

However, despite a general feeling that those working in adult critical care would be supportive of using the AI-SFM tool in the future, a number of participants felt that some staff groups, especially consultants, may not be as open to using the AI-SFM, due to a perception that they would have less interest in the using of technology:

"I think some consultants will like it and some consultants won't like it and that'll depend on how frequently it gets used and utilised" (P13, nurse)

However, it was also suggested that having evidence for the benefits of the AI-SFM, such as time and money saved or improved patient outcomes, would be crucial for gaining support for the future use of the AI-SFM tool.

5.4.8.3. Sub-theme 3: Organisational changes needed to apply the AI-SFM tool.

Participants provided suggestions for what the organisation would need to change for the AI-SFM tool to be used in adult critical care, as seen in Table 5.18.

Table 5.18: Participant-reported organisational changes that may be necessary to apply the AI-SFM tool

Organisational change	Description	Illustrative quote
Update resources	The organisation would need to update current guidelines, policies, and pathways to consider the AI-SFM tool.	*“So maybe the existing guidelines that we have would need to have see how they fit it in with the AI” (P16, pharmacist)*
Provide new or updated Infrastructure	The organisation would need to provide basic infrastructure, such as Wi-Fi or updated software, to use the AI-SFM tool. There would also be a need to move to an electronic platform to get the data necessary to use the AI-SFM tool.	*“And have in some cases been introduced without adequate backup or adequate infrastructure or adequate IT infrastructure to actually support them… it's a thing that they need to do that is almost designed to fail in some ways” (P8, trainee doctor)*
Training and support	The need for training and support alongside the AI-SFM tool, including helping staff members see the benefits of using the AI-SFM tool and clearly explaining how it should be used. Training needs would not be universal and may depend on the individual needs of the setting.	*"I think generic training on just why we're using it in how to use it probably." (P11, ACCP)*
Time allotment	The organisation would need to provide allocated time to setting up the AI-SFM tool, changing guidelines and potentially populating the data once used in routine practice.	*“I think there would have to be time put into this setup of it. So anything, any sort of new procedure… so they would have to be time within my day, or whoever's day that was responsible from pharmacy for updating that guideline” (P1, pharmacist)*
New job roles	The organisation may need to create a new role in the future to help with the management of healthcare data. There was also discussion about who would be responsible for the upkeep of the AI-SFM tool once implemented.	*“I suspect that will come with a shift in the workforce to having people whose role is to manage the healthcare data at a clinical level almost” (P15, consultant)*
Increased space	The organisation may need to increase space in adult critical care if additional computers or servers are required for the AI-SFM tool.	*“I suppose, do you need to server to run these things? So would you need? An extra space in the server room for the AI. That's only thing I could think of space wise” (P2, ACCP)*
Culture	The organisational culture would need to change to allow staff to embrace new technology and adjust perceptions of AI in general to improve trust in the outputs. The organisation would need to work to help with the behaviour change of those currently working in adult critical care.	*“…I think. I think there's a lot of clinicians that will struggle with the idea that a computers better than they are, even though that's intuitively correct because the computer can process so much more information than the human can” (P15, consultant)*
Investment and cost	It was indicated that the organisation would need to fund the AI-SFM tool and purchase any new software or equipment necessary.	*“The big thing is money… they'd have to fund, at the very least, a little bit more IT infrastructure within the unit for it to be really useful and meaningful, and for it to be something people would actually be incentivized to use” (P8, trainee doctor)*

AI-SFM =artificial intelligence sepsis fluid management, ACCP = advanced critical care practitioner

5.5. Discussion

This study aimed to assess user needs for an AI tool for sepsis fluid management (AI-SFM tool) in Scottish adult critical care. The study used semi-structured interviews to understand the participant's current work system and the changes necessary within that work system to facilitate the use of the AI-SFM tool. Interviews were structured and analysed using the six components of the extended Work System Model: *AI technology, person(s), other tools and technology, physical environment, tasks*, and *organisation* (see Table 5.2) and conducted with 20 clinicians working within adult critical care. A framework approach was taken to analyse the data, where inductive sub-themes were derived from the data under the six extended Work System Model components.

Participants suggested that the AI-SFM tool could be useful within adult critical care for individualising patient care (Table 5.9). However, this usefulness depended on factors such as the job role of the clinician, and there were concerns that the AI-SFM tool may cause conflict within the team due to differing opinions on AI technology (Figure 5.4). Participants also suggested changes to the development and output of the AI-SFM tool, including whether the tool should be integrated and its level of explainability (Figure 5.5). The clinicians' current characteristics were understood, with participants indicating that their current confidence and IT skills were sufficient to use the AI-SFM tool, but only if it was not complex. Interestingly, however, participants suggested that unless the tools' interface was easy to use, they may need increased knowledge of AI technology in general. The process taken for sepsis fluid management that participants reported was inductively synthesised under five main tasks, with corresponding sub-tasks (Figure 5.10, Table 5.16). Participants suggested that their clinical judgment rather than specific guidance often supported them in their sepsis fluid management tasks. There were mixed views on how the AI-SFM tool may impact their current tasks; however, some participants indicated that the tool could increase their workload initially and would want to know the extent of this impact before the AI-SFM tool was fully integrated. Participants indicated variations in the use of other tools and technologies and the physical environment of adult critical care, including whether sepsis fluid management was completed on electronic platforms and the size and scale of the unit (Figure 5.7). It was suggested that the variation in the adult critical care setting could result in challenges when integrating new technology and that aspects of the setting may need to change to allow the AI-SFM tool to be used effectively. Participants felt that these changes would need to be managed by the organisation, including upgrading the adult critical care unit and providing training on using the AI-SFM tool.

While the data were presented under the individual work system components and associated sub-themes in the results, there was an interrelation between them. Therefore, within this discussion, the work system components and associated sub-themes are presented under three main headings to reflect this interrelatedness: the AI-SFM tool (which represents the AI technology component), the clinicians and their tasks (which encompasses the person(s) and tasks components) and the adult critical care setting (which encompasses the other tools and technology, physical environment, and organisation components). The following discussion will provide a commentary on the results in the context of the wider evidence. The study's strengths and limitations will then be discussed, along with ideas for future research and finally, conclusions will be drawn.

5.5.1. The AI-SFM tool

This section refers to findings about the technology concept presented to participants through the vignette. It contains results from the *AI technology* component and associated sub-themes (Section 5.4.4 of results).

Overall, participants felt that the AI-SFM tool would be useful for individualising patient care, which aligns with previous research suggesting that providing the right fluid volume for a specific patient is vital for their recovery (70). This individualisation of patient care, also known as precision medicine, is currently seen as a priority within Scottish healthcare, and specifically for sepsis, as patients will receive a treatment that is not a one-size-fits-all volume but one tailored to their characteristics (70, 275). Using AI technology for optimising sepsis treatment has been reported previously, with research concluding that the technology could support clinicians in providing patients with individualised care (65). However, despite an overall feeling from participants in this current study that the AI-SFM tool would be useful, there was some suggestion that this would depend on the job role of the clinicians themselves. For example, the findings suggested that pharmacists may be less involved in the fluid management for patients with sepsis than other clinicians. Therefore, the AI-SFM tool may be less applicable to the pharmacist’s role. However, participants surmised that this may change in the future. This reflects existing evidence, which shows that the role of pharmacists is expanding within critical care to help improve patient outcomes and mitigate against risk (276). Furthermore, participants shared concerns about using the AI-SFM tool, including that it may cause conflict within the team (Figure 5.4). For example, individual clinicians may have differing levels of trust in the AI-SFM tool output and AI technology in general, resulting in clinicians disagreeing on the final treatment volume. The conflict caused by these different levels of trust may result in issues with teamwork and support, which is important in critical care due to the vulnerable nature of patients (37, 277). Previous research has shown that a lack of trust in healthcare AI technology is a key barrier to adoption and can be influenced by factors such as user education, past experiences, and the technology's properties (37). Therefore, as the development of the AI-SFM tool continues, factors that may influence clinician trust could be targeted to help reduce team conflict within adult critical care.

Participants provided suggestions for developing AI-SFM tools, highlighting the importance of involving stakeholders while developing a new AI tool, which is a key principle within human factors research (141, 245, 275, 278). Therefore, stakeholders should continue to be involved in developing this AI-SFM tool to ensure that it is developed based on their specific needs. Furthermore, most participants stated they would want the AI-SFM tool integrated into their current or future electronic platforms used in adult critical care. Participants' wishes to integrate the AI-SFM tool reflect priorities identified in previous research completed by Kushniruk and Borycki (2021), who posed that a characteristic of a successful AI application is to have the new technology embedded within the current electronic platform used (129). However, the authors also shared that integrating AI technology into current electronic applications in healthcare may be difficult due to the complexity of the technology already used in the setting (129). Therefore, to ensure that the AI-SFM tool is successfully integrated, further focus should be given to the practical application of integrating the tool into the technology currently used in adult critical care and any barriers to this integration.

In this study, participants raised concerns about the output of the AI-SFM tool and how the AI technology explains to users how the fluid volume calculation was generated. Providing users with an explanation of how AI technology came to a decision is highlighted as important when developing the AI technology to ensure the decision is understandable (82, 129). The AI-SFM tool concept used in this study aims to provide users with a patient's mortality risk if given the volume of fluid suggested by the technology, as outlined in the contextual vignette. Including this mortality calculation produced mixed opinions from participants who were concerned it could be misinterpreted, as predicted mortality scores often do not support clinicians' decision-making within adult critical care (Section 5.4.4.2, *ii)*. However, for example, mortality prediction scores have been used previously as an output in a machine learning-based decision tool created to predict mortality risk in COVID-19 patients (279). Furthermore, another study described an AI tool created for critical care, which aimed to provide clinicians with patient mortality prediction scores to help detect those who should be given immediate care (280). However, the objective of these AI technologies was to prioritise patient care, which differs from the purpose of the AI-SFM tool in the current study, which is to provide individualised fluid volumes. Therefore, to improve user perceptions, providing clinicians with examples highlighting that predicted mortality can be used as an explanation output from AI technology may be beneficial.

5.5.2. The clinicians and their tasks

This section refers to the clinicians' characteristics and the work they undertake for sepsis fluid management. Due to the interrelatedness of the extended work system components this section contains results from the *person(s)* and *tasks* components (sections 5.4.3 and 5.4.7).

Regarding the characteristics of participants, it was suggested that an increase in knowledge of AI technology would be needed to use the AI-SFM tool unless the new tool was easy to use. It may be that this lack of knowledge is the result of AI technology not being discussed during the formal education of clinicians at the university level and beyond (275). To combat this lack of knowledge, efforts have been made to include AI teaching in medical education to fully prepare new clinicians for the introduction of AI technology in healthcare (281). Furthermore, one study aimed to develop medical undergraduates' digital health skills, by involving the students in developing a new AI tool (282). The study's results suggested that this method was an innovative way of helping future doctors develop the competencies necessary to use this type of technology in practice (282). However, it would be important for all clinicians, not just medical staff, to be educated on using AI technology, as multi-disciplinary teamwork is an important aspect of working in the critical care setting (277).

Participants felt that their current job role or personal experience of technology would allow them to feel confident in using the AI-SFM tool. This was a positive result as research has suggested that low confidence in using technology has previously been a barrier to implementing innovations within healthcare as seen in one study examining what factors influence clinicians' use of technology in the neurorehabilitation setting (283). Furthermore, most participants in the current study felt their current IT skills would be suitable for using the AI-SFM tool once integrated. However, participants also surmised that this may not be the case for all clinicians within adult critical care and that increased IT literacy would generally be needed across the healthcare setting. This need for increased IT or digital literacy is also seen within the wider literature, with research suggesting that during COVID-19, limited IT literacy was a barrier to using technology, such as telehealth video consultations (284). Despite the general feeling that participants' current confidence and IT skills would be suitable, it was suggested that changes to these characteristics would be necessary if the AI-SFM tool was complex and difficult to use. This need for AI technology to be easy to use and accessible is also found in previous literature, with a study completed by Buck et al. on general practitioners' attitudes towards AI tools finding that participants wanted these technologies to be easy to use due to only having short patient appointments (285).

To the author's knowledge, this is the first study that has mapped out the tasks clinicians may complete for sepsis fluid management in adult critical care (Figure 5.10, Table 5.16). Understanding the current tasks taken is important when developing AI innovations, as previous research has suggested that integrating this new technology may negatively impact the clinical workflow unless considered during the design (286, 287). The need to understand the clinical workflow where a future AI-based clinical decision support technology will be integrated is also reflected in Chapter 4's scoping review findings, which suggested that this approach should be taken before a prototype is developed. Data synthesis suggested that five main tasks may be completed for sepsis fluid management, with corresponding sub-tasks. When asked if they used any guidelines for conducting the sepsis fluid management process, participants suggest they often primarily rely on their clinical judgement, but certain guidance, such as the Sepsis Six bundle, may underpin their decision. This use of clinical judgment is understandable, as external guidelines can vary in specificity (288-290). The lack of consistency in the sepsis fluid management process was highlighted as a challenge by participants in the current study, possibly due to the potential differences in fluid volume decisions that will be made between patients (291). To combat this, research has been completed on how standardised processes for sepsis management could be provided, with one study surveying clinical champions (clinicians involved in leading an initiative) in the hospital setting. The study found that it may be possible to produce guidance on managing sepsis at a hospital-wide level, but only if a clinical champion facilitated and supported the development and education of staff (292). Therefore, within Scottish adult critical care, developing consistent guidance on conducting sepsis fluid management may be possible if a program of work is put in place that supports the process.

Participants were asked how the integration of the AI-SFM may impact their current tasks. While AI technology in healthcare is often promoted as reducing a user's (e.g. clinicians) workload (61), participants did raise concerns that their current workload may increase initially due to the introduction of the AI-SFM tool. This perception may be due to clinicians not fully trusting the AI-SFM tool, as previous research has suggested that those who trust AI technology believe that it will reduce their workload (293). Furthermore, participants in the current study indicated that knowing how the AI-SFM tool would impact their workload would be important before fully integrating the technology into adult critical care. This reflects the results found in Chapter 4, which suggested that a prototype should be created and tested before the technology is fully implemented into practice. Therefore, creating a future prototype of the AI-SFM tool may be important to provide a more comprehensive understanding of its impact on clinician workload and any other challenges associated with the technology's implementation.

5.5.3. The adult critical care setting

The adult critical care setting refers to where the AI-SFM tool will be integrated and, due to the interrelatedness of the extended work system components, contains results from the *other tools and technologies, physical environment*, and *organisation* components (Sections 5.4.5, 5.4.6 and 5.4.8).

Participants indicated that they use a mix of paper and electronic-based tools and technologies for sepsis fluid management, suggesting variation across Scotland. The variation in the tools and technologies used within Scottish healthcare has been highlighted in a previous study, which focused on the potential barriers to using real-time data in the country (294). The study found that as each health board in Scotland is responsible for deciding what software is used, it has resulted in the platforms chosen rarely integrating with other health boards. However, this varied use of healthcare technology is not limited to Scotland. For example, in rural hospitals within the United States of America, research has suggested variation in the uptake of health information technology (295). Consequently, this varied use of different tools and technologies may be a barrier to the uptake of AI tools in the future, as it will be difficult to share patient information across health boards, hospitals and departments (286).

Variation was also found in the physical environment of adult critical care, including how the units were designed. This difference in how a unit is designed has been cited as an area of concern in a previous study looking at teamwork, suggesting that having a poorly designed critical care unit may negatively impact patient care (277). The variation found in the current study was discussed across several aspects of the physical environment of adult critical care, including the different types of workstations and number of beds. Participants indicated that several workstations were used within adult critical care, such as a computer at the bedside or on wheels (Figure 5.8). The number of workstations may be due to guidelines indicating that if any electronic platform is used, there needs to be an appropriate number of computers to facilitate patient care (296). Therefore, the workstations may vary as some adult critical care units could use paper-based tools and technology, and others use electronic-based platforms. Regarding the number of beds, participants suggested that each critical care unit had a different capacity and indicated that some units could be expanded for winter pressures or during pandemics such as COVID-19. This ability to expand, when necessary, may suggest that adult critical care is adaptable to new challenges and potentially new technologies, which may facilitate the integration of the AI-SFM tool in the future (297, 298).

Overall, the variation suggested by participants in the adult critical care setting may indicate a lack of organisational readiness to integrate the AI-SFM tool. Organisational readiness refers to an organisation's willingness and ability to adopt a change and has been previously highlighted as a barrier to the uptake of AI technology in healthcare (133). Therefore, this suggests that the organisational readiness of adult critical care needs to be understood further and changed, as this may be a barrier to future uptake of the AI-SFM tool.

Participants highlighted other areas of adult critical care that would need to change to be able to use the AI-SFM tool. As previously indicated, some adult critical care units currently use paper-based tools for sepsis fluid management. Therefore, participants felt that to use the AI-SFM tool, their unit would have to move to an electronic platform, and additional technology would be necessary (Table 5.12). This additional technology may require extra space in the unit, which previous research has highlighted as difficult due to adult critical care already lacking space, especially within older hospitals (277, 299). Participants suggested that, as a result, adult critical care units may need to be updated or rebuilt to integrate the AI-SFM tool or other future AI technology. Previous research has suggested that future critical care unit designs must be developed with a technological focus and consider AI technology to allow it to be fully and effectively applied (275, 300). As a result, if an adult critical care unit undergoes a major update, there are now guidelines on how to consider healthcare technology in the design of units, which may help to overcome some of the challenges cited in the current study (296). Furthermore, the necessary changes in adult critical care units would need to be driven at an organisational level, including monetary investment and a culture change. These findings align with the literature, which suggests that for AI technology to be successfully integrated into healthcare, attention must be given to the organisational readiness to ensure its full potential is realised (133).

Training clinicians on using the AI-SFM in adult critical care was also highlighted as a key change that the organisation would need to facilitate. The current evidence base suggests that training is necessary for using new AI technology, specifically in interpreting the decision provided and knowing whether users should interrogate the output further to understand how it came to that conclusion (61, 301). For example, one study focusing on an AI clinical decision support tool for depression treatment used simulation methods to understand the technology's perceived utility (302). The study found that while overall, the participants found the tool useful, if they were given increased training, their perceived utility of the AI technology would increase (302). This current study's participants also indicated that any training should be adapted to individual adult critical care units. However, previous research has shown the importance of creating competencies for clinicians to allow AI technology to be used effectively and ethically in clinical practice (303). Therefore, it may be that while training for the use of the AI-SFM tool in the future should be adaptable for each adult critical care setting, it should also ensure that clinicians' key competencies are developed and maintained.

5.5.4. Strengths and limitations

To the author's knowledge, this is the first study that has applied a sociotechnical model to understand users' needs for healthcare clinical decision support AI technology. The application of the extended Work System Model was a key strength of the study, with previous research suggesting that for any new healthcare AI technology to be effective within clinical practice, developers need to consider the clinical work system the technology will be used within (61, 265). Therefore, through this study applying the extended Work System Model, the interviews were able to consider the important components that interact to create the work system in which the AI-SFM tool may be integrated. However, while understanding the full sociotechnical work system is a strength, there may be challenges with the interrelatedness of the different components within the model. The interrelatedness may cause issues when deciding which component data sits within, for example, guidelines, which could be considered tools but were placed within the tasks section due to them influencing how participants may conduct the process of sepsis fluid management. To mitigate against the potential challenges associated with the interrelatedness within the components, validation was completed during analysis to support the consistency of coding and subthemes under each component, and the discussion was structured in a way that highlighted how the components overall might interrelate.

A further limitation of applying the extended Work System Model was that it did not consider the external influences that may impact the use of the AI-SFM tool. These external influences may include wider societal views and the influence of the media around AI technology perceptions and positions. Further, government regulation and policy may also have an external influence on an individual's perceptions. An example of this policy is the Scottish Government's 'Scotland's Artificial Intelligence Strategy' which sets out how Scotland will become a leader in AI technology development (18). While these external influences are not considered in the extended Work System Model, other sociotechnical models such as SEIPS does consider them. Research has highlighted that the media can influence how receptive an individual is to the use of AI technology and therefore participant views on this would have been beneficial to consider (128). However, having AI technology as a separate component that interacts with the rest of the work system was important for this research. Therefore it may be that in the future, the extended Work System Model is expanded to include external influences as a seventh component to fully understand how AI technology will interact with the work system where it will be integrated.

A limitation of the current study was that only one nurse working in adult critical care was recruited, which may have resulted in a lack of perspective from that job role. However, there was suitable representation from ACCPs, who often come from a nursing background and have undergone further training, and therefore, may be able to provide some understanding from a nursing perspective (304). Furthermore, half of the participants were from NHS GGC, which was not unexpected as this health board has the largest proportion of the Scottish population and has the most hospitals and adult critical care units in Scotland (see Chapter 1, Table 1.1). However, participants were recruited from nine regional and special health boards representing rural and urban locations across Scotland. To further ensure that any lack of representation did not impact the generalisability of the results, an established data saturation approach was used, which ensured the robustness of the analysis and results (270-272). The current study focused on clinicians who work in adult critical care, with no inclusion of patients as participants. Previous literature (see Chapter 4, section 4.4.2) has highlighted that patients should be included in the development of AI technology due to the increase in precision medicine that this new type of technology may bring (128). However, it was felt that focusing only on clinicians would be appropriate for the current study as patients have less direct involvement in the fluid management for their sepsis diagnosis due to the severity of their illness and potential incapacity due to ill-health. Future studies could focus on patients' perceptions of clinicians using the AI-SFM tool for their care, as well as any needs they would have for the use of this new technology.

A further strength of this study is that it highlights the benefits and importance of applying a human factors approach when developing healthcare AI technology (239). This was beneficial as it showed potential barriers within the current work system that may impact the integration of the AI-SFM tools, such as the mix of paper and electronic tools and technologies and lack of knowledge of AI technology. The study also provided suggestions for the AI-SFM tool regarding its development and output (e.g., integration and explainability), which will help ensure the new technology is developed for the users. Overall, applying a human factors approach allowed for a full understanding of the work system in which the AI-SFM tool will be utilised and may support the development of the tool's future iterations and implementation into adult critical care.

5.5.5. Future directions and recommendations

The methods used in this study provided an understanding of the work system where an AI tool for sepsis fluid management may be integrated and how the tool may impact the components within that work system. Therefore, to help validate the human factors approach taken in the current study, future research should replicate the approach and methods used on other AI-based clinical decision support tool concepts for healthcare. Replicating this approach will help further evidence the benefit of applying the discipline of human factors when developing future AI technology.

To the author's knowledge, this is the first time the tasks and sub-tasks clinicians complete within adult critical care for sepsis fluid management have been mapped within Scotland. This initial mapping is useful, as the need to understand the workflow within the environment where a new AI technology will be integrated was highlighted as a key approach in Chapter 4's scoping review. However, understanding the workflow for sepsis fluid management was not the sole purpose of this study. Therefore, future research could ensure that the tasks synthesised in the current study accurately represent the workflow in adult critical care through observations of the sepsis fluid management process.

The results suggested a lack of organisational readiness for AI technology in adult critical care, with participants highlighting the importance of the organisation driving the changes necessary within the setting. This is in line with previous research, which highlighted that increased consideration should be given to the organisational readiness of healthcare and how to overcome the associated challenges that may hinder the integration of AI technology (133). Therefore, it would be helpful to explore further what is necessary for effective organisational readiness in the healthcare setting to support the future integration of AI technology.

5.5.6. Conclusions

The current study aimed to apply a human factors approach to understand the user needs of clinicians working within Scottish adult critical care for an AI tool for sepsis fluid management. The study took a sociotechnical perspective to understand clinicians' current work system and any necessary changes or suggestions for that work system to use the AI-SFM tool. Results suggested that participants felt the AI-

SFM tool would be a useful addition and that their current confidence and IT skills would be suitable to use the AI-SFM tool. However, it was indicated that some aspects of the participant's current work system might be a barrier to its use, such as the clinician's job role, the AI-SFM tool's ease of use, and the adult critical care setting itself. The study also indicated areas of development and change for the AI-SFM tool, which will help ensure that future iterations of the concept will be based on user preferences. The findings of this study may benefit AI developers and researchers, as it highlights the importance of understanding the user needs during the design of AI technology, as without it, barriers to its use may not be recognised until it is already implemented. It may also be of interest to regulators or policymakers, as it is evidence of the importance of having human factors integrated into AI development standards or regulations. Overall, the results from this study emphasise the benefits of applying a human factors approach early in the development of healthcare AI technology, as it will ensure that new tools will be created for the users and their work system. It would be beneficial for future research to build on the current study's findings to understand the work system further and overcome barriers to AI technology's future integration, including the level of organisational readiness.

Chapter 6: Organisational readiness for artificial intelligence technology in healthcare: a scoping review of resources

6.1. Introduction

Within healthcare, there is a drive to develop artificial intelligence (AI) technology, with strategies being created globally and specifically within Scotland to help implement these tools (10, 17, 18) (See Chapter 1, Sections 1.1.3 and 1.1.5). However, despite this drive, previous research has suggested a strong focus on the technological development of AI algorithms and not on how the new technology will work within a healthcare work system (81, 82) (Chapter 1, Section 1.2.4). The focus on technological development was highlighted in Chapter 4's scoping review, which found that over a ten-year period (2013-2023), only 64 studies had reported on the development of AI-based clinical decision support (AI-CDS) tools in hospitals using a human factors approach (See Chapter 2 for an overview of human factors). Despite the limited number of studies, taking a human factors approach has been highlighted as important for developing AI tools, as the technology will substantially change how work is conducted within a healthcare sector (129, 142). This change may result from AI technology being considered a multidisciplinary team member, which differs from how previous healthcare technology has been considered (129) (see Chapter 2, Section 2.4). Therefore, AI technology should be developed to work alongside individuals already within the chosen setting and consider their needs during the design phase (see Chapter 5). However, in addition there also needs to be sufficient organisational readiness for the introduction of AI technology to ensure a willingness and ability within a setting to consider clinician needs and change how work is done (133).

Organisational readiness refers to an 'organisation's willingness and ability to adapt to change' and is a key human factors-related principle when applying AI technology in healthcare (Chapter 2, Section 2.4) (130, 131). To ensure appropriate organisational readiness, a systems perspective can be taken, which allows for an understanding of the readiness levels of the entire work system where the AI technology will be integrated (131). The benefits of taking a systems perspective was highlighted in Chapter 5's study, where the results indicated a need for increased focus on organisational readiness in adult critical care for an AI sepsis fluid management tool, which aligned to three of six components of the extended Work System Model (other tools and technology, physical environment and organisation). However, the purpose of Chapter 5's study was not to understand organisational readiness levels. Therefore, the other components (AI technology, person(s) and tasks) may have been associated had organisational readiness been the focus. The need for sufficient organisational readiness is especially important in healthcare due to the complex sociotechnical nature of the sector, which can already result in difficulties when developing technology (102). Resources can be created to define and assess organisational readiness and highlight factors within a sector that may need to be addressed before an innovation can be integrated. For healthcare technology generally, resources regarding organisational readiness for various technological implementations have been created; for example, an e-health readiness assessment framework was created for developing countries to identify factors that need to be considered when planning the development of e-health innovations (305). Further examples are matrixes developed to understand nurses' current organisational readiness for digital technology (306) and a longitudinal qualitative evaluation study to understand the readiness of the United Kingdom for digital health (307). However, as previously mentioned, AI tools will be considered part of the multidisciplinary team, as opposed to a passive tool such as existing technology (Chapter 2, Section 2.4). Therefore, organisational readiness resources should be specifically developed, using a system perspective, for healthcare AI tools to ensure full consideration of the new way of working.

Despite the understood importance, research suggests that limited attention has been given to the organisational readiness of healthcare for AI technology. This includes the results found in Chapter 4's review, which indicated variation in whether AI-CDS technologies were integrated into the electronic health record in the exiting evidence base (Section 4.4.3). This may be due to a lack of organisational readiness, as previous research has suggested that if AI technology is to be used effectively in healthcare, it should be integrated into the current electronic health record platforms (Chapter 5, Section 5.4.5.2) (238). Furthermore, findings in Chapter 5 suggested that there may currently be a lack of readiness for a sepsis fluid management AI tool in adult critical care due to variations in the types of technology used and the physical environment of the settings. For example, participants suggested that the online platforms used within adult critical care often differed from other wards within the hospital and that the age of the unit often made using new equipment difficult (Chapter 5, Sections 5.4.5. & 5.4.6.). The findings from Chapter 4 and 5 would suggest a need for increased focus on the organisational readiness of healthcare for AI technology as it could be a barrier to the effective use of future tools. This was also highlighted in a viewpoint article by Alami et al, where it was indicated that more focus should be given to the organisational readiness of the healthcare sector to ensure successful integration of new technology (133).

Whilst there has been limited focus in the healthcare sector, other sectors have created resources to measure and evaluate organisational readiness factors for AI technology. This focus may be due to the maturity of AI development in these sectors or more investment from companies or researchers to ensure that organisational readiness needs are considered. Consequently, this study aims to collate and assess the factors within organisational readiness resources developed for AI technology in any sector. It is hoped that learning from the resources other sectors have developed to measure organisational readiness, will be of benefit.

6.2. Aim and objectives

This scoping review aimed to collate and assess the resources developed to measure organisational readiness for AI technology across any sector. The objectives were to:

1. Report on the characteristics of the established organisational readiness resources used for AI technology.
2. Assess the factors within the organisational readiness resources for AI technology using the extended Work System Model.

6.3. Methods

A scoping review can be used to bring together a large body of evidence systematically (158). This method was chosen to understanding of the factors used in measuring organisational readiness for AI technology across sectors which could then be translated into healthcare to develop a conceptual framework (308). A scoping review was chosen as it can bring together a wide body of literature to answer a broad question (unlike a systematic review, which answers a more question) in a systematic manner (unlike other review methods such as literature or narrative review which employ less systematic method) (159, 160).

The Preferred Reporting Items for Systematic Reviews and Meta-analysis for Scoping Reviews (PRISMA-ScR) 2020 checklist (161) was used throughout. The methods were completed in three steps to provide an in-depth understanding of the resources that measure organisational readiness for AI technology in any sector:

i) Step 1: Database search

Databases were searched to find studies that had developed an organisational readiness resource or had used a resource to measure organisational readiness for AI technology.

ii) Step 2: Sourcing the resources

Studies that had reported on the development of resources to measure organisational readiness for AI technology were included. Studies that used an established resource to measure organisational readiness for AI technology were also included.

iii) Step 3: Synthesis methods

The resources found in Steps 1 and 2 were analysed, including the characteristics and the factors within each resource and the studies that applied the resource.

6.3.1. Step 1: Database search

Eligibility criteria

Table 6.1 sets out the eligibility criteria for this scoping review.

Table 6.1: Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Studies that reported the development of resources or applied resources that measure organisational readiness for artificial intelligence technology, partially or fully, in any sector.	Studies that did not report on the development of resources or applied resources to measure any aspect of organisational readiness or focused solely on organisational readiness for any other technology, not artificial intelligence technology.
Studies that have undergone peer-review and have been published in academic journals or as conference papers	Opinion or discussion articles; commentaries; letters.
Studies were published in English and from 2013 onwards. This was chosen to be consistent with the review completed in Chapter 4, when IBM Watson was first used in healthcare (49). If a resource was used in a study completed after 2013 but was originally developed before 2013, it was included.	Studies not published in English and published before 2013.

Information sources

Research database searches were conducted on 10/01/2024 to capture studies that reported the development or the application of organisational readiness resources for AI technology. The databases searched were Web of Science, SCOPUS, Ergonomics Abstracts and PsychINFO. Web of Science was chosen as it is a large database containing articles from various sectors, including life science, engineering and computer science. SCOPUS and PsychINFO were chosen to capture psychology and social science-related articles, and the Ergonomics Abstracts database captured articles published in human factors/ergonomics journals.

The first 10 pages of Google Scholar© results were searched. Ten pages were chosen as this has previously been stated as the appropriate number of pages to capture the most relevant studies (309). The references of included studies were also hand-searched.

Search strategy

The search strategy was developed using key terms and synonyms under three main headings: 'Organisational readiness', 'AI technology' and 'Resources'. The search strategy was informed by relevant AI technology terms in Chapter 4, a previously completed review focusing on organisational readiness containing relevant search terms (310), and searching for appropriate MESH and Emtree terms related to these main headings. The search strategy was reviewed by the supervisory team and another PhD candidate (AF) with experience conducting scoping reviews and human factors research. Syntaxes were applied where appropriate to find word variations, and the Boolean terms 'AND' were used between the three main headings, and 'OR' was used between each search term. The search terms used for the databases can be seen in Table 6.2, and the search terms with database syntaxes can be seen in Appendix 8.

Table 6.2: Search terms used for scoping review

Main heading	Search terms
Organisational readiness	Organisational readiness; change readiness; organisations readiness to change; readiness; readiness to change; organisational innovation; organisational change, change management; organisational change management
Artificial intelligence technology	Artificial intelligence; machine learning; deep learning; meta-learning; reinforcement learning; supervised learning; semi-supervised learning; unsupervised learning; support vector machine; computer neural network; artificial neural network; deep neural network; convolutional neural network; recurrent neural network; machine intelligence; artificial learning; chatbot; virtual assistants; computer assisted image processing; image processing; image classification
Resource	Resources; index; model; framework; theory; tool; instrument; matrix; measurements; scale; guidance; outcome measure

Selection process

To find the resources, the researcher conducted the database searches, and Covidence© software (164) was used to screen the results. The researcher completed

100% of the screening, a random 20% were independently screened at both title and abstract screening as well as full text by another PhD candidate (AF) to ensure validation. The level of agreement was calculated, with a percentage of 80-89% considered good and 90% and above as excellent (165). If a good or excellent agreement was not achieved, a further 10% were screened. If the study was not freely available online for full-text screening, the authors were contacted twice by email and through ResearchGate©. The study was excluded if the full text was unavailable or had not been received.

6.3.2. Step 2: Sourcing and extracting the resources

Finding the resources

If an included study found in Step 1 had used an organisational readiness resource in its methodology, the original resource paper was then found and included in the final review.

Data charting

The data extracted can be seen in Table 6.3. A data extraction template was developed in Microsoft Excel© for the resource characteristics. The data pertaining to the factors used to measure and assess organisational readiness was extracted into Nvivo©. Where a study had applied an established resource, the factors developed for the study that had applied the resource were also extracted. A factor refers to the content developed to understand the key areas that may impact organisational readiness. The term factor may be referred to using different terminology (e.g. element or subtheme) depending on the resource or study but was extracted as a factor if the content was used to measure organisational readiness.

Table 6.3: Data extracted from the resources

Data extracted into Microsoft Excel©	Data extracted into NVivo©
1. Title of resource 2. Author(s) 3. Year published 4. Sector (e.g. aviation, nuclear) 5. How the resource was developed 6. How to apply the resource 7. How the resource has been applied previously	1. The factors (and a description of that factor) used to measure organisational readiness for each resource or study that applied an established resource to AI technology.

To validate the data charting process, each of the resources included was given an ID number, and data from a random 20% was extracted by another PhD candidate (AF) for validation. If a good (80-89%) or excellent (90%+) percentage of agreement was reached, then the researcher continued with extraction. If the agreement level was below 80%, a further 10% of studies were screened, and a supervisor (ED) was consulted.

6.3.3. Step 3: Synthesis methods

A PRISMA flow chart was created to show the screening process used to identify the included resources. The synthesis methods used for each objective were as follows:

Objective 1: Report on the characteristics of the established organisational readiness resources for AI technology.

The resource characteristics were collated in a table, including the title, author(s), year of publication, aim of the resource, how the resource was developed, whether it was developed initially for AI technology, whether it had been applied in any studies, and the number of factors in each resource used to measure organisational readiness.

Each factor extracted from the resources or studies that applied a resource was tabulated and presented by resource alongside a description in the appendix. If an included resource had been applied, the factors from the original resource and any factors developed for the studies that had applied the resource were included under the original resource heading. If there was a direct overlap between how the factor was named in the original resource and any study that had applied a resource, these were combined and a reference to the resource or studies that used this factor terminology was made. The description for each factor was either taken directly from the resource or a study that applied the resource, or if the description was lengthy, convoluted, or based on more than one resource or study that applied the resource, the researcher summarised it based on the extracted content. The descriptions summarised by the researcher were marked with the † symbol.

A further summary of each resource was then provided, including details on the sectors the resource had been applied to or developed for, how to apply the resource in practice, and how the resources had been applied previously.

Objective 2: Compare and contrast the resources using the extended Work System Model.

The individual factors extracted from each organisational readiness resource and study that had applied an established resource to AI technology underwent content analysis methodology, defined as *"any technique for making inferences by objectively and systematically identifying specified characteristics of messages"* (166).

Step 1: Firstly, the factors extracted from the resources and studies that had applied an established resource to AI technology were aligned under the components of the extended Work System Model (see Figure 6.1 for the model). The extended Work System Model was chosen as it can support the translation of the resources created in other sectors into healthcare while also ensuring a systems approach.

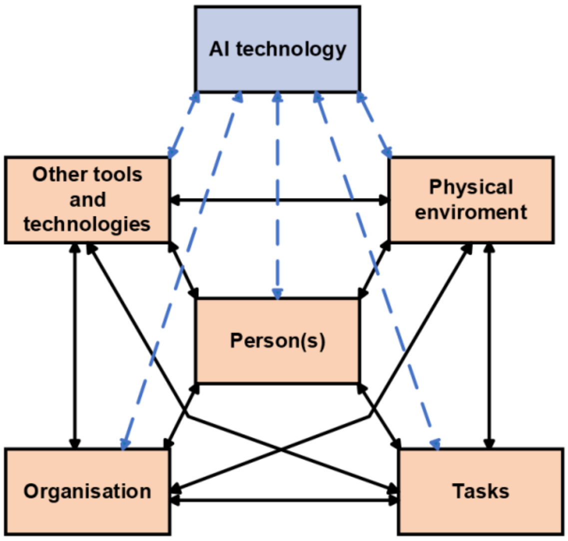

Figure 6.1: The extended Work System Model
Adapted from (155)

Working definitions of the extended Work System Model (see Table 6.4) were developed to help inform the process of aligning the factors using definitions from the original article and the results found in Chapter 5's interview study (155). To validate the analysis, another PhD candidate (AF) aligned the factors found in 20% of the resources under the extended Work System Model components, with any disagreement discussed. If consensus could not be reached, a supervisor (ED) was consulted. The components each resource had factors aligned under was tabulated.

Table 6.4: Working definitions of the extended Work System Model
Informed by (155) and results from Chapter 5

Component	Work system component working definition	Examples of the types of factors associated with each work system component
Person(s)	Factors associated with a person(s) individual characteristics such as perceptions, skills and expertise.	• Stakeholders' knowledge and perceptions of AI technology. • Stakeholders' confidence in using AI technology.
AI technology	Factors associated with the AI technology that is being created.	• Ensuring that the AI technology is useful within the setting. • Ensuring that the AI technology is designed for the setting.
Other tools and technology	Factors to do with the objects, hardware, or software (other than the AI itself) that people use to do work or assist them in doing the work.	• Integrating any electronic or digital platforms currently used • Moving from paper systems to electronic or digital solutions
Physical environment	Factors associated with the environment that the participants work in, such as the layout, workstation, and noise.	• Upgrading the physical work setting. • Noise levels of the work setting.
Tasks	Factors around the specific actions taken and the attributes or characteristics of the tasks such as difficulty, complexity, variety etc.	• The process that the AI technology will be integrated within. • How the tasks may change if AI technology is used
Organisation	Factors to do with the structures that are external to a person, such as time, space, resources, and activity.	• How the culture will need to change • Updating the guidelines already used in the setting

AI = Artificial Intelligence

Step 2: Inductive content analysis methodology was used to synthesise and group the factors aligned under each component into meaningful subthemes based on each factor's description and purpose. To validate this process, AF completed the inductive content analysis with 20% of the resources, with any disagreement discussed. If consensus could not be reached, a supervisor (ED) was consulted. The extracted factors and how they aligned under each subtheme were presented in an appendix matrix table to highlight how each factor was used to create the subthemes.

The subthemes developed were then given an appropriate description based on the descriptions of the factors aligned under the subtheme. The factors and descriptions were presented in a table, with reference to the resource that included the factors used to develop the subtheme. This table was developed to give the reader a clear overview of the subthemes and how they are aligned under the extended Work System Model. To ensure the description of each subtheme was appropriate, the final table was checked by another PhD candidate (AF) (170).

6.4. Results

6.4.1. Resource selection

The database searches between 2013 and January 2024 identified 2,085 studies and after both title and abstract and full-text screening, 17 studies were included. From those 17 studies, 10 organisational readiness resources that had been applied to AI technology were found (See Figure 6.2 for PRISMA flowchart). The percentage of agreement for the title and abstract screening was 97% (excellent), and for full-text screening, there was an agreement percentage of 94% (excellent).

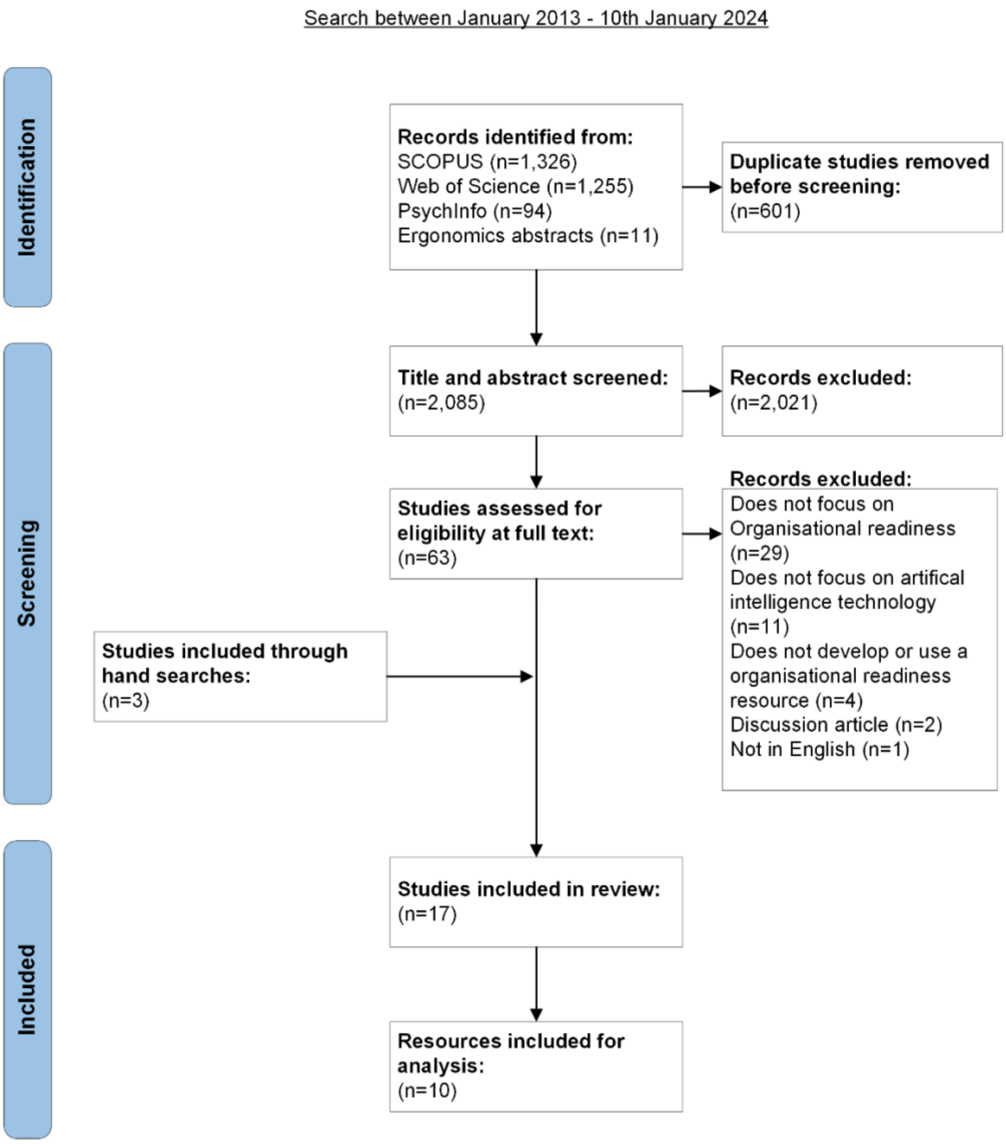

Figure 6.2: PRISMA flow chart showing the number of studies and resources identified at each stage

6.4.2. Resource characteristics

The characteristics of each of the included resources can be seen in Table 6.5. There were 10 unique resources that have been applied in 17 studies since 2013. Of the 17 studies, seven (41.2%) applied a variation of the Technology-Organisation-Environment (TOE) framework, two (11.8%) used a part of the Benefit-Organisation-Environment (BOE) model, and the remaining eight (47.1%) developed a new resource. There was various methods for developing the 10 resources, with the most common being a form of literature review (n=5, 50.0%) which was done either systematically or not systematically. Three (30.0%) of the resources were developed using qualitative research methods, such as interviews with those in the organisation or card sorting techniques. The remaining two (20.0%) used methods such as theory driven development and data from the organisation on the development of an innovation. Of the ten resources, two (20.0%) were not originally developed for AI technology but had been applied in further studies, three (30.0%) had been applied to AI technology within the original resource development study and the remaining five (50.0%) had not been applied. Across the ten resources, 180 factors were used to measure organisational readiness for AI technology (see Appendix 9 for the factors within each resource, alongside a description).

Table 6.5: Characteristics of included organisational readiness resources for AI technology (n=10)

Resource	Author(s) of resource (year published)	Aim of resource	How it was developed	Was the resource developed initially for AI technology	Studies that applied the resource for AI technology	Number of organisational readiness factors associated with each resource
Technology-Organisation-Environment (TOE) framework (311)	Tornatzky (1990)	Understand how a context influences adoption and implementation of an innovation	Theory-driven development	✘	Applied in (312-318)	47*
Benefits-Organisation-Environment (BOE) model (319)	Lacovou et al (1995)	Understand the reasons for adoption behaviour of small firms	Developed based on adoption of electronic data interchange in small business IT data	✘	Applied in (320, 321)	9**
Conceptual framework of organisational readiness (322)	Chatterjee et al (2019)	To check if an organisation is ready to adopt a customer relationship management AI tool	Developed through a general review of the literature where the appropriate information was found	✓	Not applied, only developed	15
AI readiness model (323)	Heimberger et al (2023)	To assess the organisational readiness levels of manufacturing companies in production	Developed based on existing literature	✓	Applied in a case study in the original development study (323)	6
AI readiness framework (324)	Holmstrom (2022)	To assess the organisational readiness for AI and show an organisations ability to deploy AI	Developed based on existing literature	✓	Applied in a case study in the original development study (324)	8

Resource	Author(s) of resource (year published)	Aim of resource	How it was developed	Was the resource developed initially for AI technology	Studies that applied the resource for AI technology	Number of organisational readiness factors associated with each resource
Organisational AI readiness factors (325)	Jöhnk et al (2021)	Highlight the organisational readiness factors necessary for AI adoption	Developed using qualitative research approach using interviews, card sorting methods and focus groups	✓	Not applied, only developed	18
Readiness model (326)	Nortje and Grobbelaar (2020)	To assess organisational readiness to help implement AI into business structures	Developed using two systematic literature reviews	✓	Not applied, only developed	43
Model of AI readiness (327)	Tehrani et al (2023)	Investigate the requirements for businesses to become AI ready	Developed using semi-structured interviews	✓	Not applied, only developed	24
Organisational readiness model 1 (328)	Quan-Hoang et al (2019)	Evaluate the AI readiness for the healthcare sector in developing countries	Developed using an extensive review of the literature	✓	Applied in a case study in the original development study (328)	4
Organisational readiness model 2 (329)	Youssef et al (2023)	Understand the organisational readiness factors impacting data sharing for AI in health organisations	Developed using interviews	✓	Not applied, only developed	6

AI = Artificial Intelligence, Factor = the content within each resource, or study that applied a resource which was used to measure and assess organisational readiness
* Three organisational readiness factors are associated with the original TOE framework, with the remaining associated with studies that have applied the TOE framework to AI technology
** Two organisational readiness factors are associated with the original BOE model, with the remaining associated with studies that have applied the BOE model to AI technology

Further detail on each of the resources can be seen below, including any information on the sectors the resource had been applied to, or developed for, how to apply the resource in practice and how the resources had been applied previously.

Technology-Organisation-Environment (TOE) framework

The *TOE framework* (311) was initially developed by Tornatsky in 1990 as a way to explain how the adoption of information technology is influenced by various factors. The authors created the *TOE framework* to be a theoretical underpinning for understanding adoption, which could be adapted to each new technology and setting. Whilst the original *TOE framework* was not developed specifically for AI technology, the current review found that seven (41.2%) studies had applied the resource to measure organisational readiness for AI technology in several sectors. There were two main ways in which the *TOE framework* was used to measure organisational readiness for AI technology:

(i) Used to underpin the assessment of organisational readiness

AlSheibani et al. (312) study set out the rationale for why and how the authors would use the *TOE framework* to develop an AI-readiness framework for organisations. The authors stated that the next steps would include developing and validating the framework developed in small to medium enterprises in both private and public service organisations in Australia. Furthermore, Polisetty et al. (317) used the *TOE framework* to develop a model for examining how AI readiness influences the adoption of AI technology in small and medium scale manufacturing firms. The authors used mixed methods to understand organisational readiness using the *TOE framework*, which found that the resource could highlight factors influencing the ability to adopt AI technology in small to medium-sized enterprises in India (317).

(ii) Adapted and expanded to measure organisational readiness

Frangos et al. (313), combined the *TOE framework* with the Technology Acceptance Model to create a new framework to measure organisational readiness for AI technology at the firm level. The authors state that this new framework can address the complexity that AI technology may bring to an organisation. Another study conducted by Hradecky et al. (314) used the *TOE framework* alongside the Technology Readiness Index to create an organisational readiness model for the Exhibition Sector, which can be used to understand inhibitors and motivations for AI adoption. Further, Najdawi (315) combined the *TOE framework* with the Diffusion of

Innovation theory to present a framework that will consider the socio-technical elements of organisations in the United Arab Emirates. Another study that expanded the TOE framework was Pathak and Bansal (316), where the authors combined the *TOE framework* with the Human-Organisation-Technology fit framework to create a resource that could be used to measure organisational readiness for Indian insurance organisations. Lastly, Pumplun et al (2019) expanded the *TOE framework* using interviews with stakeholders in large organisations to adapt the framework to the context of AI technology (318) The authors conclude that the initial findings expand the TOE framework to AI technology, but that future research should be conducted to adapt the framework to different setting, cultures and organisation sizes.

Benefits-Organisation-Environment (BOE) model

The *BOE model* (319) was developed by Lacovou et al. in 1995 to understand the reasons for adoption behaviours in small firms. The BOE model focuses on several aspects of adoption behaviour, with one section focusing on organisational readiness. In the original study, the *BOE model* was used as a theoretical underpinning for interviews, which were conducted to measure the adoption of Electronic Data Interchange technology. While the original resource was not developed specifically for AI technology, the current review found that since the initial development two studies have applied the organisational readiness section of the resource to AI technology. Firstly, Atwal et al. (320) applied the organisational readiness section of the *BOE model* to the Burgundy Wine industry. The authors were able to use the BOE model to highlight factors that may impact the organisational readiness of the wine sector for adopting AI technology. Secondly, Baciluliene (321) applied the organisational readiness section of the *BOE model* to the Argi-food production industry. Like the latter study, the authors were able to use the BOE model to highlight factors that may impact the adoption of AI technology in the Agri-food production industry.

Conceptual framework of organisational readiness

The *Conceptual framework of organisational readiness* (322) was developed by Chatterjee et al. in 2019 to measure the organisational readiness of customer relationship management activities for the adoption of AI technology. To support the use of the resource, the authors developed the indicators of: Red (showing the organisation is not ready), Amber (showing the organisation is somewhat ready), and Green (showing the organisation is fully ready). These indicators can be used to identify the organisation's readiness level for each factor within the resource. The resource is in development and has not yet been applied to AI technology.

AI readiness model

The *AI readiness model* (323) was developed by Heimberg et al. in 2023 to measure the readiness of manufacturing companies in production for the adoption of AI technology. To help use the resource to measure organisational readiness, the authors developed a matrix which can be scored up to two points. These scores will then determine whether the organisation has a high, moderate, low or no AI readiness level. The authors of the resource applied it to two case studies, one for a medium sized company which focused on special machine construction and solutions in the automotive and aerospace industry, and another for medium sized production company which specialised in turning and milling of precision parts. Using the matrix, the authors were able to analyse the readiness of the two organizations through observations and determined that one company had moderate AI readiness (the latter) and the other had high AI readiness (the former).

AI readiness framework

The *AI readiness framework* (324) was developed by Holmstrom in 2022 to show an organisation's AI readiness and ability to deploy AI technology. To help apply the resource, the authors created a scorecard, which measures the factors between zero and four through self-evaluation of those working in the organisation. The authors applied the framework to an insurance organisation as a case study to showcase the resource. The authors used a workshop to fill out the scorecard and were able to show the level of organisational readiness for AI technology and the reasons for that level such as the perceived ability of the organisation to implement new technologies.

Organisational AI readiness factors

The *Organisational AI readiness factors* (325) were developed by Johnk et al. in 2021 to highlight the factors necessary for AI adoption. The authors developed indicators to support the assessment of each factor within the resource which could be used to determine an organisation's readiness level. The resource was not applied in Johnk et al's study, however, the authors highlighted that future research should validate the factors within the resource, and could go on to examine the potential impacts of factor prioritisation on AI adoption.

Readiness model

The *Readiness model* (326) was developed by Nortje and Grobbelaar in 2020 to help implement AI technology into business structures. The resource has not been applied but the authors suggested that when the resource is applied, that methods such as analytical hierarchical process or Likert scales could be completed, through input from subject matter experts with experience of implementing AI technologies. However, the authors state that the resource is in the early stages of development and that further validation is necessary to produce guidance on applying the resource in practice.

Model of AI readiness

The *Model of AI readiness* (327) was developed by Tehrani et al. in 2023 to investigate the requirements for multinational corporations to become AI-ready. The resource was underpinned by a work system theory developed in by Alter in 2013 (330). The authors did not provide details on how to apply the resource to an organisation. However, the authors state that in the future the factors should be translated into 'actionable tactics' and be applied to help mangers to understand the organisational needs and changes necessary to adopt AI technology.

Organisational readiness model 1

The *Organisational readiness model 1* (328) was developed by Quan-Hoang et al. in 2019 to evaluate the AI readiness of healthcare sectors in developing countries. The authors suggest that to measure organisational readiness, researchers can assess the published literature on a country's current use of AI technology using the *Organisational readiness model 1*. The resource was applied in the study to the Vietnam healthcare setting, where the author looked at the published literature on how the country currently uses AI technology in healthcare and used this evidence to assess AI readiness and potential barriers and facilitators using the resource.

Organisational readiness model 2

The *Organisational readiness model 2* (329) was developed by Youssef et al. in 2023 to understand the factors impacting data sharing for AI technology in health organisations. The resource had not been applied but was able to highlight the importance of motivation and capabilities of a healthcare organisation to be AI ready.

6.4.3. Assessment of resources using extended Work System Model

The 180 factors (See Appendix 9 for these factors presented by resource, alongside a description) extracted from the 10 resources and the studies that had applied one of the 10 resources to AI technology were aligned under the extended Work System Model (see Table 6.6). Of the 10 resources that were applied to AI technology, all referred to factors associated with the organisation component (n=10, 100.0%). This was closely followed by the AI technology component, referred to by nine (90.0%) resources. The least cited component was the physical environment, referred to by three (30.0%) resources. Furthermore, only one resource covered all six components (327), with most of the resources focusing on five or four components.

Table 6.6: Extended Work System Model components used for each resource

Resources	Component					
	Person(s)	AI technology	Other tools and technologies	Physical environment	Tasks	Organisation
Technology-Organisation-Environment (TOE) framework (311-318)	✓	✓	✓			✓
Benefits-Organisation-Environment (BOE) model (319-321)	✓	✓	✓			✓
Conceptual framework of organisational readiness (322)	✓	✓	✓		✓	✓
AI readiness model (323)		✓	✓			✓
AI readiness framework (324)		✓			✓	✓
Organisational AI readiness factors (325)	✓	✓	✓		✓	✓
Readiness model (326)	✓	✓	✓		✓	✓
Model of AI readiness (327)	✓	✓	✓	✓	✓	✓
Organisational readiness model 1 (328)				✓		✓
Organisational readiness model 2 (329)	✓	✓		✓		✓

AI = Artificial Intelligence

5.5.6.1. Subthemes found under each component of the extended Work System Model

Once the factors were aligned under the components of the extended Work System Model, they were grouped into subthemes. Overall, 19 subthemes were identified across the extended Work System Model, with the majority under the organisation component (n=6, 31.6%), followed by the AI technology component (n=4, 21.1%), person(s) (n=3, 15.8%), other tools and technology (n=3, 15.8%), tasks (n=2, 10.5%)

and lastly physical environment (n=1, 5.3%). See Appendix 10 for a matrix of how the extracted factors align with the subthemes under the extended Work System Model.

The subthemes found within each component, alongside a description and the associated resources, can be seen in Table 6.7. Under the person(s) component, seven (70.0%) resources were aligned under three subthemes, with the most common subtheme being Expertise in AI technology (n=6, 85.7%), followed by Knowledge of AI technology (n=5, 71.4%). The *TOE framework*, *BOE model* and *Model of AI readiness* were found across all subthemes (n=3, 100.0%), with the *Readiness model* and *Organisational readiness factors* found within two subthemes (66.7%).

Nine (90.0%) resources had subthemes that referred to the AI technology component. There were four subthemes, the most common being the Availability and structure of data (n=8, 88.9%), followed by the Design of the AI technology (n=4, 44.4%). The *TOE framework* was associated with all the subthemes (n=4, 100.0%) under the AI technology component, and the *Organisational readiness factors* and *Readiness model* were associated with three subthemes (75.0%).

Under the other tools and technology component, six (60.0%) resources were associated with three subthemes, with the most common subtheme being Current uses of technology (n=4, 66.7%), followed by IT infrastructure (n=3, 50.0%). The *TOE framework* was associated with all three subthemes, with the remaining resources only being aligned with one subtheme.

Three resources (30.0%) referred to the physical environment component under one subtheme: IT facilities.

Under the tasks component, five (50.0%) resources were aligned under two subthemes, the most common being Process changes. There were no commonalities in resources across the two subthemes.

Finally, all ten resources (100.0%) were aligned with the subthemes under the organisation component. There were six subthemes altogether, with the most common being the Culture of the organisation and Strategies for successful adoption (n=7, 70.0%), followed by Cost and budget (n=6, 60.0%). The *Model of AI readiness* was aligned with all of the six themes (100.0%), followed by the *TOE framework* and *Readiness model*, which was associated with five themes (n=5, 83.3%).

Table 6.7: Subthemes under the components of the extended Work System Model

Sub-theme	Description of subtheme	Resource
Person(s)		
Expertise in AI technology	Staff with expertise in AI technology and those who can champion its adoption within the organisation are needed to support the integration of the technology.	*TOE framework* (311, 313, 315, 318) *BOE model* (320) *Conceptual framework of organisational readiness* (322) *Organisational AI readiness factors* (325) *Model of AI readiness* (327) *Organisational readiness model 2* (329)
Knowledge of AI technology	Those working in the organisation need to have some knowledge of AI technology to ensure competence once integrated. Those impacted, for example, customers and patients, should also have a level of understanding of AI technology.	*TOE framework* (313, 315) *BOE model* (321) *Organisational AI readiness factors* (325) *Readiness model* (326) *Model of AI readiness* (327)
Perceptions of AI technology	There needs to be an understanding of the perception of AI technology within the organisation, including acceptance levels, perceived benefits, perceived risk, perceived ease of use and level of trust in the technology.	*TOE framework* (314, 316, 317) *BOE model* (320) *Readiness model* (326) *Model of AI readiness* (327)
AI technology		
Availability and structure of data	The organisation needs to have data that is available and accessible within the organisation and be of sufficient quality to ensure the AI technology is trained effectively and produces accurate output. This data should be structured appropriately and flow smoothly from its source to the organisation.	*TOE framework* (312, 314-318) *BOE model* (321) *Conceptual framework of organisational readiness* (322) *AI readiness model* (323) *Organisational AI readiness factors* (325) *Readiness model* (326) *Model of AI readiness* (327) *Organisational readiness model 2* (329)
Design of the AI technology	The AI technology should be designed to be compatible with the structures and requirements of the users within the organisations. The AI technology should produce an explainable and interoperable output for the user.	*TOE framework* (312, 315-317) *Organisational AI readiness factors* (325) *Readiness model* (326) *Model of AI readiness* (327)
Benefit of using AI technology	There needs to be a benefit and advantage to using AI technology by those working in the organisation.	*TOE framework* (312, 315, 316, 318) *Organisational AI readiness factors* (325)

Sub-theme	Description of subtheme	Resource
Current and planned uses of AI technology	There needs to be an assessment of the organisations current and future uses of AI technology and any challenges associated with the use.	*TOE framework* (314) *Conceptual framework of organisational readiness* (322) *AI readiness framework* (324) *Readiness model* (326)
	Other tools and technology	
Current uses of technology	The organisation's current use of technology, tools and applications should be understood.	*TOE framework* (311) *BOE model* (319) *AI readiness model* (323) *Model of AI readiness* (327)
IT infrastructure	An appropriate IT infrastructure is needed, including computers with sufficient capabilities to handle the AI technology.	*TOE framework* (312, 316) *Conceptual framework of organisational readiness* (322) *Organisational AI readiness factors* (325)
Network infrastructure	Ensure there are appropriate cloud resources and networks within the organisation to integrate AI technology, facilitating communication between those within the organisation.	*TOE framework* (314) *Readiness model* (326)
	Physical environment	
IT facilities	There should be the appropriate facilities to store any new infrastructure required to use AI technology.	*Model of AI readiness* (327) *Organisational readiness model 1* (328) *Organisational readiness model 2* (329)
	Tasks	
Process changes	There should be an understanding of how AI technology may change the processes and how work is done within the organisation.	*Conceptual framework of organisational readiness* (322) *Organisational AI readiness factors* (325) *Model of AI readiness* (327)
Current and potential impact on activities	Assess how any current uses of AI technology impact the activities completed. Additionally, understand how AI technology may impact the organisation's future activities.	*AI readiness framework* (324) *Readiness model* (326)
	Organisation	
Cost and budget	The organisation will need to have the financial resources available to integrate the AI technology, which is influenced by the size of the organisation. Costs include the installation of the AI technology, ongoing maintenance and any associated hardware.	TOE framework BOE model (319-321) *Organisational AI readiness factors* (325) *Readiness model* (326) *Model of AI readiness* (327) *Organisational readiness model 1* (328)

Sub-theme	Description of subtheme	Resource
Culture of organisation	There will need to be an innovative culture throughout the organisation that embraces the integration of AI technology. This includes the organisation's management being supportive of AI technology and having suitable change management structures.	*TOE framework* (312, 313, 315, 316, 318) *BOE model* (320) *Conceptual framework of organisational readiness* (322) *Organisational AI readiness factors* (325) *Readiness model* (326) *Model of AI readiness* (327) *Organisational readiness model 1* (328)
Strategies for successful adoption	Organisations will need to have strategies in place to ensure that AI technology is successfully integrated. These strategies include ethical considerations, governance, implementation roadmaps, technology monitoring, resource planning, risk management, security and privacy planning, quality management and training on the new technology.	*TOE framework* (313, 314, 316, 317) *Conceptual framework of organisational readiness* (322) *AI readiness model* (323) *Organisational AI readiness factors* (325) *Readiness model* (326) *Model of AI readiness* (327) *Organisational readiness model 2* (329)
Teamwork and leadership	There will need to be appropriate leadership to ensure that AI technology is integrated and used effectively and that this is considered in the employee structures of the organisation. Effective teamwork and communication will also be needed among the organisation's employees.	*TOE framework* (311, 315, 317) *BOE model* (320) *Organisational AI readiness factors* (325) *Readiness model* (326) *Model of AI readiness* (327)
External impacts	How external regulations impact the organisation will need to be considered and how world events, such as pandemics, impact the ability to use AI technology. Competition with other organisations and the availability of technology vendors also need to be assessed.	*TOE framework* (311, 312, 314-316, 318) *Model of AI readiness* (327)
Organisational goals	How any current use of AI technology has impacted the organisational goals should be understood alongside how any future AI technology may impact the organisational goals.	*AI readiness framework* (324) *Readiness model* (326) *Model of AI readiness* (327) *Organisational readiness model 2* (329)

AI = Artificial Intelligence, TOE = Technology-Organisation-Environment, BOE = *Benefits-Organisation-Environment*

6.4. Discussion

This review collated and assessed the resources developed to measure organisational readiness for AI technology in any sector. It is hoped that these results will not only provide a summary of the available resources but also highlight important organisational readiness subthemes across the work system that should be considered when developing AI technology for the healthcare sector. The review found 17 studies that developed or used an organisational readiness resource since 2013. Of those 17 studies, there were ten unique resources. Two resources were developed for the healthcare sector with the most common being the *Technology-Organisation-Environment (TOE) framework* which was applied in seven (41.2%) studies. The ten resources were developed using various methods, including literature review (systematic and not systematic) and qualitative research (interviews) and of the ten resources, eight (80.0%) were created specifically for AI technology. Two of the ten resources had been applied outwith the original development study (20.0%), three resources had been applied to an organisation within the original resource development study (30.0%), and the remaining had only developed the resource, with no application (n=5, 50.0%). Within the ten resources there was 180 factors used to measure and assess organisational readiness. A number of authors had described how to apply the resource in practice, with some developing checklists or matrixes that can be used to facilitate use.

The organisational readiness resources were assessed using the extended Work System Model. This analysis was conducted to support the translation of the factors within the resources to the healthcare sector while also considering the whole work system. Results found that only one (10.0%) resource had factors associated with all six of the extended Work System Model components (327), with the most common component highlighted being organisation. Overall, 19 subthemes were found across the six extended Work System Model components. Most subthemes (n=6) were found under the organisation component, followed by the AI technology component (n=4). The person(s) and other tools and technology components had three subthemes, with the tasks component comprising two subthemes, followed by the physical environment, which had one subtheme.

In the context of the wider evidence base, the following discussion will provide a commentary on the resources found within the review and the assessment of factors under the extended Work System Model. The strengths and limitations of the review and recommendations for future research will then be discussed, and a conclusion will be made.

6.4.1. Characteristics of resources

Within the 17 studies included, ten individual resources had been explicitly developed or adapted to measure organisational readiness. There was variation across the organisational readiness resources. For example, there was different terminology regarding how the resources were named, with some being referred to as models while others were conceptual frameworks. This may reflect the different terminology used across sectors; however, it may cause difficulty when deciding which resource is most suitable for an organisation. Previous research has highlighted that the terminology used in organisations should be standardised for various reasons, such as ensuring constancy across documents, increased clarity of the subject and finding the necessary information (331). However, it would be beneficial if language could be standardised across organisations and sectors to improve the transferability of information and learning, which is often done within the human factors discipline.

Further variation was seen in how the resources were developed, which often consisted of conducting a systematic or unsystematic literature review or completing qualitative research with those in the organisation. This variation in development may mean some resources were not developed using empirical methods, resulting in reduced validity. For example, some resources were developed using unsystematic reviewing methods, where the authors may not have applied reporting guidelines such as the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRIMSA) (332). By not using guides for reporting, important steps may not have been considered, such as validation of screening, causing results to lack quality and transparency (332). Therefore, there may be a need for more standardisation and guidance on developing these types of resources to ensure there is a standardised level of rigor in the methodology. To the researcher’s knowledge, there is currently no guidance on developing resources for organisational readiness; however, there is guidance for other types of resources. For example, The Chartered Institute of Ergonomics and Human Factors (CIEHF) has developed guidance on developing standard operating procedures (SOPs) for the healthcare sector. This document provides health and social care teams with advice and guidance on how to create human-centred SOPs and highlights important points to consider at each stage of development (333). Another area where there is a standardised approach to the development of resources is within the National Institute for Health and Care Excellence (NICE), where evidence-based guidance is produced (334). Furthermore, guidance is also published around ensuring a resource is accessible, for example, for those with visual impairment (335). Therefore, by referring to the guidance developed for other resources and presenting a set of rules considering the accessibility, terminology and development method to follow when creating a resource for organisational readiness, standardisation could be achieved.

Interestingly, despite previous research suggesting that currently there is limited focus on the organisational readiness of healthcare for AI technology (133), two resources were developed for the sector (328, 329). However, these resources were developed for specific countries (non-western) and for specific tasks related to AI technology (data sharing). Therefore, these resources could not be generalised to AI technology across the healthcare sector. The most common resource used to measure organisational readiness for AI technology was the *Technology-Organisation-Environment (TOE) framework*, which had been adapted or expanded within seven studies. However, the *Technology-Organisation-Environment (TOE) framework* was not initially developed for AI technology and, in most cases, underwent some adaption to be applied to AI technology, including being expanded to include other models such as the Technology Acceptance Model. This may suggest that the framework in its original form may only be partially suitable for measuring organisational readiness for AI technology. Therefore, it may be that the *Technology-Organisation-Environment (TOE) framework* needs to be adapted to AI technology or that another resource needs to be highlighted as the most appropriate for measuring organisational readiness. As previous literature has suggested, taking a systems perspective when measuring organisational readiness can be beneficial. Taking a systems perspective was also found in one of the included resources, which used a work system theory to underpin the final resource (327). Therefore, a systems model could be highlighted as the best resource for measuring organisational readiness (148). The current review used the extended Work System Model to translate the resource factors into healthcare, highlighting how organisational readiness factors can cover the full work system. While the extended Work System Model was developed specifically for AI technology in healthcare, other systems-based resources could be applied to any sector, such as the sociotechnical systems theory (See Chapter 2, Section 2.3.1)(149). Overall, using a systems model to help underpin the development of future organisational readiness resources for AI technology will help understand the full system where the technology will be integrated and increase the consistency across resources.

6.4.2. Subthemes under the extended Work System Model

Results found that most resources had factors aligned with four or five of the components within the model, with only one resource having factors aligned with all six components. Interestingly, the one resource that aligned with all six components was also underpinned by a work system theory, which may explain why it aligned fully under the extended Work System Model (327). Moreover, it is encouraging that most of the resources are aligned with the majority of the components, as this shows that in the past, a systems approach was mostly taken when measuring organisational readiness for AI technology. However, as only one resource had factors aligned with all six components, this further highlights that a standardised format, underpinned by a work system model that is developed specifically for AI technology would be beneficial.

The following sections discuss the subthemes found under each component of the extended Work System Models and how these relate to the wider evidence base.

5.5.6.2. Person(s)

The results found three main subthemes under the Person(s) component: Expertise, Knowledge and Perceptions of AI technology.

Having sufficient knowledge of AI technology and its capabilities was also highlighted as a key requirement in Chapter 5's interview study (Section 5.5.3.2), where participants suggested an increased knowledge of AI technology was needed to use the AI-based sepsis fluid management (AI-SFM) tool. This need for sufficient knowledge before AI technology can be used in an organisation was highlighted in the wider literature, which suggested that increased AI literacy was necessary across sectors. However, there is a debate over the level of knowledge individuals should have, for example, whether users only need to understand how a specific AI technology works or go further and understand the design of the technology and the ethical concerns (282, 336). Resources also suggested a need for specific expertise regarding AI technology within an organisation alongside champions for the technology. There is evidence in the wider literature that having a champion within the organisation would facilitate using AI technology (204). Regarding expertise, Chapter 5's study did highlight the need to bring in those with AI expertise; however, this was found within the organisation component due to participants highlighting that the management within the organisation would need to facilitate any additional team members (Section 5.5.8.3). This shows how components may interact within the work system and the impact of different contexts and settings, which is a strength of using a systems model (148).

Finally, the subtheme related to perceptions indicated a need to understand how those within the organisation perceive AI technologies. The benefit of understanding the perceptions of individuals impacted by the technology was highlighted in Chapter 5's interview study, where asking how participants felt about the technology indicated key barriers that would need to be overcome before the AI-SFM tool could be applied (Section 5.5.4.1). A key perception highlighted in the resources was the perceived trust in AI technology. Previous research has suggested that having insufficient trust, caused by concerns about the quality of the technology, would be a challenge to the use of AI technology in the healthcare sector (37, 129). Further, a study by Choung et al. in 2022 found a significant relationship between a person's trust level and overall acceptance of AI technology (337). Therefore, understanding the perceptions, including trust, is important to ensure that any barriers caused by these perceptions do not impact the final integration.

5.5.6.3. AI technology

The results found four main subthemes within the AI technology component: Availability and structure of data, Design of the AI technology, Benefit of using the AI technology, and Current and planned uses of AI technology.

The resources highlighted that having available data that is structured correctly was key to ensuring sufficient organisational readiness. This need for accurate data is seen within the literature, as previous research has highlighted that historical biases towards characteristics, such as gender or ethnicity, can often influence AI technology (142). This bias may impact the accuracy of the output from the AI technology, which may, in turn, reduce trust in the technology (37). While it may not be possible to remove all biases, research is now being conducted on what should be done within organisations to mitigate against any found bias (241, 338). How the AI technology is designed was also highlighted as a key subtheme that impacts organisational readiness levels. The included resources suggested that AI technology should be designed to fit the users' needs and that the output given by the technology should be understandable to those users. The need for AI technology to be designed for the future user was highlighted as a key part of the development lifecycle of AI technology in the literature found in Chapter 4’s scoping review and the results in Chapter 5. Chapter 5’s study highlighted what the users would change about the AI-SFM tool to use it within adult critical care (Section 5.5.4.2). These changes were associated with how the AI tool was developed (e.g. how the tool should be dynamic and updated based on new information) and the output (e.g. the explainability of the final result from the tool). Finally, the benefits and advantages of using AI technology was considered a key subtheme influencing organisational readiness under the AI technology component. Previously, the benefit of using AI technology, such as time-saving or increased efficiency, has been suggested as a key facilitator for clinicians adopting AI technology (129). This was also shown in Chapter 5’s study, where participants indicated that the various benefits for clinicians and patients impacted their perceived usefulness of the AI-SFM tool (Section 5.5.4.1).

5.5.6.4. Other tools and technology

Results found three main subthemes within the other tools and technology components: current uses of technology, IT infrastructure and network infrastructure.

The most common subtheme under the other tools and technologies component focused on understanding the current uses of technology. Understanding the current work system alongside the necessary changes is important for developing AI technology. This process will help indicate any tools and technology that may need to be upgraded or replaced if AI technology is integrated (155). Understanding current technology may align with the other two subthemes within the component, which focus on having appropriate IT and network infrastructure to use the AI technology. The need for the appropriate IT and network infrastructure was highlighted as important in Chapter 5’s study, where participants stated that they would need to move from a paper-based to an electronic-based platform in adult critical care to use the AI-SFM tool (Section 5.5.5.2). Interestingly, the resources in the current review did not highlight the need to ensure platforms are electronic, despite it being considered an important barrier to using the AI-SFM tool. However, research has suggested that the healthcare sector is often slow when adopting and developing technology (339). Therefore, it may be that other sectors where organisational readiness resources have been developed have already become fully electronic and, as a result, this is no longer considered a requirement before AI technology can be applied. This would suggest that while the factors found in previously developed resources can be adapted to the healthcare sector, further analysis may be needed to ensure that all are captured.

5.5.6.5. Physical environment

There was one main subtheme aligned with the physical environment: IT facilities.

The subthemes aligned with the physical environment component indicated that the IT facilities available within the organisation should be appropriate, as without these, there may not be appropriate storage or space for the new AI technology. Availability of space and hospital age were highlighted as potential barriers to using the AI-SFM tool in Chapter 5 (Section 5.5.6.1). However, less emphasis was given to the physical environment within the organisational readiness resources despite the importance highlighted in Chapter 5. Similar to the other tools and technology components, this may also be due to healthcare being slow to adopt technologies, resulting in other sectors being further ahead in their ability to apply AI technology (339). This is further emphasised as two of the three resources aligned with this component's subtheme were developed for the healthcare sector. This again highlights the importance of continuing this translation into healthcare through further research to ensure all important subthemes are considered.

5.5.6.6. Tasks

Two subthemes aligned with the tasks component: process changes and current and potential impact on activities.

Understanding the potential process changes within an organisation was highlighted as a key approach within Chapter 4’s review, where studies had completed an analysis of the workflow to understand how the AI technology may integrate (Section 4.4.4). For example, Abdel-Raham et al. assessed the clinical workflow in 2016 and 2020 by creating process charts and decomposing the individual tasks completed within the setting (180, 193). The results were then used to understand how the AI technology would fit within this process (180, 193). Further, process changes that may result from AI technology were also found within Chapter 5, where participants highlighted the current steps taken for sepsis fluid management and how the AI-SFM tool may impact these (Section 5.5.7.1 & Section 5.5.7.2). The second subtheme aligned with the task component was understanding how AI technology currently impacts activities and how future AI technology may also impact the activities. This will be an important aspect as AI technology may be able to support certain activities such as quality improvement or completing audits (340). Therefore, understanding how AI technology can support or hinder the activities completed currently or in the future will help plan future innovations.

5.5.6.7. Organisation

The organisation was the most common component and contained six subthemes: cost and budget, the organisation's culture, strategies for successful adoption, teamwork and leadership, external impacts and organisational goals.

Having the necessary budget was a key subtheme aligned with the organisation component. This need for financial resources was also highlighted in Chapter 5, where participants stated that the organisation's management would need to ensure a sufficient budget to integrate the AI-SFM tool (Section 5.5.8.3). To support this need for sufficient financial resources, there has been a push to allocate more money to developing AI technology within healthcare and healthcare research. For example, in 2023 the UK government set up a fund of 100 million to help capitalise on the potential of AI technology in healthcare and life sciences (341). Further to having the appropriate financial capabilities, the organisation's culture was considered important to ensure organisational readiness for AI technology. An organisations culture has been indicated as a barrier to adopting AI technology in previous research (342) and was also highlighted in Chapter 5 as an area where the organisation's management would need to change to use the AI-SFM tool (Section 5.5.8.3).

Having appropriate strategies in place was highlighted as necessary to ensure there was sufficient organisational readiness for AI technology. These strategies include having appropriate governance and training to ensure AI technology is used safely and effectively. Having a training strategy in place was discussed by participants in Chapter 5, where it was indicated that the organisation's management would need to ensure appropriate training was in place so that the AI-SFM tool was used correctly (Section 5.5.8.3). A further subtheme under the organisation component focused on how the AI technology would work within the team and how that team would work alongside the technology. As Chapter 2 (Section 2.4) indicates, AI technology in healthcare will differ from previous technology as it will become a multidisciplinary team member (79, 82). Therefore, having sufficient teamwork and leadership within an organisation will be of great importance to ensure that AI technology can be used to its best ability. Finally, another subtheme that should be considered when measuring organisational readiness is the external impacts such as regulations. Regulation regarding AI technology and its uses is becoming more apparent, for example, with the development of the AI Act (see Chapter 2, Section 1.2.1) (55). Therefore, understanding how regulation may impact AI technology use will be important to ensure good organisational readiness.

6.4.3. Strengths and limitations

To the researcher's knowledge, this is the first review that assessed the resources developed to measure organisational readiness for AI technology and then used a work system model to translate the factors found within the resources into the healthcare sector. This review highlights that using a model can support the translation of human factors research from one sector into another. As discussed in Chapter 5, using the extended Work System Model to complete the analysis is a strength as it allows for a full understanding of the system where the AI technology will be utilised (61, 265). However, while using a work system model can be considered a strength overall, challenges may occur due to the interrelatedness of the components. This may impact the analysis of the factors found within the resources, as which component the factors are under can be subjective. To mitigate against any impacts of the interrelation between the components, 20% of the studies included within the analysis were validated by another researcher with experience in human factors research.

The review was limited to peer-reviewed research that either applied or developed an organisational readiness resource and, therefore, did not include any resources not published in research journals (grey literature). Some sectors may publish research differently and instead produce documents such as whitepapers or policies. However, it was felt that, on balance, only focusing on published resources would not impact the final result and would ensure the organisational readiness resources were of good quality as they had undergone peer review. Furthermore, the resources were limited to those applied or developed for AI technology after 2013 to align with the scoping review completed in Chapter 4. While this may have resulted in missing relevant resources, all the resources were applied or developed after 2018. Therefore, it is felt that this limit did not impact the final result.

6.4.4. Future research

This review created an initial set of subthemes that can be used to assess the organisational readiness of healthcare for using AI technology. To the researcher's knowledge, this is the first study that provides organisational readiness subthemes to consider when developing AI technology for healthcare, despite the understood importance. Therefore, the results should be disseminated to the wider healthcare AI technology and human factors researchers and developers to support future development. By applying the knowledge found in this review, the organisational readiness of healthcare for AI technology will be considered, allowing for the technology to be integrated and used effectively.

The current review was also able to consolidate the resources that had been developed to measure organisational readiness for AI technology across sectors. Therefore, creating a database of these resources, which highlights the factors within the resource, alongside any appropriate information for how to apply the resource and case studies of how the resource has previously been applied would be useful. This would allow future researchers and developers to choose the most appropriate resource for the new AI technology and organisation across any sector.

Further research should be conducted to ensure that key subthemes have not been missed, for example, only one subtheme was found within the physical environment component. Results found in Chapter 5 suggest that this component has a greater influence on the organisational readiness level in the healthcare sector. Therefore, further research should be conducted to capture all subthemes, which may involve interviews with those working within healthcare or conducting Delphi methodology to gain consensus on the important organisational readiness subthemes necessary for healthcare (343). Furthermore, it would be beneficial if future research could conduct an extensive grey literature search to highlight any resources developed to measure organisational readiness that had not been published in peer-reviewed journals. This could be completed through searches of key organisation websites and discussions with key personnel within the field.

6.4.5. Conclusions

This review consolidated the resources developed to measure organisational readiness for AI technology across sectors. Results found that across 17 studies, ten resources were found that measure organisational readiness for AI technology, which had been developed for several sectors using various methods and different terminology. Further, while it is encouraging that most resources covered the majority of the extended Work System Model components, overall, the findings highlight the need for a standardised method for the development resource, which considered the whole work system. Results indicated the need for sufficient knowledge of AI technology within an organisation and that the perceptions of those within that organisation should be understood so that any barriers they highlight are overcome. Further, organisations will need to ensure that appropriate data is used to develop and validate the AI technology, and in line with previous chapters, the design of the AI technology should consider the needs of the users of the technology. Ensuring the appropriate network and IT infrastructure, alongside the necessary space to accommodate any new technology or tools needed for the AI technology, was also considered key to ensuring organisational readiness. How the AI technology will fit within the organisation's processes and activities was also highlighted, alongside understanding how it may impact future activities, such as auditing, within the organisation. Finally, aspects of the organisation should be considered, such as the culture and the financial resources, to ensure sufficient organisational readiness. The results from this review developed subthemes that can be used to assess the organisational readiness of healthcare for AI technology. These results will be useful and should be disseminated among AI researchers and developers to ensure the organisational readiness of healthcare is considered when developing AI technology, to allow it to be used effectively in the sector. Further the results of this study may be of interest to those working in healthcare, as it may highlight what aspects of organisational readiness are already of interest via the resources contained within this review, and may highlight what the areas of priority or what may need to be overcome if AI technology is going to be used within their setting.

Chapter 7: Final discussion

This chapter aims to summarise the results found within this thesis and describe the potential impact this research has on the development of artificial intelligence (AI) technology in healthcare. Furthermore, this chapter will discuss the strengths and limitations of the research completed in this thesis, provide recommendations for future research and AI technology development, and make final conclusions.

7.1. Overview of key findings

Stage 1

The development of AI technology is increasing in healthcare, especially for clinical decision support in the hospital setting (51, 156). Research has focused mostly on the technological development of AI technology rather than how it will fit within the clinical work system (81). To help ensure the work system is fully considered in the development of new AI healthcare technology, human factors approaches can be applied across the development lifecycle (61, 82). Therefore, a systematic scoping review was conducted to gain insight into how previous human factors approaches have been applied to AI-based clinical decision support technology in the hospital setting. The review found 64 studies that had applied a human factors approach to AI-based clinical decision support technology in the hospital setting published between January 2013 and August 2023. The review found that the human factors approaches identified had been applied to several types of AI technology, including rules-based and learning-based, for various tasks and conditions, including diagnosing and treating sepsis. Twenty of the included studies specifically mentioned that they used a human factors approach in their exploration of AI healthcare technology. The human factors approaches were aligned under the Stages of the AI technology lifecycle: Design, Implementation and Use. Under the Design stage, seven approaches were grouped into three categories: pre-development analysis, development of a prototype, and prototype testing. Under the Implementation stage, four approaches were grouped into three categories: testing in practice, implementation process and post-implementation testing. Finally, under the Use stage, three approaches were grouped into two categories: testing in practice and understanding stakeholders' perspectives. The approaches applied various techniques, including qualitative and quantitative data collection methods, and the application of models, theories, and frameworks that were used to support the approach. A key output from this stage highlighted how human factors approaches can be applied from the outset of AI technology development, including assessing the needs of users.

Stage 2

Stage 2 of this thesis applied the *Assessment of user needs* approach found in Stage 1 to an AI tool for sepsis fluid management (AI-SFM tool). This approach was chosen to demonstrate further the benefit and importance of including human factors approaches from the outset of AI technology development as it will allow for system perspective to be taken and the technology to be developed for the users and their work system. Stage 2 involved conducting 20 semi-structured interviews informed by the extended Work System Model (155) with clinicians (six trainee doctors, five pharmacists, four consultants, four advanced critical care practitioners, and one nurse) working in Scottish adult critical care. The extended Work System Model is made up of six components (AI technology, person(s), other tools and technology, physical environment, tasks and organisation) was chosen to ensure that there was consideration for the full work system, including the new AI technology. Results were presented under the extended Work System Model, where under the AI technology component clinicians suggested that the AI-SFM tool would be useful within adult critical care. Nevertheless, participants had some suggestions for the AI-SFM tool's development, including that it should be integrated into their current or future electronic platforms and how the tool should explain to the user how a fluid volume decision was made. Under the person(s) and tasks component, participants highlighted that there would need to be an increase in knowledge of AI technology overall and there were concerns regarding a potential increase in workload. Under the other tools and technology, physical environment and organisational components, barriers were suggested regarding the variation in the current tools and technologies used across Scotland as well as limitations in the design of adult critical care which could potentially hinder the integration of the AI technology. It was further suggested that these barriers would need to be addressed and overcome by the organisation. These results suggest that adult critical care in Scotland currently lacks the organisational readiness necessary to integrate and use AI technology.

Stage 3

The findings in Stage 2 indicated a lack of organisational readiness for AI technology in Scottish adult critical care. Organisational readiness has been highlighted as a key barrier in the literature for adopting AI technology in healthcare (130, 131). Still, limited focus has been given to overcoming these barriers despite research in other sectors developing resources for measuring organisational readiness (133). Therefore, in Stage 3 conducted a scoping review to collate the developed resources used to measure organisational readiness for AI technology across sectors. The resources and any study that had applied a resources were then analysed using the extended Work System Model to support the translation into the healthcare sector. Overall, 17 studies were found that applied ten resources to measure organisational readiness for AI technology in any sector, with the most common resource being the *Technology-Organisation-Environment (TOE)* framework. The organisational readiness factors within each resource, and by the studies that had applied an established resource to AI technology, were aligned under the six components of the extended Work System Model. One resource, *Model of AI readiness* (327), was found to align with all six components of the extended Work System Model, with most resources aligning with four or five components. When the organisational readiness factors aligned under each component were analysed results suggested a need for sufficient knowledge of AI technology and appropriate data to ensure the technology is developed effectively. Further, results suggested having sufficient IT and network facilities alongside the necessary infrastructure and processes were necessary implement AI technology. Finally, resources indicated that financial means need to be in place, and a culture that accepts AI technology must be established across the organisation to ensure the technology is integrated effectively. The results from this stage aim to support future developers and researchers in deciding what to consider when assessing organisational readiness for AI technology in healthcare.

7.2. Implications of research

Overall, the research completed in this thesis adds to the evidence base of how the discipline of human factors may support the development of AI technology for the healthcare sector. The need for increased evidence was highlighted in Stage 1, where only 64 studies were found to have applied a human factors approach to AI-based clinical decision support between January 2013 and August 2023 in a hospital setting. This contrasts with the research focusing on AI's technological development across all healthcare settings, where from 2010 to 2020, it was suggested that there were over 12,000 studies published and indexed in PubMed (42). However, despite the number of studies published, evidence suggests AI technology is often not integrated or used effectively in healthcare (61, 82). This lack of effectively integrated AI technology in healthcare may be the result of the limited focus on the human factors discipline, resulting in AI technology not being developed for the work system where it will be integrated. Therefore, the research completed in this thesis and the results produced can add to the evidence base on the application of the human factors discipline to the development of AI technology.

Specifically, the research completed in Stage 1 of this thesis identified a set of approaches to use while developing AI-based clinical decision support technology, and potential techniques to apply to those approaches. Previous research has highlighted the importance of applying the human factors discipline throughout the AI technology development lifecycle (134). Therefore, researchers and developers can use the results found in this stage to help decide what human factors approaches could be taken when developing a specific AI technology. To highlight the benefits of applying the human factors discipline from the outset of AI technology development, Stage 2 took an approach that could be completed during the initial conception of an AI technology and applied to an AI-SFM tool. To support the approach, the extended Work System Model was used to underpin the semi-structured interviews and analysis. The use of the extended Work System Model was able to highlight key areas within the Scottish adult critical care unit work system that need to change to integrate the AI-SFM tool. Participants were also able to provide further details on how the AI-SFM tool should be designed, including its presentation and outputs. When the results from this stage were fed back to the developer of the AI-SFM tool algorithm, they had been unaware of the potential barriers to using AI technology within this setting, especially regarding the lack of consistency in terms of the tools and technologies used within healthcare. This highlights the benefit of human factors approaches from the outset of the development of AI technology, and utilising a Work System Model that has been extended to AI technology, as the barriers may not have been discovered until later, and the technology users' needs and wants would not be included in the design.

The results from Stage 2 highlighted a potential lack of organisational readiness for AI technology, which was considered an important area to change within adult critical care. However, this is not limited to adult critical care in Scotland, with literature highlighting a general lack of organisational readiness in healthcare for AI technology (133). This is despite other sectors developing resources for measuring and assessing organisational readiness. Therefore, the results in Stage 3 were able to add to this evidence by bringing together the resources other sectors (including healthcare) have developed for measuring organisational readiness and using the extended Work System Model to support the translation of the factors into the healthcare sector. Therefore, the output from this stage can be used by researchers to understand the key areas to consider when looking at the organisational readiness of a chosen healthcare setting for AI technology, which is based on the established literature.

The results of this thesis could also help support the aims set out in previously published digital and AI strategies. In Scotland, specifically, the Digital Health and Care Strategy was developed in 2021 and sets out the vision for using digital technology to deliver healthcare services (17). One of the key aims of this strategy is to develop digital technologies that are person-centred, safe, secure, and ethical to ensure confidence in the output. The results of this thesis can contribute to this aim to help make sure that the development of AI technology considers the user of the technology. For example, based on previous literature, Stage 1 of this thesis sets out human factors approaches that could be applied to ensure AI technology is developed for the user. The benefit of applying a human factors approach to an AI technology concept is then highlighted in Stage 2, as the study showed key barriers to using the AI-SFM tool in Scottish adult critical care across the work system. Overall, key findings within this thesis can help support specific aims set out in the Digital Health and Care strategy by helping to ensure future AI technology is person-centred in its development.

The Scottish Government has also produced an Artificial Intelligence strategy (2021) (18), which was developed to help the country become a leader in developing and using trustworthy, ethical and inclusive AI technology across all sectors, including healthcare. The strategy sets out several principles, which can be supported by the research conducted in this thesis. For example, one principle refers to AI technology benefiting people and the planet by driving inclusive growth, sustainable development and well-being. The approaches found in Stage 1, including the assessment of user needs completed in Stage 2 of this thesis could be applied to help ensure that any AI technology being developed benefits the users and their full work system and, therefore, supports the completion of this principle. However, while the strategy does have some reference to ensuring that future AI technology is developed for the users, it does not reference how the discipline of human factors can be used to support this.

Therefore, it may be useful to communicate the findings in this thesis to the developers of this strategy within the Scottish Government so that any future iterations consider the human factors discipline.

The results found in this thesis have been used to help support the work completed by the Chartered Institute of Ergonomics and Human Factors (CIEHF) special interest group on AI and Digital Health. The special interest group's overarching aim is to formulate the CIEHF's position on designing and using AI and digital health technology for healthcare and then represent that position. The results have been iteratively fed back to the group, and the researcher has been able to use the knowledge gained to help contribute to the group’s outputs. One of these outputs is a deployment guideline for clinicians interested in developing AI technology, which sets out steps to be taken when integrating AI technology into healthcare. The researcher was able to use knowledge gained throughout this thesis to support the development of the final guide which will be presented at the CIEHF annual conference in April 2024. Further, the results from this thesis have been used to support the write up of opinion articles for the CIEHF membership magazine ‘The Ergonomist’. The articles focus on providing the CIEHF community with current discussions and research on the use of the human factors discipline for developing AI technology (344, 345).

7.3. Strengths and limitations

The application of the extended Work System Model applied during Stages 2 and 3 of this thesis can be considered a strength, because it considers new AI technology as a separate component that interacts with the other components within that work system to create an outcome (155). Having AI technology as a separate component is important as it allows for an understanding of how the AI technology will interact with the other components within the work system. This understanding is critical, because AI technology will become a member of the multidisciplinary team and result in a new way of working in healthcare. Therefore, understanding how AI technology impacts the other components currently in the work system is key to ensuring the technology is used effectively. However, a limitation of using a work system model for analysis was the potential interrelation between the components, resulting in the researcher often using their subjective opinion to decide where data would be best placed within the six components. However, to help mitigate against any potential challenges with the subjective opinion, validation was completed at all stages of analysis, and definitions were developed using the literature before completing the analysis to ensure consistency.

Qualitative data collection and analysis methods (semi-structured interviews, framework and content analysis) were used during all stages of this thesis. Specifically, the use of semi-structured interviews in Stage 2 can be seen as a strength, as these methods allow for an in-depth understanding of what clinicians would change about their current work system to use an AI-SFM tool (261). Moreover, the use of interviews was the most common data collection method found to complete the approaches in Stage 1. However, challenges are associated with applying qualitative research, including the possibility of the researcher's subjective opinions and biases influencing the final data analysis. Therefore, as previously mentioned with regard to the extended Work System Model, validation was completed for data analysis throughout all stages of this thesis to mitigate any subjective opinions and potential biases.

An iterative approach that was used throughout this thesis when deciding on the topic of each stage can be seen as a strength. Stage 1 was completed to understand how human factors approaches had been applied during the AI technology lifecycle. An approach found in Stage 1 was then used to underpin Stage 2 to highlight further how the human factors discipline can be used to understand and support the development of AI technology. One of the key outputs from Stage 2 was that within Scottish adult critical care, there is currently a limited organisational readiness for AI technology. The lack of organisational readiness was then used to inform the research conducted in Stage 3. This iterative approach was taken deliberately as each stage of the thesis informed the next, to ensure the approach taken was evidence-based.

Adult critical care settings care for the most complex patients within hospitals and, therefore, require strong collaboration between clinicians to ensure that care is completed to the highest standards. Therefore, having input from a range of clinicians involved with the fluid management of sepsis was a key strength of the interviews conducted in Stage 2 of this thesis. However, Stage 2 did not gain insights from others who may be impacted by using the AI-SFM tool, including patients, family members/carers and non-healthcare professionals. This was despite the review in Stage 1 finding that research should include all stakeholders whom the new AI technology may impact to understand the work system fully. While it may have been beneficial to include other groups who may be impacted by the AI-SFM tool, such as patients, it was felt that clinicians would be the main group that would be impacted by the use of such a new technology in the first instance. This was due to the severity of illness that patients would be experiencing while in adult critical care and may, therefore, not have the level of influence in their treatment that they may have in other units.

A potential limitation of the research was that the results in Stage 2 cannot be generalised to wider healthcare settings, as it is limited to Scottish adult critical care and the needs of the clinicians working in that setting. However, the focus on a single setting was specifically chosen as AI technology in its current form is often only developed to support a single task or condition. Nonetheless, the results have highlighted the benefits of the human factors approach, which could be applied and adapted to any new AI technology or setting.

7.4. Recommendations for future AI technology

The results of this thesis have added to the limited evidence on the application of the discipline of human factors to the development of AI technology in the healthcare sector. However, based on this evidence, there are recommendations to help ensure human factors are considered during the development of AI technology in the healthcare sector in future. These recommendations are structured to highlight who they be of interest to.

AI developers and human factors specialists

AI technology can potentially support the healthcare sector, especially for clinical decision-making regarding conditions such as sepsis (36). However, research would suggest that once AI technology is applied in clinical practice, its benefits are reduced, which may result from human factors approaches not having been applied during the development. The research completed in this thesis aimed to add to the evidence base on the benefit of applying human factors approaches to the development of AI technology. Furthermore, it is hoped that the results of this thesis will provide practical outputs that can be applied to other AI technologies being developed. These outputs include the human factors approaches that could be applied to AI-based clinical decision support technology in hospitals, and the areas of organisational readiness that should be considered for AI technology in healthcare. Therefore, the results of this thesis should be communicated to the wider AI and human factors community so that future researchers and developers will consider and apply these human factors approaches routinely during the development of AI technology.

Researchers

Future research should provide further evidence of the benefits of applying human factors approaches throughout the AI development lifecycle. To achieve this, firstly, the scoping review completed in Stage 1 should be continually updated to ensure it is considering any new evidence. Secondly, the application of the approaches set out in Stage 1 could be continued with the AI-SFM tool, which may include completing further research to understand the workflow within adult critical care through observations. However, this should also include assessing further the organisational readiness of Scottish adult critical care, using the output from Stage 3 to ensure any related barriers to the use of the AI-SFM tool are overcome. By applying the extended Work System Model during Stages 2 and 3 of this thesis, the results were able to highlight how AI technology will interact with other components within the work system, while also understanding the AI technology separately. Therefore, future research should continue to utilise the extended Work System Model when completing a human factors approach.

Previous research has suggested that AI technology will become a member of the multidisciplinary team in healthcare and highlights the importance of sufficient human-AI teaming to ensure the AI technology is used effectively (79, 82). However, previous research and the results of Stage 1 highlighted that it will not only be clinicians who will impacted by AI technology but also non-clinical staff and patients. In Stage 2, only clinicians were included in the analysis, as they were considered key for understanding the needs within adult critical care for the AI-SFM tool. However, future research should ensure that all those within the chosen healthcare setting that could be impacted by AI technology are included in the assessment. This could include completing the approach taken in Stage 2 with non-clinical staff and patients to understand the needs of all those with whom the AI technology will interact. Additionally, it may be beneficial to create patient and public steering groups that can provide insights and support the development of AI technology in healthcare.

Regarding the output of Stage 3, it may also be beneficial to complete further validation with key stakeholders working on AI for healthcare to ensure all important aspects of organisational readiness are considered. Once this is completed the output from Stage 3 could be considered a useful resource for assessing the organisational readiness of a healthcare setting for using AI technology. Therefore, the outputs representing the key organisational readiness subthemes under the extended Work System Model could be disseminated to the wider human factors and AI communities so that future researchers and developers can apply the findings.

Policy makers and regulators

Regulations and standards are being published for AI technology, such as the AI Act created by the European Union (55). As AI technology becomes more prominent in the healthcare sector, more policies and regulations will be created. These regulations and standards will set out the best practices for developing AI technology, which should be followed by AI developers to ensure the technology is trustworthy and developed to the highest standard. There has been some limited integration of human factors recently (2023) including for British Standards, which published 'BS30440: Validation Framework for the use of AI in healthcare' (346). However, within this standard, human factors were only considered at one stage focusing on the development of the technology and not throughout. Therefore, the key results from this thesis could be of use to regulators, and those involved with creating government policy to highlight the importance of incorporating human factors approaches across the development lifecycle of AI technology. For example, this may include presenting and sharing how the work completed in this thesis could inform future policy and practice in Scottish healthcare.

Human factors specialists

To support the increased application of human factors to the development of AI technology, future work could continue to be completed alongside the Chartered Institute of Ergonomics and Human Factors AI and Digital Health special interest group. In 2022 the special interest group produced a white paper on human factors and AI technology, which was used as a key reference throughout this thesis (82). The work completed in this thesis could influence future publications, which may include developing an updated version of the white paper and producing guidelines for policy makers on how to integrate the human factors discipline into future AI technology policy.

7.5. Final conclusions

AI technology can potentially support the healthcare sector, especially within the hospital setting, for complex conditions such as sepsis. However, if research continues to focus on developing AI technology with a technology-centred focus and less so with a human-centred approach, how it will fit within healthcare work systems may not be fully understood, and its potential may not be fully realised. To ensure the full potential of AI technology is brought to fruition, the discipline of human factors can be applied to understand the work systems within healthcare.

This thesis has provided an understanding of the human factors approaches that can be applied throughout the development of AI technology. Furthermore, by using one of these approaches and utilising the extended Work System Model, this thesis highlights the benefits of applying human factors, as it suggests areas to change and barriers to using an AI-SFM tool for adult critical care. Finally, a scoping review of resources indicated key areas that could support the assessment of the organisational readiness of healthcare for integrating AI technology. Throughout this thesis, efforts have been made to develop outputs that can be adapted and used practically by future researchers and developers to ensure the discipline of human factors is considered throughout the development of AI technology. Future efforts should be made to further evidence the benefit of applying human factors approaches to the development of AI technology and use the results to support and influence the creation of regulation and policy. Moreover, efforts should be made to increase the organisational readiness of healthcare to integrate AI technology and ensure that future use can be applied effectively and safely. Overall, the research conducted in this thesis has contributed to the evidence base on the benefit of applying the human factors discipline to developing AI technology from the outset in healthcare settings.

Chapter 8: References

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Chapter 9: Appendices

Appendix 1: Syntaxes used for each database

Database (website used)	Types of terms used	Syntaxes
Medline (Ovid)	MESH terms/key terms	• '.tw.' – limit search to title and abstract • 'OR' – includes either both or one of the terms • 'AND' – Includes both terms • 'Adj*n*' – words need to be adjacent within *n* words of each other regardless of order. • '*' – to search all forms of the word
Embase (Ovid)	EMtree terms/key terms	• '.tw.' – limit search to title and abstract • 'OR' – includes either both or one of the terms • 'AND' – Includes both terms • 'Adj*n*' – words need to be adjacent within *n* words of each other regardless of order. • '*' – to search all forms of the word
PsycINFO (EBSCO)	Key terms	• W*n* – finds the words if they are within *n* of each other in order typed. • N*n* - finds the words if they are within *n* of each, regardless of order. • '*' – to search all forms of the word • '(…)' - exact phrase searching • 'OR' – includes either both or one of the terms • 'AND' – Includes both terms
Ergonomics abstract (EBSCO)	Key terms	• W*n* – finds the words if they are within *n* of each other in order typed. • N*n* - finds the words if they are within *n* of each, regardless of order. • '*' – to search all forms of the word • '(…)' – exact phrase searching • 'OR' – includes either both or one of the terms • 'AND' – Includes both terms
Engineering village (Elsevier)	Key terms	• '{…}' – exact phrase searching • 'OR' – includes either both or one of the terms • 'AND' – Includes both terms • 'NEAR/*n*' - finds the words if they are within *n* of each, regardless of order.

Appendix 2: Search strategy for each database

Medline (Ovid)	Embase (Ovid)	PsychInfo (EBSCO)	Engineering Village (Elsevier) – Compendex and Inspec	Ergonomics abstracts (EBSCO)
Human factors				
	Human factors research/			
Human factor* research.tw.	Human factor* research .tw.	Human W0 factor* W0 research		Human W0 factor* W0 research
Human factor*.tw.	Human factor*.tw.	Human W0 factor*	{Human factor} OR {Human factors}	Human W0 factor*
Ergonomics/ or "task performance and analysis"/	Ergonomics/			
Ergonomic*.tw.	Ergonomic* .tw.	Ergonomic*	{Ergonomic} OR {ergonomics}	Ergonomic*
Task* performance*.tw. and analysis.tw.	Task* performance*.tw. and analysis.tw.	Task* N0 performance* N0 and N0 analysis	{Task performance and analysis}	Task* N0 performance* N0 and N0 analysis
Macro ergonomic*.tw.	Macro ergonomic*.tw.	Macro ergonomic*	{Macro ergonomics}	Macro ergonomic*
Exp occupational health/	Exp occupational health/			
Exp psychology, industrial/				

Human engineering.tw.	Human engineering.tw.	Human W0 engineering	{Human engineering}	Human W0 engineering
Occupational health.tw.	Occupational health.tw.	Occupational W0 health	{Occupational health}	Occupational W0 health
(cognitive or industrial or organisational) adj1 psychology.tw.	(cognitive or industrial or organisational) adj1 psychology.tw.	(Cognitive or industrial or organisational) N1 psychology	{Cognitive} or {industrial} or {organizational} or {organizational} NEAR/1 {psychology}	(Cognitive or industrial or organisational) N1 psychology
Resilience engineering.tw.	Resilience engineering.tw.	Resilience W0 engineering	{Resilience engineering}	Resilience W0 engineering
Safety adj1 science.tw.	Safety adj1 science.tw.	Safety N1 science	{Safety} NEAR/1 {science}	Safety N1 science
Accident prevention/ or exp patient harm/ or exp patient safety/ or exp safety management/or exp accidents, occupational/	Accident prevention/			
	exp patient harm/			
	exp patient safety/			
	exp occupational accident /			
Accident* adj2 prevention.tw.	Accident* adj2 prevention.tw.	Accident* N2 prevention	{Accident} NEAR/2 {prevention}	Accident* N2 prevention
Patient adj2 harm.tw.	Patient adj2 harm.tw.	Patient N2 harm	{Patient} NEAR/2 {harm}	Patient N2 harm
Patient* adj2 safety.tw.	Patient* adj2 safety.tw.	Patient* N2 safety	{Patient} NEAR/2 {safety}	Patient* N2 safety

Safe* adj1 manage*.tw.	Safe* adj1 manage*.tw.	Safe* N1 manage*	{Safe} NEAR/1 {management} OR {Safety} NEAR/1 {management}	Safe* N1 manage*
occupational accident*.tw.	occupational accident*.tw.	occupational W0 accident*	{occupational accidents} OR {occupational accident}	Occupational W0 accident*
"Quality of health care"/	Health care quality/			
Quality adj1 health*care.tw.	Quality adj1 health*care.tw.	Quality N1 health*care	{Quality} NEAR/1 {healthcare}	Quality N1 health*care
	Safety culture/			
Safe* adj2 culture*.tw.	Safe* adj2 culture*.tw.	Safe* N2 culture*	{Safety} NEAR/2 {culture}	Safe* N2 culture*
Open culture* .tw.	Open culture*.tw.	Open W0 culture*	{Open culture} OR {Open cultures}	Open W0 culture*
Just culture* .tw.	Just culture*.tw.	Just W0 culture*	{Just culture}	Just W0 culture*
"hazard analysis and critical control points"/				
Hazard* analysis.tw. and critical control point*.tw.	Hazard* analysis.tw. and critical control point*.tw.	Hazard* W0 analysis W0 and critical W0 control W0 point*	{Hazard analysis and critical control points}	Hazard* W0 analysis W0 and critical W0 control W0 point*
	"alert fatigue (health care)"/			
Workplace adj2 (Fatigue or stress) .tw.	Workplace adj2 (Fatigue or stress) .tw.	Workplace N2 (Fatigue or stress)	{Workplace} NEAR/2 {fatigue} or {stress}	Workplace N2 (Fatigue or stress)
Alert fatigue.tw.	Alert fatigue.tw.	Alert W0 fatigue	{Alert fatigue}	Alert W0 fatigue
Work* adj1 stress*.tw.	Work* adj1 stress*.tw.	Work* N1 stress*	(347) NEAR/1 {stress}	Work* N1 stress*

Cognitive adj1 (workload or effort or load) .tw.	Cognitive adj1 (workload or effort or load) .tw.	Cognitive N1 (workload or effort or load)	{Cognitive} NEAR/1 {workload} or {effort} or {load}	Cognitive N1 (workload or effort or load)
Workaround*.tw.	Workaround*.tw.	Workaround*	{Workarounds} OR {workaround}	Workaround*
Human* adj1 performance*.tw.	Human* adj1 performance*.tw.	Human* N1 performance*	{Human} NEAR/1 {performance}	Human* N1 performance*
Performance adj2 variability.tw.	Performance adj2 variability .tw.	Performance N2 variability	{Performance} NEAR/2 {variability}	Performance N2 variability
Human-centred.tw.	Human-centred.tw.	Human-centred	{Human-centred}	Human-centred
Human adj2 centred.tw.	Human adj2 centred.tw.	Human N2 centred	{Human} NEAR/2 {centred}	Human N2 centred
User-computer interface/				
User-centred .tw.	User-centred.tw.	User-centred	{User-centred}	User-centred
User adj2 centred .tw.	User adj2 centred.tw.	User N2 centred	{User} NEAR/2 {centred}	User N2 centred
Resource* adj2 availability.tw.	Resource* adj2 availability.tw.	Resource* N2 availability	{Resource} NEAR/2 {availability}	Resource* N2 availability
	Hazard assessment/			
Hazard* adj2 assessment*.tw.	Hazard* adj2 assessment*.tw.	Hazard* N2 assessment*	{Hazard} NEAR/2 {assessment}	Hazard* N2 assessment*
Systems analysis/ or systems integration/	System analysis/			
Workflow/	Workflow/			

System* adj2 analysis.tw.	System* adj2 analysis.tw.	System* N2 analysis	{System} NEAR/2 {analysis}	System* N2 analysis
System* adj2 integration*.tw.	System* adj2 integration*.tw.	System* N2 integration*	{System} NEAR/2 {integration}	System* N2 integration*
Workflow*.tw.	Workflow*.tw.	Workflow*	{Workflow} OR {workflows}	Workflow*
Work* system*.tw.	Work* system*.tw.	Work* system*	{Work system} OR {work systems}	Work* system*
Sociotechnical system*.tw.	Sociotechnical system*.tw.	Sociotechnical W0 system*	{Sociotechnical system} OR {Sociotechnical systems}	Sociotechnical W0 system*
Sociotechnical*.tw.	Sociotechnical*.tw.	Sociotechnical*	{Sociotechnical}	Sociotechnical*
Complex adj2 system*.tw.	Complex adj2 system*.tw.	Complex N2 system*	{Complex} NEAR/2 {system} OR {Complex} NEAR/2 {systems}	Complex N2 system*
Organis* adj2 system*.tw.	Organis* adj2 system*.tw.	Organis* N2 system*	{Organizational} NEAR/2 {system} OR {Organisational} NEAR/2 {system}	Organis* N2 system*
			{Organizational} NEAR/2 {systems} OR {Organisational} NEAR/2 {systems}	
System* engineering.tw.	System* engineering .tw.	System* N0 engineering	{System engineering} OR {Systems engineering}	System* N0 engineering
System* adj2 design.tw.	System* adj2 design.tw.	System* N2 design	{System} NEAR/2 {design} OR {systems} NEAR/2 {design}	System* N2 design

System* adj2 resilience.tw.	System* adj2 resilience.tw.	System* N2 resilience	{System} NEAR/2 {resilience} OR {systems} NEAR/2 {resilience}	System* N2 resilience
Systems adj1 centred.tw.	Systems adj1 centred.tw.	Systems N1 centred	{Systems} NEAR/1 {centred}	Systems N1 centred
systems adj1 thinking.tw.	systems adj1 thinking.tw.	systems N1 thinking	{Systems} NEAR/1 {thinking}	systems N1 thinking
Participatory design*.tw.	Participatory design*.tw.	Participatory W0 design*	{Participatory design} OR {Participatory designs}	Participatory W0 design*
(Unplanned or unexpected) adj2 system* adj2 condition*.tw.	(Unplanned or unexpected) adj2 system* adj2 condition*.tw.	(Unplanned or unexpected) N2 system* N2 condition*	{Unplanned} or {unexpected} NEAR/2 {system} NEAR/2 {condition}	(Unplanned or unexpected) N2 system* N2 condition*
Safety adj1 assessment*.tw.	Safety adj1 assessment*.tw.	Safety N1 assessment*	{Safety} NEAR/1 {assessment} OR {Safety} NEAR/1 {assessments}	Safety N1 assessment*
Safety adj2 climate.tw.	Safety adj2 climate.tw.	Safety N2 climate	{Safety} NEAR/2 {climate}	Safety N2 climate
	Risk assessment/			
Risk adj2 assessment.tw.	Risk adj2 assessment.tw.	Risk N2 assessment	{Risk} NEAR/2 {assessment}	Risk N2 assessment
Incident* report*.tw.	Incident* report*.tw.	Incident* W0 report*	{Incident report} OR {Incidents report} OR {Incident reporting} OR {Incidents reporting} OR {incident reports}	Incident* W0 report*
Standard operat* procedure*.tw.	Standard operat* procedure*.tw.	Standard W0 operat* W0 procedure*	{Standard operating procedures} OR {Standard operating procedure}	Standard W0 operat* W0 procedure*

Work as done.tw.	Work as done.tw.	Work W0 as W0 done	{Work as done}	Work W0 as W0 done
Work as imagined.tw.	Work as imagined.tw.	Work W0 as W0 imagined	{Work as imagined}	Work W0 as W0 imagined
Safety management/ or risk management/	Error/ or medical error/			
Diagnostic errors/	Diagnostic errors/			
medical errors/ or medication errors/	Medication errors/			
	Adverse event/			
Safety adj1 management.tw.	Safety adj1 management.tw.	Safety N1 management	{Safety} NEAR/1 {management}	Safety N1 management
Medic* error*.tw.	Medic* error*.tw.	Medic* W0 error*	{Medical error} OR {Medical errors} OR {Medication error} OR {Medication errors}	Medic* W0 error*
Diagn* error*.tw.	Diagn* error*.tw.	Diagn* W0 error*	{Diagnosis error} OR {Diagnosis errors} OR {Diagnostic error} OR {Diagnostics errors}	Diagn* W0 error*
Error*.tw.	Error*.tw.	Error*	{Error} OR {errors}	Error*
Risk adj2 management.tw.	Risk adj2 management .tw.	Risk N2 management	{Risk} NEAR/2 {management}	Risk N2 management
Adverse adj1 event*.tw.	Adverse adj1 event*.tw.	Adverse N1 event*	{Adverse} NEAR/1 {event}	Adverse N1 event*
Human* error*.tw.	Human* error* .tw.	Human* W0 error*	{Human error} OR {human errors}	Human* W0 error*

Error* adj1 report*.tw.	Error* adj1 report*.tw.	Error* N1 report*	{Error} NEAR/1 {report} OR {Errors} NEAR/1 {report}	Error* N1 report*
Ethnographic analysis.tw.	Ethnographic analysis.tw.	Ethnographic W0 analysis	{Ethnographic analysis}	Ethnographic W0 analysis
Task* analysis.tw.	Task* analysis.tw.	Task* W0 analysis	{Task analysis} OR {Tasks analysis}	Task* W0 analysis
Process map*.tw.	Process map*.tw.	Process W0 map*	{Process map} OR {process mapping} OR {Process maps}	Process W0 map*
Mapping.tw.	Mapping.tw.	Mapping	{Mapping}	Mapping
Flow chart*.tw.	Flow chart*.tw.	Flow W0 chart*	{Flow chart} or {flow charts}	Flow W0 chart*
Usability adj1 test*.tw.	Usability adj1 test*.tw.	Usability N1 test*	{Usability} NEAR/1 {test} OR {Usability} NEAR/1 {tests} OR {Usability} NEAR/1 {testing}	Usability N1 test*
Human* performance model*.tw.	Human* performance model*.tw.	Human* W0 performance W0 model*	{Human performance model} OR {Human performance models}	Human* W0 performance W0 model*
User* adj2 analysis.tw.	User* adj2 analysis.tw.	User* N2 analysis	{User} NEAR/2 {analysis} OR {users} NEAR/2 {analysis}	User* N2 analysis
Error* adj2 analysis.tw.	Error* adj2 analysis.tw.	Error* N2 analysis	{Error} NEAR/2 {analysis} OR {Errors} NEAR/2 {analysis}	Error* N2 analysis
Work* adj2 analysis.tw.	Work* adj2 analysis.tw.	Work* N2 analysis	(347) NEAR/2 {analysis}	Work* N2 analysis
Hierarchical task* analysis.tw.	Hierarchical task* analysis.tw.	Hierarchical W0 task* W0 analysis	{Hierarchical task analysis} OR {Hierarchical tasks analysis}	Hierarchical W0 task* W0 analysis

healthcare failure mode.tw. and effect analysis.tw.	healthcare failure mode.tw. and effect analysis.tw.	healthcare W0 failure W0 mode W0 and W0 effect W0 analysis	{healthcare failure mode and effect analysis}	healthcare W0 failure W0 mode W0 and W0 effect W0 analysis
The sociotechnical systems theor*.tw.	The sociotechnical systems theor*.tw.	The W0 sociotechnical systems W0 theor*	{The sociotechnical systems theory} OR {The sociotechnical systems theories}	The W0 sociotechnical systems W0 theor*
Systems Engineering Initiative for Patient Safety.tw.	Systems Engineering Initiative for Patient Safety.tw.	Systems W0 Engineering W0 Initiative W0 for Patient Safety	{Systems Engineering Initiative for Patient Safety}	Systems W0 Engineering W0 Initiative W0 for Patient Safety
SEIPS.tw.	SEIPS.tw.	SEIPS	{SEIPS}	SEIPS
Human Factors framework.tw.	Human Factors framework.tw.	Human W0 Factors W0 framework	{Human Factors framework}	Human W0 Factors W0 framework
Safety-I.tw.	Safety-I.tw.	Safety-I	{Safety-I}	Safety-I
Safety-II.tw.	Safety-II.tw.	Safety-II	{Safety-II}	Safety-II
Leavitts organi*ational model.tw.	Leavitts organi*ational model.tw.	Leavitts W0 organi*ational W0 model	{Leavitts organisational model} OR {Leavitts organizational model}	Leavitts W0 organi*ational W0 model
Reasons accident causation model.tw.	Reasons accident causation model.tw.	Reasons W0 accident W0 causation W0 model	{Reasons accident causation model}	Reasons W0 accident W0 causation W0 model
Community Health Integration through Pharmacy Process.tw. and Ergonomics Redesign.tw.	Community Health Integration through Pharmacy Process.tw. and Ergonomics Redesign.tw.	Community W0 Health W0 Integration W0 through W0 Pharmacy W0 Process W0 and W0 Ergonomics W0 Redesign	{Community Health Integration through Pharmacy Process and Ergonomics Redesign}	Community W0 Health W0 Integration W0 through W0 Pharmacy W0 Process W0 and W0 Ergonomics W0 Redesign
CHIPPER.tw.	CHIPPER.tw.	CHIPPER	{CHIPPER}	CHIPPER

SHEEP model.tw.	SHEEP model.tw.	SHEEP W0 model	{SHEEP model}	SHEEP W0 model
Systems thinking for everyday work model.tw.	Systems thinking for everyday work model.tw.	Systems W0 thinking W0 for W0 everyday W0 work W0 model	{Systems thinking for everyday work model}	Systems W0 thinking W0 for W0 everyday W0 work W0 model
Hospital				
Exp hospitals/	Exp hospitals/			
Exp health facility administration/				
Exp hospital units/				
	Hospital subdivisions and components/			
Pharmacy service, hospital/	Hospital pharmacy/			
Hospital*.tw.	Hospital*.tw.	Hospital*	{Hospital} OR {Hospitals}	Hospital*
Hospital* pharmac*.tw.	Hospital* pharmac*.tw.	Hospital* W0 pharmac*	{Hospital pharmacies} OR {Hospital pharmacy}	Hospital* W0 pharmac*
Hospitalization/	Hospitalization/			
Hospitali*ation*.tw.	Hospitali*ation*.tw.	Hospitali*ation*	{Hospitalisation} OR {Hospitalization} OR {Hospitalisations} OR {Hospitalizations}	Hospitali*ation*
Secondary care/	Secondary health care/			
Secondary care .tw.	Secondary care.tw.	Secondary W0 care	{Secondary care}	Secondary W0 care

Infirmary.tw.	Infirmary.tw.	Infirmary	{Infirmary}	Infirmary
Accident.tw. and emergency .tw.	Accident.tw. and emergency.tw.	Accident W0 and W0 emergency	{Accident and emergency}	Accident W0 and W0 emergency
Emergency room* .tw.	Emergency room*.tw.	Emergency W0 room*	{Emergency room} OR {Emergency rooms}	Emergency W0 room*
Critical care/				
Critical care.tw.	Critical care.tw.	Critical W0 care	{Critical care}	Critical W0 care
	Intensive care/			
Intensive care.tw.	Intensive care.tw.	Intensive W0 care	{Intensive care}	Intensive W0 care
	Emergency ward/			
Emergency ward*.tw.	Emergency ward*.tw.	Emergency W0 ward*	{Emergency ward} OR {emergency wards}	Emergency W0 ward*
Outpatients/	Outpatient care/ or Outpatient/ or Outpatient department/			
outpatient clinics, hospital/				
Outpatient*.tw.	Outpatient*.tw.	Outpatient*	{Outpatient} OR {outpatients}	Outpatient*
Outpatient* adj2 (care or clinic* or department*).tw.	Outpatient* adj2 (care or clinic* or department*).tw.	Outpatient* N2 (care or clinic* or department*)	{Outpatient} NEAR/2 (347) or {clinic} or {clinics} or {department} or {departments}	Outpatient* N2 (care or clinic* or department*)

Clinical Decision Support				
Decision Support Systems, Clinical/	Decision support system/ or clinical decision support system/			
Decision making, computer- assisted/ or diagnosis, computer assisted/ or therapy, computer-assisted/				
Clinical decision support system*.tw.	Clinical decision support system*.tw.	Clinical W0 decision W0 support W0 system*	{Clinical decision support system} OR {Clinical decision support systems}	Clinical W0 decision W0 support W0 system*
Clinical decision support technolog*.tw.	Clinical decision support technolog*.tw.	Clinical W0 decision W0 support W0 technolog*	{Clinical decision support technology} OR {Clinical decision support technologies}	Clinical W0 decision W0 support W0 technolog*
Clinical decision support.tw.	Clinical decision support.tw.	Clinical W0 decision W0 support	{Clinical decision support}	Clinical W0 decision W0 support
Computer assisted decision making.tw.	Computer assisted decision making.tw.	Computer W0 assisted W0 decision W0 making	{Computer assisted decision making}	Computer W0 assisted W0 decision W0 making
Computer assisted diagnosis.tw.	Computer assisted diagnosis .tw.	Computer W0 assisted W0 diagnosis	{Computer assisted diagnosis}	Computer W0 assisted W0 diagnosis
Computer assisted therap*.tw.	Computer assisted therap* .tw.	Computer W0 assisted W0 therap*	{Computer assisted therapy} OR {Computer assisted therapies}	Computer W0 assisted W0 therap*

Computer assisted triage*.tw.	Computer assisted triage*.tw.	Computer W0 assisted W0 triage*	{Computer assisted triage} OR {Computer assisted triages}	Computer W0 assisted W0 triage*
Computer assisted prognosis.tw.	Computer assisted prognosis.tw.	Computer W0 assisted W0 prognosis	{Computer assisted prognosis}	Computer W0 assisted W0 prognosis
decision support techniques/ or analytic hierarchy process/ or clinical decision rules/ or data interpretation, statistical/				
Decision* support technique*.tw.	Decision* support technique*.tw.	Decision* W0 support W0 technique*	{Decision support technique} OR {Decisions support technique} OR {Decision support techniques} OR {Decisions support techniques}	Decision* W0 support W0 technique*
Analytic* hierarc* process*.tw.	Analytic* hierarc* process*.tw.	Analytic* W0 hierarc* W0 process*	{Analytic hierarchy process} OR {Analytic hierarchy processes}	Analytic* W0 hierarc* W0 process*
Clinical decision rule*.tw.	Clinical decision rule*.tw.	Clinical W0 decision W0 rule*	{Clinical decision rule} OR {Clinical decision rules}	Clinical decision W0 rule*
Statistical data interpretation*.tw.	Statistical data interpretation*.tw.	Statistical W0 data W0 interpretation*	{Statistical data interpretation} OR {Statistical data interpretations}	Statistical W0 data W0 interpretation*
Decision* support.tw.	Decision* support.tw.	Decision* W0 support	{Decision support} OR {Decisions support}	Decision* W0 support

Patient* decision* aid* .tw.	Patient* decision* aid* .tw.	Patient* W0 decision* W0 aid*	{Patient decision aid}	Patient* W0 decision* W0 aid*
artificial intelligence/ or machine learning/ or deep learning/ or supervised machine learning/ or unsupervised machine learning/	Artificial intelligence/			
	Deep learning/			
	Supervised machine learning/			
	Unsupervised machine learning/			
Artificial* intelligen*.tw.	Artificial* intelligen*.tw.	Artificial* W0 intelligen*	{Artificial intelligence} OR {Artificially intelligent}	Artificial* W0 intelligen*
Machine learning.tw.	Machine learning.tw.	Machine W0 learning	{Machine learning}	Machine W0 learning
Deep learning.tw.	Deep learning.tw.	Deep W0 learning	{Deep learning}	Deep W0 learning
Meta learning.tw.	Meta learning.tw.	Meta W0 learning	{Meta learning}	Meta W0 learning
Reinforcement learning.tw.	Reinforcement learning.tw.	Reinforcement W0 learning	{Reinforcement learning}	Reinforcement W0 learning
Supervised adj2 learning.tw.	Supervised adj2 learning.tw.	Supervised N2 learning	{Supervised} NEAR/2 {learning}	Supervised N2 learning
Semi-supervised adj2 learning.tw.	Semi-supervised adj2 learning.tw.	Semi-supervised N2 learning	{Semi-supervised} NEAR/2 {learning}	Semi-supervised N2 learning

Unsupervised adj2 learning.tw.	Unsupervised adj2 learning.tw.	Unsupervised N2 learning	{Unsupervised} NEAR/2 {learning}	Unsupervised N2 learning
Support vector machine*.tw.	Support vector machine*.tw.	Support W0 vector W0 machine*	{Support vector machine} OR {Support vector machines}	Support W0 vector W0 machine*
Computer intelligence.tw.	Computer intelligence.tw.	Computer W0 intelligence	{Computer intelligence}	Computer W0 intelligence
Neural networks, computer/	Artificial neural network/			
	Deep neural network/			
	Convolutional neural network/			
	Recurrent neural network/			
Computer neural network*.tw.	Computer neural network*.tw.	Computer W0 neural W0 network*	{Computer neural network} OR {Computer neural networks}	Computer W0 neural W0 network*
Artificial neural network*.tw.	Artificial neural network*.tw.	Artificial W0 neural W0 network*	{Artificial neural network} OR {Artificial neural networks}	Artificial W0 neural W0 network*
Deep neural network*.tw.	Deep neural network*.tw.	Deep W0 neural W0 network*	{Deep neural networks} OR {Deep neural network}	Deep W0 neural W0 network*
Convolutional neural network*.tw.	Convolutional neural network*.tw.	Convolutional W0 neural W0 network*	{Convolutional neural networks} OR {Convolutional neural network}	Convolutional W0 neural W0 network*
Recurrent neural network*.tw.	Recurrent neural network*.tw.	Recurrent W0 neural W0 network*	{Recurrent neural network} OR {Recurrent neural networks}	Recurrent W0 neural W0 network*

Machine intelligence .tw.	Machine intelligence.tw.	Machine W0 intelligence	{Machine intelligence}	Machine W0 intelligence
Artificial* learn*.tw.	Artificial* learn*.tw.	Artificial* W0 learn*	{Artificial learning} OR {Artificially learned}	Artificial* W0 learn*
Chatbot*.tw.	Chatbot*.tw.	Chatbot*	{Chatbots} OR {Chatbot}	Chatbot*
Virtual assistant* .tw.	Virtual assistant*.tw.	Virtual W0 assistant*	{Virtual assistants} OR {Virtual assistant}	Virtual W0 assistant*
Image processing, computer-assisted/				
	Image processing/			
Computer*assisted image processing .tw.	Computer*assisted image processing.tw.	Computer*assisted W0 image W0 processing	{Computer assisted image processing}	Computer*assisted W0 image W0 processing
Image adj2 processing.tw.	Image adj2 processing .tw.	Image* N2 processing	{Image} NEAR/2 {processing}	Image N2 processing
Medical adj2 imag* adj2 analysis.tw.	Medical adj2 imag* adj2 analysis.tw.	Medical N2 imag* N2 analysis	{Medical} NEAR/2 {image} NEAR/2 {analysis}	Medical N2 imag* N2 analysis
Imag* adj2 classification.tw.	Imag* adj2 classification.tw.	Imag* N2 classification	{Image} NEAR/2 {classification}	Imag* N2 classification

Appendix 3: Completed Consolidated criteria for Reporting Qualitative research checklist

Adapted from (260)

COREQ (COnsolidated criteria for REporting Qualitative research) Checklist

A checklist of items that should be included in reports of qualitative research. You must report the page number in your manuscript where you consider each of the items listed in this checklist. If you have not included this information, either revise your manuscript accordingly before submitting or note N/A.

Topic	Item No.	Guide Questions/Description	Reported on Page No.
Domain 1: Research team and reflexivity			
Personal characteristics			
Interviewer/facilitator	1	Which author/s conducted the interview or focus group?	106
Credentials	2	What were the researcher's credentials? E.g. PhD, MD	N/A
Occupation	3	What was their occupation at the time of the study?	N/A
Gender	4	Was the researcher male or female?	N/A
Experience and training	5	What experience or training did the researcher have?	N/A
Relationship with participants			
Relationship established	6	Was a relationship established prior to study commencement?	N/A
Participant knowledge of the interviewer	7	What did the participants know about the researcher? e.g. personal goals, reasons for doing the research	101-105
Interviewer characteristics	8	What characteristics were reported about the inter viewer/facilitator? e.g. Bias, assumptions, reasons and interests in the research topic	N/A
Domain 2: Study design			
Theoretical framework			
Methodological orientation and Theory	9	What methodological orientation was stated to underpin the study? e.g. grounded theory, discourse analysis, ethnography, phenomenology, content analysis	99 - 100
Participant selection			
Sampling	10	How were participants selected? e.g. purposive, convenience, consecutive, snowball	102-103
Method of approach	11	How were participants approached? e.g. face-to-face, telephone, mail, email	103-104
Sample size	12	How many participants were in the study?	106-107
Non-participation	13	How many people refused to participate or dropped out? Reasons?	N/A
Setting			
Setting of data collection	14	Where was the data collected? e.g. home, clinic, workplace	106
Presence of non-participants	15	Was anyone else present besides the participants and researchers?	N/A
Description of sample	16	What are the important characteristics of the sample? e.g. demographic data, date	106-107
Data collection			
Interview guide	17	Were questions, prompts, guides provided by the authors? Was it pilot tested?	100-102
Repeat interviews	18	Were repeat inter views carried out? If yes, how many?	N/A
Audio/visual recording	19	Did the research use audio or visual recording to collect the data?	104
Field notes	20	Were field notes made during and/or after the inter view or focus group?	104
Duration	21	What was the duration of the inter views or focus group?	N/A
Data saturation	22	Was data saturation discussed?	102-103
Transcripts returned	23	Were transcripts returned to participants for comment and/or correction?	N/A
Domain 3: analysis and findings			
Data analysis			
Number of data coders	24	How many data coders coded the data?	106
Description of the coding tree	25	Did authors provide a description of the coding tree?	N/A
Derivation of themes	26	Were themes identified in advance or derived from the data?	106
Software	27	What software, if applicable, was used to manage the data?	106
Participant checking	28	Did participants provide feedback on the findings?	N/A
Reporting			
Quotations presented	29	Were participant quotations presented to illustrate the themes/findings? Was each quotation identified? e.g. participant number	106-142
Data and findings consistent	30	Was there consistency between the data presented and the findings?	106-142
Clarity of major themes	31	Were major themes clearly presented in the findings?	106
Clarity of minor themes	32	Is there a description of diverse cases or discussion of minor themes?	106-142

Developed from: Tong A, Sainsbury P, Craig J. Consolidated criteria for reporting qualitative research (COREQ): a 32-item checklist for interviews and focus groups. *International Journal for Quality in Health Care*. 2007. Volume 19, Number 6: pp. 349 – 357

Once you have completed this checklist, please save a copy and upload it as part of your submission. DO NOT include this checklist as part of the main manuscript document. It must be uploaded as a separate file.

Appendix 4: Contextual vignette

Vignette: Use of an artificial intelligence (AI) clinical decision tool for fluid management in sepsis

A 40-year old man enters the emergency department with severe shortness of breath. He is diagnosed with acute onset pneumonia and admitted to the intensive care unit.

After observation it is suspected that the patient has sepsis. As per the SIGN guidelines, the **Sepsis Six bundle** is started:

1) Administer oxygen
2) Take blood cultures
3) Give IV antibiotics
4) Give IV fluids
5) Check serial lactates
6) Measure urine output

Give IV fluids

The clinician is aware of the risks of either under-loading or over-loading a patient with fluids.

↓

The clinician decides to ask the AI clinical decision tool to predict a safe total volume of fluids that can be given to the patient over the course of the day.

↓

The patients data is given to the AI, which includes their demographics, clinical history and physiological characteristics such as vital signs and lab results.

↓

Using this data the AI builds a description of the patients disease state by identifying relevant patterns in the data using neural networks. The AI then uses this information to estimate a fluid volume that is most likely to improve the patient's outcomes.

↓

At the same time the AI also calculates the patients mortality risk based on the data inputted. This will be used to provide explanation for the output.

↓

Output for clinicians

The AI provides the clinican with the optimal volume of fluid and the patients mortality risk if that volume is given.

To provide interpretability, the AI can then provide detail on how the mortality risk changes if different volumes of fluid are given. This gives the clinician insight into the effects of fluid volume on the patient and provides justification for the decision.

Appendix 5: Interview schedule

Questions		Prompts	Notes
General questions			
1	Depending on answer given to question 7 on the demographics: ***Yes:*** *I see from the demographics questionnaire you filled in that you HAVE used AI technology before, and have given some information on this, could you please tell me more about this?* ***No:*** *I see from the demographic questionnaire you filled in that you HAVEN'T used AI technology before; can you tell me if there are any particular reasons why you haven't?* ***Not sure:*** *I see from your demographics that you WEREN'T SURE whether you have used an AI before, can you tell me more about this?*	**If 'No':** ○ No opportunity to ○ Preferred not to	
Person Now I want to ask about your personal perceptions of both AI in general and in the vignette.			
2	*What do you think of healthcare AI in general?*		

3	*What do you think of the AI described in the vignette?*		
4	*Is there anything about yourself that would need to change to be able to use the AI described in the vignette?*	○ IT skills ○ Confidence ○ Expertise	
AI technology Now I’m going to ask you some questions about the AI described in the vignette, so thinking about the vignette that you were asked to read prior to the interview:			
5	*How useful do you think the AI described in the vignette would be? And why?*	○ To yourself ○ For patients ○ Your team	
6	*What would you change about AI technology described in the vignette to be able to use it?*	○ Explainable ○ Where placed ○ Alerts ○ Data input	
Other tools and technology What are the other technology and tools you use sepsis fluid management, not the AI described in the vignette.			

7	*Tell me about any other things you use, such as tools and technologies during sepsis fluid management.*	○ Prescribing system ○ Health records ○ Decision support tools ○ Monitoring ○ Communication tools ○ Apps ○ Paper based tools	
8	*Can you tell me about how your current tools and technologies would need change to be able to use the AI technology described in the vignette, if at all.*	○ Any additional tools	
Tasks Next, I want to talk about the activities you complete at work for sepsis fluid management:			
9	*Can you talk me through the steps you would take during sepsis fluid management? From start to finish of your involvement.*	○ Protocols	
10	*Tell me about any changes to the steps you take currently to be able to use the AI described in the vignette?*	○ Less tasks	

Physical environment Next, I want you to think about where you work, such as the ward.			
11	*Can you please describe the physical environment you work in during sepsis fluid management?*	○ Layout ○ Workstation ○ Noise level ○ Number of staff ○ Number of patients ○ Ratio of staff to patients	
12	*Tell me about how your physical environment would need to change to be able use the AI described in the vignette, if at all?*	○ Layout ○ Workstation ○ Noise level ○ Number of staff ○ Number of patients ○ Ratio of staff to patients	
Organisation Now, I want you to think about the organisation that you work for:			

13	*How supportive of using healthcare technology is your organisation currently?*	○ Health board ○ Hospital ○ Department	
14	*How supportive do you think your organisation would be in the use of the AI described in the vignette?*	○ Health board ○ Hospital ○ Department	
15	*How would (insert organisational level) need to change in order for you to be able to use the AI described in the vignette, if at all?* **Repeat for each organisation as appropriate**	○ Time ○ Workload ○ Training ○ Team ○ Resources ○ Space	
Final Questions			
16	*Is there anything else that you would like to say about the AI described in the vignette?*		

Appendix 6: Participant information sheet and consent form

Participant Information Sheet

Name of department: Strathclyde Institute of Pharmacy and Biomedical Science
Title of the study: Assessing the needs of users for an artificial intelligence clinical decision tool for the fluid management of sepsis in Scotland.

Introduction

My name is Kate Preston, and I am a PhD student at the University of Strathclyde. You can contact me on: kate.preston@strath.ac.uk. Before you decide whether to participant in this study, please read the information below which contains details on what will be involved.

What is the purpose of this research?

Artificial Intelligence (AI) technology has the potential to transform healthcare, especially within the domain of clinical decision support. However, previous research has suggested that the needs of the users interacting with it are not often considered when this technology is developed. Therefore, the purpose of this study is to understand the needs of those who are involved in the sepsis fluid management of patients in Scottish adult critical care.

Do you have to take part?

No. Your participation is voluntary. You can refuse to take part or withdraw from the study without giving any reason. This decision will not impact you or your employment in anyway.

What will you do in the study?

This study will involve taking part in an interview, which will last no more than one hour. You will be given the option to take part either over the phone, using video conferencing software or in-person. Before the interview, you will also be asked to complete a short demographics questionnaire, which will take no more than one hour. If at any point during the interview you are adversely affected by the discussion, the interview will be terminated, and you would be signposted to the appropriate support.

Why have you been invited to take part?

You have been asked to take part as you work within Scottish adult critical care and have been involved with sepsis fluid management of patients.

What information is being collected in the study?

The interviews will be recorded. The interview aims to firstly understand your current work system, including the tasks you complete and the environment in which you work. You will then be asked about your needs for an AI clinical decision tool for the fluid management of sepsis patients in Scottish adult critical care. You will also be asked to complete a short demographics questionnaire which will ask some details about yourself, such as your gender and years working in critical care, for example.

Who will have access to the information?

Only members of the research team will have access to the identifiable information you provide during the interview. No one at your workplace or your NHS Health Board will have access to your individual data. The University of Strathclyde is registered with the Information Commissioner's Office who implements the Data Protection Act 2018. All personal data on participants will be processed in accordance with the provisions of the Data Protection Act 2018 and GDPR regulations.

Where will the information be stored and how long will it be kept for?

All copies of your data will be stored in either a locked cabinet or on a password protected computer system. Any personal data will be destroyed at the end of the research period. Please read our privacy notice for more information about your rights under the legislation.

Thank you for reading this information – please ask any questions if you are unsure about anything.

What happens next?

If you want to participate, please complete the consent form on the next screen and then continue onto the demographic's questionnaire. If you have read this information and you do not want to take part, then thank you for your attention. If at any time you require further information, please contact myself (Kate Preston) for feedback, or the Chief Investigator (details below):

Lead researchers contact details:	Chief Investigator details:
Ms Kate Preston	Prof Marion Bennie
Strathclyde Institute of Pharmacy & Biomedical Science, 161 Cathedral Street, Glasgow, G4 0NR	Strathclyde Institute of Pharmacy & Biomedical Science, 161 Cathedral Street, Glasgow, G4 0NR
Email: kate.preston@strath.ac.uk	Email: marion.bennie@strath.ac.uk

This research was granted ethical approval by the SIPBS Ethics Committee.

If you have any questions/concerns, during or after the research, or wish to contact an independent person to whom any questions may be directed or further information may be sought from, please contact:

Dr Christopher Prior
Chair, SIPBS Departmental Ethics Committee
Strathclyde Institute of Pharmacy and Biomedical Sciences
University of Strathclyde
161 Cathedral Street
GLASGOW
G4 0RE
United Kingdom

Consent Form

Name of department: Strathclyde Institute of Pharmacy and Biomedical Science
Title of the study: Assessing the needs of users for an AI clinical decision tool for the fluid management of sepsis in Scotland.

Please read the following statements and if you consent, state your name and the date below. If you do not consent then thank you for your time, you can close the window.

- I confirm that I have read and understood the Participant Information Sheet for the above study and the researcher has answered any queries to my satisfaction.
- I confirm that I have read and understood the Privacy Notice for Participants in Research Projects and understand how my personal information will be used and what will happen to it (i.e. how it will be stored and for how long).
- I understand that my participation is voluntary and that I am free to withdraw from the study at any time, up to the point of completion of the study, without having to give a reason and without any consequences.
- I understand that I can request the withdrawal from the study of some personal information and that whenever possible researchers will comply with my request. This includes the following personal data:
    - audio recordings of interviews that identify me;
    - my personal information from transcripts.
- I understand that anonymised data (i.e. data that do not identify me personally) cannot be withdrawn once they have been included in the study.
- I understand that any information recorded in the research will remain confidential and no information that identifies me will be made publicly available.
- I consent to being a participant in the study.
- I consent to being audio and/or video recorded as part of the study.

(PRINT NAME)

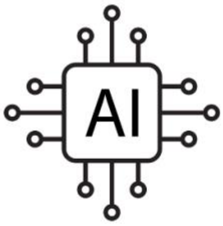
Appendix 7: Advert used for recruitment

Want to help develop an artificial intelligence for critical care?

University of Strathclyde Glasgow

We want to know your needs for a new artificial intelligence-based clinical decision support for sepsis fluid management in critical care!

Who can participate?



- Doctors, Pharmacists and Advanced Critical Care Practitioners who work in Scottish adult critical care.

What will you do?

- You will be asked to read a short vignette, which describes the artificial intelligence.
- You will then be asked to complete an interview, which will last no more than one hour.
- This interview will consist of questions to understand your current work, and what you would need to be able to use this new AI in your current practice.

Want to take part or know more?

If you have any questions or want to take part then please email the study researcher at: **kate.preston@strath.ac.uk**

Appendix 8: Syntaxed search terms used for each database

Web of Science	SCOPUS	PsychINFO	Ergonomics abstracts
Organisational readiness			
“Organi*ation* readiness”	“Organi*ation* readiness”	“Organi*ation* readiness”	“Organi*ation* readiness”
“Change readiness”	“Change readiness”	“Change readiness”	“Change readiness”
“Organi*ation* readiness to change”	“Organi*ation* readiness to change”	“Organi*ation* readiness to change”	“Organi*ation* readiness to change”
Readiness	Readiness	Readiness	Readiness
“Readiness to change”	“Readiness to change”	“Readiness to change”	“Readiness to change”
“Organi*ation* innovation”	“Organi*ation* innovation”	“Organi*ation* innovation”	“Organi*ation* innovation”
“Organi*ation* change”	“Organi*ation* change”	“Organi*ation* change”	“Organi*ation* change”
“Change management”	“Change management”	“Change management”	“Change management”
“Organi*ation* change management”	“Organi*ation* change management”	“Organi*ation* change management”	“Organi*ation* change management”
AI technology			
“Artificial intelligence”	“Artificial intelligence”	“Artificial intelligence”	“Artificial intelligence”
“Machine learning”	“Machine learning”	“Machine learning”	“Machine learning”
“Deep learning”	“Deep learning”	“Deep learning”	“Deep learning”
“Meta-learning”	“Meta-learning”	“Meta-learning”	“Meta-learning”
“Reinforcement learning”	“Reinforcement learning”	“Reinforcement learning”	“Reinforcement learning”
“Supervised learning”	“Supervised learning”	“Supervised learning”	“Supervised learning”
“Semi-supervised learning”	“Semi-supervised learning”	“Semi-supervised learning”	“Semi-supervised learning”
“Unsupervised learning”	“Unsupervised learning”	“Unsupervised learning”	“Unsupervised learning”
“Support vector machine”	“Support vector machine”	“Support vector machine”	“Support vector machine”
“Computer neural network”	“Computer neural network”	“Computer neural network”	“Computer neural network”
“Artificial neural network”	“Artificial neural network”	“Artificial neural network”	“Artificial neural network”
“Deep neural network”	“Deep neural network”	“Deep neural network”	“Deep neural network”
“Convolutional neural network”	“Convolutional neural network”	“Convolutional neural network”	“Convolutional neural network”
“Recurrent neural network”	“Recurrent neural network”	“Recurrent neural network”	“Recurrent neural network”
“Machine intelligence”	“Machine intelligence”	“Machine intelligence”	“Machine intelligence”
“Artificial learning”	“Artificial learning”	“Artificial learning”	“Artificial learning”
“Chatbot”	“Chatbot”	“Chatbot”	“Chatbot”
“Virtual assistants”	“Virtual assistants”	“Virtual assistants”	“Virtual assistants”

Web of Science	SCOPUS	PsychINFO	Ergonomics abstracts
“Computer assisted image processing”	“Computer assisted image processing”	“Computer assisted image processing”	“Computer assisted image processing”
“Image processing”	“Image processing”	“Image processing”	“Image processing”
“Image classification”	“Image classification”	“Image classification”	“Image classification”
Resources			
Resource*	Resource*	Resource*	Resource*
Index*	Index*	Index*	Index*
Model*	Model*	Model*	Model*
Framework*	Framework*	Framework*	Framework*
Theor*	Theor*	Theor*	Theor*
Tool*	Tool*	Tool*	Tool*
Instrument*	Instrument*	Instrument*	Instrument*
Matrix*	Matrix*	Matrix*	Matrix*
Measure*	Measure*	Measure*	Measure*
Scale*	Scale*	Scale*	Scale*
Guid*	Guid*	Guid*	Guid*
“Outcome measure*”	“Outcome measure*”	“Outcome measure*”	“Outcome measure*”

Appendix 9: The factors under each organisational readiness resource

Factor under each organisational readiness resource	Description of factor
Technology-Organisation-Environment (TOE) framework (311-318)*	
The environmental context (311)	Includes the structure of the industry, the presence or absence of technology service providers, and the regulatory environment†
The organisational context (311)	Refers to the characteristics and resources of the firm, including linking structures between employees, intra-firm communication processes, firm size, and the amount of slack resources†
The technological context (311)	The internal and external technologies within the organisation – including the availability and characteristics of the tools and technology and their processes†
Competitive pressure (312, 318)	Threat of losing the competitive advantage, which motivates the organisational to adopt a new innovation (AI technology) which helps them gain competitive advantage†
Top management support (312, 318)	Refers to the engagement and support of leaders for the adoption of AI technology†
Government regulations (312, 315, 318)	Assistance provided by the government authority to encourage the adoption of AI technology†
Organisation size (312, 315, 318)	Size of the organisation directly affects the adoption of innovation†
Relative advantage (312, 315, 318)	Perceived benefit for adoption the AI at an organisational level†
Resources (312, 315, 318)	Having the technological resources in place to adopt the AI technology effectively†
Compatibility (312, 315, 317, 318)	Compatibility refers to the extent the AI technology aligns with the technology used, the business processes and cases and the culture of the organisation†
Competence (313)	Organisational competence positively influences the perceived usefulness of AI and leads to AI adoption intention
Knowledge (313)	The more collective knowledge an organization has on AI, the more ready employees will embrace the technology
Culture (313, 315)	The willingness of an organisation to change and accept innovation. Incudes areas such as top management support, change management and innovative culture†
Connectivity (314)	Digital maturity is vital for implementing new emerging technologies†
COVID-19 as a transformational force (314)	How COVID-19 has helped move forward the adoption of AI technology†
Data management and privacy (314)	There needs to be significant data and policymakers wot protect the customers†
Excitement and positive perceptions (314)	The excitement and positive perceptions towards the AI technology adoption†
Lack of AI practice and discomfort (314)	Internal technological practices also affect organizational adoptions of AI†
Organisational size and financial resources (314)	Most participants saw larger organizations as faster adopters with better potential and financial resources for adopting new technologies, including AI†
Organisations strategic plans (314)	Lack of vision and progressivity from CEOs as a key obstacle to AI adoption†
Customer AI readiness (315)	Requires an understanding of the complexity and lack of transparency of learning algorithms†
Industry requirements (315)	The requirements within the industry for the AI technology†

Factor under each organisational readiness resource	Description of factor
Organisational structure (315)	The organisational structures in place†
AI system capabilities (316)	A lack of understanding of the capabilities needed in the firm's business process could inhibit AI adoption†
AI system quality (316)	AI systems possess a wide range of capabilities which may transform the various aspects of the business†
Anthropomorphism of AI systems (316)	The level of human-like characteristics the AI system has†
Availability of the technology vendors/partners (316)	How available technology partners are determines the adoption intention†
Competition (316)	AI technology could be adopted to gain competitive advantage in the market, or due to competitive pressure†
Data ecosystem in the firm (316)	Need for a suitable data ecosystem, including a strategy for the acquisition and curation of data†
Financial readiness/Financial competence of the firm (316)	Having sufficient financial readiness will help strengthen the intention to adopt AI systems†
Information Security/Cybersecurity (316)	Having appropriate cybersecurity (confidentiality, authenticity and non-replicability) is important for AI adoption intention†
Interpretability/Explainability (316)	The transparency and explainability of AI systems are important as the outcomes will significantly affect the customer experience†
IT infrastructure of the firm (316)	Ensure there is the correct infrastructure to allow for AI technology requirements†
Perceived benefits (316)	Perceived benefits refer to the potential advantages that an organization expects to gain from implementing AI technology. These benefits may be anticipated by leaders, employees, customers, or other stakeholders within the organization†
Perceived compatibility of AI systems (316)	Having compatibility with AI systems within the organisation exiting IT infrastructure plays an important role in determining AI adoption intention†
Perceived complexity of AI systems (316)	Perceived complexity occurs where there is little understanding of the technology, there will be a lack of perceived control over the technology, with higher effort expectancy†
Perceived ease of use (316)	Perception of how easy the AI technology will be to use†
Perceived privacy concerns (316)	The user's perceived privacy concerns significantly affect individuals adoption intention†
Perceived usefulness (316)	Perceptions of the usefulness of AI technology†
Regulatory environment (316)	The regulatory environment that surrounds the organisation†
Strategic alignment of AI systems (316)	The AI systems need to be strategically aligned with the organisations business goals, customer expectation and regulatory†
Support from top management (316)	The support from those in top management is quintessential for the adoption of AI systems†

Factor under each organisational readiness resource	Description of factor
Perceived trust (316, 317)	Perceived trust refers to the level of confidence and trust that individuals within the organization have in the AI technology being adopted and its ability to perform as intended†
Data quality (317)	Data quality refers to the degree to which data used in AI systems is accurate, complete, consistent, relevant, and timely
AI ethics (317)	AI ethics refers to the moral principles and values that guide the design, development, implementation, and use of AI technologies in a responsible and ethical manner
Data governance (317)	Data governance refers to the process of managing and controlling the collection, storage, use, sharing, and protection of data used in AI systems
Role clarity (317)	Refers to the understanding an definition of the roles and responsibilities if individuals and teams involved in the adoption, implementation and use of AI technology within the organisation
Benefits-Organisation-Environment (BOE) model (319-321)**	
Technological readiness (319)	The level of sophistication of the organisation's IT and IT management†
Financial resources (319-321)	There needs to be the necessary financial resources to be able to maintain the AI system, such as the budget, investment required for AI and the need for more money to support using AI technology uninterruptedly†
Culture (320)	The willingness of an organisation to change and accept innovation†
Knowledge (320)	Having a lack of knowledge of AI technology was considered a barrier†
Leadership (320)	Influence of leaders on employees to adopt AI technology, removing job loss fears†
Risk (320)	The perceived risk of the AI technology will impact trust†
Vison (320)	Having a vision for the use of AI technology†
Artificial intelligence, data access (321)	Having access to relevant open data sources for the AI technology†
Digital literacy (321)	Digital literacy not only captures the level of technological expertise, but it is important to assess the level of technology management and support for the use of technology to achieve organizational goals†
Conceptual framework of organisational readiness (322)	
Analytical approach	The vision and target of a business organization are to analyse scientifically the captured data, and the organization is supposed to define appropriately the metrics which matter that vision of the organization.
Any additional challenges	Any other challenges that come with the adoption of AI technology†
Auditing approach	After getting the appropriate sources for capturing relevant data, timely audit is required to be conducted.
Close alignment between business & IT	The business and IT teams of organizations should be engaged to continuously audit and monitor the actions so created by application of AI tools

Factor under each organisational readiness resource	Description of factor
Close all possible gaps	By adopting appropriate approaches to make the data fit for use by AI mechanisms and after meeting the challenges, it has been possible to close the gap to a great extent between business intelligence and experience of customers.
Context challenges	The stakeholders are required to upgrade their ideas and to enrich them by learning how application of AI in CRM would transform sales, IT, marketing and services by effectively automating mundane tasks.
Data challenges	It is to be borne in mind that success in business does not depend on how much volume of data, a business organization has been able to capture, but it matters how those data containing different essential information of customers have been effectively arranged and organized.
Effective change management strategy	Ensure there is a strategy in place for change management†
Effective training and readiness strategy	Ensure there is a strategy in place for training, and also for ensuring the organisation is ready for the technology†
Expertise challenges	A business organization may have effective data storage, but this will not fetch complete business benefit unless the organization is capable of having effective expertise to scientifically analyse those available data and to act on it
Infrastructure challenges	For having the power to apply and run AI algorithms, there is need of availability of effective and congenial infrastructure relating to handle modern computing system
Integration approach	In connection with these different applications, the CRM system should be appropriately integrated for obtaining real-time data along with key data covering the activities of the potential customers
Push information to organisation	The basic tools required would pull the information of customers, whereas the most intelligent and effective tools would push information to the organization. This helps the organizations to anticipate what the organizations want to know
Regularisation approach	To ensure best results through applications of AI on CRM, it will be better if the business organizations take holistic attempts to enrich the data so collected and captured with the observed statistical or observed behavioural data.
Social approach	This is achieved by investigating the different ways through which it is possible for customers to reach the organizational selling activities.
AI readiness model (323)	
Collection and use of operational data	How the data used for the AI technology is collected and then used to ensure it is safe and secure†
Implementation of CPS-related technologies in production	Organisations should implement technologies that are related to the cyber-physical system (CPS) to support production†
Implementation of data protection measures	Ensure there is data production measures in place for the AI technology†

Factor under each organisational readiness resource	Description of factor
Product features with digital elements	The extent to which technologies with digital elements are currently used in the organisation†
Product-related services	The extent to which the organisation offers services such as condition monitoring and predictive maintenance, based on their current digital technology†
Use of advanced robotics	The organisations current use of advanced robotics†
AI readiness framework (324)	
Current uses of AI technology	The current uses of AI technology in the organisation†
Future uses of AI technology	Strategies in place for using AI technology in the future to add value to our organisation†
How does AI impact current activities	How current key activities are supported by AI in ways that add value to the organisation†
How does AI impact current goals	How current uses of AI supports foals in ways that add value to the organisation†
How has AI changed the boundaries	How current organisational boundaries are stretched by AI in ways that add value to the organisation†
How may AI impact future activities	Strategies in place for using AI to support key activities in ways that add value to our organisation†
How may AI impact future goals	Strategies for using AI to support goals in ways that add value to the organisation†
How will AI impact future boundaries	Strategies for using AI to change our organisational boundaries in ways that add value to the organisation†
Organisational AI readiness factors (325)	
AI awareness	AI awareness ensures that employees have adequate understanding and expectations toward AI
AI-business potentials	AI-business potentials ensure that AI adoption is beneficial and suitable for the organization
AI-process fit	AI-process fit through standardization, reengineering, and implementation of new processes facilitates AI adoption
Change management	Change management helps employees to understand and cope with AI-induced organizational change
Collaborative work	Collaborative work enables employees to work in teams and combine different skills
Customer AI readiness	Customer AI readiness enables internal or external customers to appropriately use AI-integrated offerings
Data accessibility	Data accessibility facilitates AI experts to easily prototype and develop AI solutions
Data availability	Data availability within the organization fuels AI solutions
Data flow	Data flow between its source and its use ensures high data accessibility to AI experts
Data quality	Data quality ensures accurate AI outcomes
Data-driven decision making	Data-driven decision-making fosters AI adoption because both utilize data and statistical methods to gain insights

Factor under each organisational readiness resource	Description of factor
AI ethics	AI ethics comprise measures to prevent bias, safety violations, or discrimination in AI outcomes
Financial budget	Strategic allocation of the financial budget for AI adoption supports the overcoming of initial obstacles and uncertainty
Innovativeness	Innovativeness increases employees' willingness to change the status quo through the application of AI
IT infrastructure	T infrastructure enables AI-related activities and AI integration
Personnel	AI specialists and business analysts with AI know- how facilitate AI adoption
Top management support	Top management support signals AI's strategic relevance to the organization and fosters AI initiatives
Upskilling	Upskilling enables employees to learn and develop AI or AI-related skills
Readiness model (326)	
Agent based applications	Conduct agent-based simulations or modelling to indicate the possible impacts of AI on business processes
Agile delivery	Development of agile strategy for AI technology
Benefits	Employees' perception of the benefits of AI technology
Budget	Allocation of budget for AI technology
Business acceptance	Business acceptance of AI technology
Business cases	Identification of business cases for AI technology.
Business clarity	Perceived business clarity with regard to AI technology
Business opportunity	Identification of applicable business opportunities for AI technology
Certainty	How certain employees are in AI technology results/how much they trust the AI technology.
Cloud resources	Identification of cloud computing and deployment models, understanding and satisfying those requirements.
Collaboration	Willingness of employee collaboration with AI
Communication networks	Identification of communication networks included with the operation of AI technology
Compatibility with existing values and practices	Compatibility of AI with business values and practices
Cost management	Identification of cost management structures for AI technology
Cyber security	Identification and development of management of cyber security for AI technology.
Cyber security	Identification and development of management of cyber security for AI technology.
Enterprise resource planning in terms of databases and software	Identification of enterprise resource planning
Executive support	The executive support regarding AI technology

Factor under each organisational readiness resource	Description of factor
Human resource planning	Documentation of data regarding the short to long term goals of the AI project and efforts regarding the identification of the types of resources, people and competencies that will be required
Information networks	Identification of information networks involved with the implementation, operation and management of AI technology
Infrastructure platform	Identification of required infrastructure in terms of cloud resources, as well as additional infrastructural sections.
Job security	Perceptions of job security with regard to AI technology
Management of information system and data processing	Initiation of the development of management structures
Network connectivity	Understanding the network connectivity required
Observable results	Identification of methods and criteria involved with generating results during testing/implementation
Perceived ease of use	Employees' perception with regards to ease of use of AI
Perceived usefulness	Employees' perception on the usefulness of AI
Quality management	Identification and selection of quality management structures for AI technology
Return on investment	Calculations of the result on investment for AI technology
Services	Identification and mapping of services that will incorporate AI technology
Skills and expertise	Perception of current skills and expertise capability to implement and manage AI technology
Strategic leadership	Identification of strategic leadership which complies with the activities of a strategic leader
Technologic sustainability and position map	Development of sustainability and position map
Technological categorisation and planning	Progress made in categorisation and planning
Technological competitors’ analysis	Identification of cost management structures for AI
Technological investment and capital management	Allocation of investment and capital
Technology identification and selection	Analysis of technology compatibility, system impact and maturity of the AI technology.
Technology knowledge management	Initiation of technology knowledge management strategies
Technology prospect/forecasting	Identification of technology forecasting methods for AI technology
Technology requirement handling	Identification of technology requirement management structures
Technology risk management	Manage roles and responsibilities for managing AI risks, prioritisation and identification of informational system assets, implementation of practices, and controls to mitigate risks, assess

Factor under each organisational readiness resource	Description of factor
	the likelihood, as well as the impact of current and emerging threats, vulnerabilities and risk, implementation of improvements/updates and monitoring of risks
Technology roadmaps and scenarios	Identification of technology roadmaps and scenarios regarding AI technology
Trial-ability	The capability to conduct a certain amount of testing
Model of AI readiness (327)	
Acceptance	Customers' acceptance towards working with bots and their preference for dealings with humans over bots.
AI solutions	Knowing about the different AI technology solutions, choosing the right one, and selecting a scalable AI technology platform among different solutions.
AI use cases	Identifying where AI technology can be used, understanding where AI technology has been used previously and knowing where AI can fit into the organisation
Availability	Need for easily available data for efficient machine learning and availability of data either for store or for purchase
Customer’s needs	Forming AI projects based on the demands of the end users and any AI failures that come from a firm neglecting customers needs.
Feedback mechanism	AI technologies need a feedback loop in the system, and need human feedback
Financial resources	Budget as an important consideration, high amount of investment required for AI and need for more money to support using AI uninterruptedly
Human resources	Availability of required human resources in the market, in-house talent and HR support for recruiting and training
Integrated communication	Ensure no project failure due to limited communication, communication between the analytics team and data touchpoints.
IT resources	Computing and storage capacity, data acquiring tools and secure networks and systems.
IT support	Help employees avoid technical problems, resolve technological bottlenecks and clogging detection throughout
Leadership	Influence of leaders on employees to adopt AI technology, removing job loss fears
Managers	AI technologies alignment with managers goals and plans
Operational integration	Integrating automation with the whole system, integrating into other systems
Organisational culture	Willingness to learn and openness, collaboration and tech-friendliness
Partners	Partner’s compatible infrastructure, their coordination and acceptance, and them having the same mindset as the rest of the stakeholders.
Privacy concerns	Any privacy or security concerns, the balance between personalisation and privacy
Problem recognition	Finding the pain in your business, finding out what influences your business

Factor under each organisational readiness resource	Description of factor
Quality	Need for relevant data, need for structured data to enable AI and data accuracy
Regulatory environment	Legal repercussions in European countries, regulations about setting product through bots and regulations about storing data
Staff	Staff's acceptance of AI technology, staff's knowledge and skills to use AI technology, staff's trust in AI technology usage and benefits for them
Techniques	Ability to process data and analyse and understand the outputs and data management techniques
Technological maturity	Level of tech currently, need for mature IT for complicated AI technology uses.
Volume	Problems arising from a lack of data, need for massive training datasets and need for more data than companies usually have.
Organisational readiness model 1 (328)	
Financial	A system required continual financial resources, and therefore, priorities should include investing in AI research and development, building an AI ecosystem, and encouraging cross-industry partnerships that would make AI applications both more accessible and less costly to adopt[†]
Psycho-cultural	The psycho-cultural context can either act as the accelerator or decelerator of the transitioning to AI-powered healthcare sector[†]
Socio-political	To maintain such a system requires continual socio-political support. More specifically, the priorities should include investing in AI research and development, building an AI ecosystem, and encouraging cross-industry partnerships that would make AI applications both more accessible and less costly to adopt[†]
Technical/technological	In technical terms, as machine learning methods, especially the artificial neural networks, rely on the availability of large volumes of high-quality data, a strong and stable technological infrastructure, such as large data centres or warehouses, is needed[†]
Organisational readiness model 2 (329)	
Data-sharing priority	How much data sharing aligns with the organisations priorities
Governance	Legal and ethical matters and other aspects that pertain to external data sharing
Infrastructure	The technical infrastructure supporting data processing
Organisational mission	Organization's purpose and strategic goals for existence
People	Data experts and champions that play a role in the collaborative effort to facilitate data sharing
Resources	Resources that support the preparation of clinical data to be "AI-ready"

* Factors followed by reference (311) are extracted from the original TOE framework, factors followed by reference (312-318) are extracted from a study that applied the TOE framework .

** Factors followed by reference (319) are extracted from the original BOE model, factors followed by reference (320, 321) are extracted from a study that applied the BOE model.

[†] Description of factor summarised by the researcher

Appendix 10: How each factors under the organisational readiness resources align with the subthemes

Factors under each organisational readiness resource	Subthemes under each extended Work System Model component																		
	Expertise in AI technology	Knowledge of AI technology	Perceptions of AI technology	Availability and structure of data	Design of the AI technology	Benefit of using AI technology	Current and planned uses of AI technology	Current uses of technology	IT infrastructure	Network infrastructure	IT facilities	Process changes	Current and potential impact on activities	Cost and budget	Culture of organisation	Strategies for successful adoption	Teamwork and leadership	External impacts	Organisational goals
Technology-Organisation-Environment (TOE) framework (311-318)*																			
The environmental context (311)																		✓	
The organisational context (311)														✓			✓		
The technological context (311)							✓	✓										✓	
AI system capabilities (316)					✓														
AI system quality (316)				✓															
Anthropomorphism of AI systems (316)					✓														
Availability of the technology vendors/partners (316)																		✓	
Competition (316)																		✓	
Data ecosystem in the firm (316)				✓															
Financial readiness/Financial competence of the firm (316)														✓					

Factors under each organisational readiness resource	Subthemes under each extended Work System Model component																		
	Expertise in AI technology	Knowledge of AI technology	Perceptions of AI technology	Availability and structure of data	Design of the AI technology	Benefit of using AI technology	Current and planned uses of AI technology	Current uses of technology	IT infrastructure	Network infrastructure	IT facilities	Process changes	Current and potential impact on activities	Cost and budget	Culture of organisation	Strategies for successful adoption	Teamwork and leadership	External impacts	Organisational goals
Information Security/Cybersecurity (316)																✓			
Interpretability/Explainability (316)					✓														
IT infrastructure of the firm (316)									✓										
Perceived benefits (316)			✓																
Perceived compatibility of AI systems (316)					✓														
Perceived complexity of AI systems (316)					✓														
Perceived ease of use (316)			✓																
Perceived privacy concerns (316)			✓																
Perceived usefulness (316)			✓																
Regulatory environment (316)																		✓	
Strategic alignment of AI systems (316)																✓			
Support from top management (316)															✓				

Factors under each organisational readiness resource	Subthemes under each extended Work System Model component																		
	Expertise in AI technology	Knowledge of AI technology	Perceptions of AI technology	Availability and structure of data	Design of the AI technology	Benefit of using AI technology	Current and planned uses of AI technology	Current uses of technology	IT infrastructure	Network infrastructure	IT facilities	Process changes	Current and potential impact on activities	Cost and budget	Culture of organisation	Strategies for successful adoption	Teamwork and leadership	External impacts	Organisational goals
Perceived trust (316, 317)			✓																
Connectivity (314)										✓									
COVID-19 as a transformational force (314)																		✓	
Data management and privacy (314)				✓															
Excitement and positive perceptions (314)			✓																
Lack of AI practice and discomfort (314)							✓												
Organisational size and financial resources (314)														✓					
Organisations strategic plans (314)																✓			
Data quality (317)				✓															
Ethics (317)																✓			
Governance (317)																✓			
Role clarity (317)																	✓		
Compatibility (312, 315, 317, 318)					✓														
Competitive pressure (312, 318)																		✓	

Factors under each organisational readiness resource	Subthemes under each extended Work System Model component																		
	Expertise in AI technology	Knowledge of AI technology	Perceptions of AI technology	Availability and structure of data	Design of the AI technology	Benefit of using AI technology	Current and planned uses of AI technology	Current uses of technology	IT infrastructure	Network infrastructure	IT facilities	Process changes	Current and potential impact on activities	Cost and budget	Culture of organisation	Strategies for successful adoption	Teamwork and leadership	External impacts	Organisational goals
Top management support (312, 318)															✓				
Government regulations (312, 315, 318)																		✓	
Organisation size (312, 315, 318)														✓					
Relative advantage (312, 315, 318)						✓													
Resources (312, 315, 318)									✓										
Customer AI readiness (315)		✓																	
Industry requirements (315)																		✓	
Organisational structure (315)																	✓		
Culture (313, 315)															✓				
Competence (313)		✓																	
Knowledge (313)		✓																	
Benefits-Organisation-Environment (BOE) model (319-321)*																			
Technological readiness (319)								✓											
Financial resources (319-321)														✓					

Factors under each organisational readiness resource	Subthemes under each extended Work System Model component																		
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Culture (320)															✓				
Leadership (320)																	✓		
Knowledge (320)		✓																	
Vison (320)															✓				
Risk (320)			✓																
Data access (321)				✓															
Digital literacy (321)		✓																	
Conceptual framework of organisational readiness (322)																			
Analytical approach				✓															
Any additional challenges							✓												
Auditing approach				✓															
Close alignment between business & IT																✓			
Close all possible gaps																✓			
Context challenges							✓								✓				
Data challenges				✓															
Effective change management strategy																✓			
Effective training and readiness strategy																✓			
Expertise challenges	✓						✓												
Infrastructure challenges							✓		✓										
Integration approach				✓															

Factors under each organisational readiness resource	**Subthemes under each extended Work System Model component**																		
	Expertise in AI technology	Knowledge of AI technology	Perceptions of AI technology	Availability and structure of data	Design of the AI technology	Benefit of using AI technology	Current and planned uses of AI technology	Current uses of technology	IT infrastructure	Network infrastructure	IT facilities	Process changes	Current and potential impact on activities	Cost and budget	Culture of organisation	Strategies for successful adoption	Teamwork and leadership	External impacts	Organisational goals
Push information to organisation												✓							
Regularisation approach				✓															
Social approach				✓															
AI readiness model (323)																			
Collection and use of operational data				✓															
Data access				✓															
Implementation of CPS-related technologies in production								✓											
Implementation of data protection measures																✓			
Product features with digital elements								✓											
Product-related services								✓											
Use of advanced robotics								✓											
AI readiness framework (324)																			
Current uses of AI technology								✓											
Future uses of AI technology							✓												
How does AI impact current activities													✓						

Factors under each organisational readiness resource	Subthemes under each extended Work System Model component																		
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How does AI impact current goals																			✓
How has AI changed the boundaries																			✓
How may AI impact future activities													✓						
How may AI impact future goals																			✓
How will AI impact future boundaries																			✓
Organisational AI readiness factors (325)																			
AI awareness		✓																	
AI ethics																✓			
AI-business potentials						✓													
AI-process fit												✓							
Change management															✓				
Collaborative work																	✓		
Customer AI readiness		✓																	
Data accessibility				✓															
Data availability				✓															
Data flow				✓															
Data quality				✓															
Data-driven decision making					✓														

Factors under each organisational readiness resource	**Subthemes under each extended Work System Model component**																		
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Financial budget														✓					
Innovativeness															✓				
IT infrastructure									✓										
Personnel	✓																		
Top management support															✓				
Upskilling		✓																	
Readiness model (326)																			
Agent based applications													✓						
Agile delivery																✓			
Benefits			✓																
Budget														✓					
Business acceptance															✓				
Business cases																			✓
Business clarity															✓				
Business opportunity																			✓
Certainty			✓																
Cloud resources										✓									
Collaboration																	✓		
Communication networks										✓									

Factors under each organisational readiness resource	Subthemes under each extended Work System Model component																		
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Compatibility with existing values and practices															✓				
Cost management														✓					
Cyber security																✓			
Enterprise resource planning in terms of databases and software																✓			
Executive support															✓				
Human resource planning																✓			
Information networks										✓									
Infrastructure platform										✓									
Job security			✓																
Management of information system and data processing																	✓		
Network connectivity										✓									
Observable results					✓														
Perceived ease of use			✓																
Perceived usefulness			✓																
Quality management																✓			
Return on investment														✓					
Services							✓												

Factors under each organisational readiness resource	Subthemes under each extended Work System Model component																		
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Skills and expertise		✓																	
Strategic leadership																	✓		
Technologic sustainability and position map																✓			
Technological categorisation and planning																✓			
Technological competitors' analysis			✓																
Technological investment and capital management														✓					
Technology identification and selection					✓														
Technology knowledge management		✓																	
Technology prospect/forecasting					✓														
Technology requirement handling					✓														
Technology risk management																✓			

Factors under each organisational readiness resource	**Subthemes under each extended Work System Model component**																		
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Technology roadmaps and scenarios							✓												
Trial-ability					✓														
Model of AI readiness (327)																			
Acceptance			✓																
AI solutions					✓														
AI use cases					✓														
Availability				✓															
Culture															✓				
Customer’s needs					✓														
Feedback mechanism					✓														
Financial resources														✓					
Human resource planning																✓			
Integrated communication																	✓		
IT resources											✓								
IT support	✓																		
Leadership																	✓		
Managers															✓				✓
Operational integration												✓							
Partners															✓				
Privacy concerns			✓																
Problem recognition				✓															

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Quality				✓															
Regulatory environment																		✓	
Staff		✓	✓																
Techniques								✓											
Technological maturity							✓												
Volume				✓															
Organisational readiness model 1 (328)																			
Financial resources														✓					
Psycho-cultural															✓				
Socio-political																		✓	
Technical/ technological								✓											
Organisational readiness model 2 (329)																			
Data-sharing priority																			✓
Governance																✓			
Infrastructure											✓								
Organisational mission																			✓
People	✓																		
Resources				✓															

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** Factors followed by reference (319) are extracted from the original BOE model, factors followed by reference (320, 321) are extracted from a study that applied the BOE model.