Improving Diabetes Treatment in Ghana: Modelling the Health and Economic Benefits of Public Health Interventions

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Declaration

This thesis and the work present therein are my original work and have been composed by me. It has not been previously submitted in part or full for an examination leading to the award of a degree. I own the copyright of this thesis under the United Kingdom Copyright Act as qualified by the University of Strathclyde Regulation 3.50. I duly acknowledge the use of any materials contained in or derived from this thesis. Chapter 4 and 6 were conjoint work with Dr Itamar Megiddo (IM), Professor Robert Van Der Meer (RV), Professor Brian Godman (BG) and Professor Justice Nonvignon (JN) as described in the Table below.

Contributions of conjoint work

Paper (corresponding chapter/ section)	The PhD author	The co-authors
1 (chapter 4)	Conceived and designed the study. Conducted the analysis. Drafted the paper and led the submission and revision process for journal and conference publication	Supervised the study: IM and JN Contributed to designing the study: IM Commented on the draft paper: IM, JN and RV
2, 3 (Chapter 6)	Conceived the study. Led ethics application. Conducted interviews and the analysis. Drafted the paper and led the submission and revision process for journal and conference publication	Supervised the study: IM, JN and BG Commented on the draft paper: IM, JN, RV and BG Contributed to designing the study: IM.

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Abstract

Although the burden of Diabetes Mellitus (DM) in Ghana is escalating, evidence to support decision-making on cost-effective interventions is extremely limited in this setting. While there is ample evidence on the impact of clinical and pharmacological interventions for blood glucose control (BGC), less is known about public health (PH) interventions. The health and economic benefits of PH interventions for BGC are particularly unclear. This is significant because BGC influences the progression of DM-related complications, which are associated with hospital admissions, high treatment costs, and reduced quality of life. The WHO has recommended sugar-sweetened beverage (SSB) taxes, expanding medicine access and Universal Health Coverage for controlling DM and other NCDs, and there is evidence of their effectiveness in many countries. However, evidence of the policies' cost-effectiveness in Ghana is limited. The understanding of how patient behaviour interacts with clinical services and PH policies within Ghana's socioeconomic environment is also limited.

As a first step, this research seeks to improve understanding of the dynamic patients' SMB and how it influences BGC, medicine adherence and clinical outcomes using agent-based modelling (ABM). The research then combines ABM with cost-effectiveness analysis (CEA) to examine the health and economic benefits of selected PH interventions: a 20% SSB tax, expanding medicine availability and insurance coverage. ABM captures the complexity and heterogeneity of patients' SMB. Manual code verification, Whitebox testing, face validation, and scenario and probabilistic sensitivity analysis are used to build confidence in the ABM model. CEA compares the health outcomes and economic efficiency of the selected PH interventions, generating evidence to support policy decision-making.

This research makes various theoretical, methodological, empirical, and practical contributions. From a theoretical perspective, the research provides a conceptual model of the socioeconomic environment and clinical service delivery system, which is crucial for improving understanding of DM patients' SMB and BGC outcomes and designing interventions. The second theoretical contribution is the development of an agent-based conceptual model for simulating individual patients' SMB and how such behaviours and interactions contribute to cohort-level BGC outcomes. From a methodological perspective, this research contributes to the decision analytical modelling and health technology assessment field by applying ABM and CEA to study patients' treatment behaviour and examine the health and economic impact of selected PH interventions on patients and the government. It also applied the health belief model and the theory of planned behaviour to conceptualise SMB. Lastly, the research makes two empirical contributions. It helps improve understanding of how the patients' SMB, clinical services, and PH policies influence BGC at a cohort level. It provides insights on the cost-effectiveness of SSB tax, expanding insurance coverage and increasing medicine availability from a government and patient

perspective to support policy decision-making. Opportunities for future research and data surveillance are proposed.

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List of Abbreviations

Main and frequently used initialisms are listed below. Further initialisms are identified in sections.

BGC	Blood Glucose Control
CI	Confidence Interval
CEA	Cost-effectiveness Analysis
CEAC	Cost-effectiveness Acceptability Curve
CHPS	Community-Based Health Planning and Services
DM	Diabetes
DALYs	Disability Adjusted Life Years
DAM	Decision Analytical Modelling
DES	Discrete-Event Simulations
GDP	Gross Domestic Product
GBD	Global Burden of Disease
HTA	Health Technology Assessment
HEFRA	Health Facility Regulatory Agency
IMF	International Monetary Fund
IDF	International Diabetes Federation
LMICs	Low- and Middle-Income Countries
MDGs	Millennium Development Goals
MoH	Ministry of Health
NCD	Non-Communicable Diseases
NHIS	National Health Insurance Scheme
NHIA	National Health Insurance Authority
ODD	Overview, Design concept and Details
PEN	Package of Essential Non-communicable Disease Interventions
PRCC	Partial Rank Correlation Coefficient
PH	Public Health
RCTs	Randomised Control Trials
SDGs	Sustainable Development Goals
SD	Systems Dynamics
SSB	Sugar-Sweetened Beverage
SM	Simulation Modelling
SMB	Self-Management Behaviour
STG	Standard Treatment Guidelines

T2DM	Type 2 Diabetes
USD	United States Dollar
UN	United Nations
UHC	Universal Health Coverage
WHO	World Health Organisation

1 Introduction

1.1 Research Overview

Diabetes (DM) remains a global health burden that is rapidly increasing in prevalence, mortality, and cost, especially in Africa (Magliano and Boyko, 2021; World Health Organization, 2016). Evidence from simulation modelling (SM) can be used to improve understanding and examine interventions' effect on the disease burden, where large-scale randomised control trials (RCTs) and cohort studies are infeasible due to, but not limited to, cost, ethics and time. SM combines mathematical expressions, behaviour rules, and operational procedures to model entities and systems. Aside from the effectiveness of interventions, policymakers decide which intervention to implement amidst several alternatives and a limited budget. In LMICs, where financial and human resources for health are insufficient relative to health demands, health resource allocation must be supported by evidence of cost-effectiveness to ensure the best value for money. Combining SM with cost-effectiveness analysis (CEA) methodologies offers an opportunity to deepen understanding of the contextual factors associated with DM burden. The methods provide an opportunity to examine the effectiveness and cost-effectiveness of interventions for reducing the burden. This thesis combines SM with CEA methodology to investigate the health and economic efficiency of selected public health (PH) interventions for controlling blood glucose among DM patients receiving care in Ghana's PH sector. This introductory chapter provides the background of the study (section 1.2), shows the research's significance (section 1.3), and summarises the research approach and thesis structure (section 1.4).

1.2 Research background

1.2.1 Meaning of Diabetes

The International Diabetes Federation (IDF) and the World Health Organisation (WHO) define DM as a group of metabolic conditions associated with the inability of the body to produce sufficient insulin or properly use insulin to regulate blood sugar levels, resulting in excess sugar in the bloodstream (Magliano and Boyko, 2021; World Health Organization, 2016). Insulin is a hormone produced in the pancreatic gland, which transports sugar from the bloodstream into body cells for the body to convert into energy for present or future use. According to IDF and the WHO, there are three main types of DM: type 1, type 2 (T2DM), and gestational DM. Gestational DM is caused by a hormonal imbalance in pregnant women that usually resolves after delivery. Individuals with a history of gestational DM may develop T2DM in the future. In T1DM, the body's insulin-producing beta cells in the pancreatic

gland are destroyed by immune system processes, causing little or no insulin production. The condition is irreversible, and its exact cause is unknown. It is usually diagnosed in children and requires daily insulin injections to maintain appropriate BGC. However, in T2DM, the body's insulin cannot keep up with the demand to carry blood sugar to the body cells to be processed for use or storage. Roughly 90% of DM are T2DM, and the disease is more likely to occur in obesity and old age (above 45 years) (Magliano and Boyko, 2021). Although T2DM on its own seldom results in death, it frequently causes complications, including ketoacidosis, cardiovascular disease, renal failure, and infections that can be fatal.

1.2.2 Diabetes Burden

DM accounts for a significant proportion of morbidity, mortality, health resource consumption, lost productivity due to illness, and financial hardship to individuals and households. In the 2021 IDF Atlas report, the global DM prevalence was estimated at 10.5%, with about 16.3% of LMIC populations living with the disease (Magliano and Boyko, 2021). Should current trends continue, 106.1 million more people will live with DM by 2030. The IDF also estimated that over 9 million more people in Africa will have DM by 2030, adding to the already 24 million people with DM in 2021. The increase in Africa will be the largest on the globe. The prevalence of DM in Africa may be underestimated due to a suboptimal surveillance system and a significant proportion of undiagnosed DM on the continent.

The DM burden in Ghana is considerable. The prevalence in Ghana's neighbouring countries varies slightly: in Nigeria, the national prevalence in adults is estimated at 3.6%, and in Cameroon, it is 5.5% (Magliano and Boyko, 2021). The 2021 IDF Atlas reported Ghana's DM prevalence to be between 1.1% – 3.8% among adults aged 20 – 79 years, and roughly 77,400 – 286,800 cases are yet to be diagnosed. A systematic review and meta-analysis of studies conducted among Ghanaian residents reported a higher disease prevalence between 4.7% – 8.3%, identifying age (40 years and above), physical inactivity, and family history of DM as significant risk factors (Asamoah-Boaheng et al., 2019). Based on Asamoah-Boaheng et al.'s results, the disease burden may be larger than what IDF captured, driving many families into catastrophic health expenditures. A report from the Ministry of Health (MoH) indicates that the percentage of the national health budget spent on non-communicable diseases (NCD) has doubled from 6.19% in 2013 to 12.64% in 2015 (Ministry of Health, 2017a). However, evidence suggests that individuals and households incur catastrophic expenditures due to DM, especially from buying medicines and treating complications (Amon and Aikins, 2017; Quaye et al., 2015). Given the increasing prevalence, the health and economic consequences of DM will continue to rise without policy interventions.

1.2.3 COVID-19 and Diabetes

The COVID-19 pandemic has negatively impacted DM prevention and control efforts by placing a tremendous strain on health systems, worsening DM treatment outcomes, and increasing DM risk factor distribution in populations. A WHO survey of 155 countries in May 2020 indicated a severe disruption of NCD prevention and treatment services globally; low-income countries are the most affected (World Health Organisation, 2020a). People needing treatment for DM, cancer, and cardiovascular diseases could not receive care due to service disruptions, health staff reassignment, and postponement of screening services. Nearly half of the surveyed countries had disrupted DM service. Fifty-three per cent of countries altered their hypertension services, and almost all countries had partially or fully reassigned medical staff in NCDs' care to support COVID-19 control. The disruption has led to delays in diagnosis, with many patients on a waiting list for surgical procedures and missed opportunities to provide patients with advice on self-care management. Advanced economies such as the United Kingdom introduced new strategies for delivering healthcare: over-phone conversations, mobile applications, and internet-based video services. However, these strategies are most likely unsustainable in emerging economies due to implementation costs.

Evidence suggests a potential pathogenetic relationship between DM and COVID-19. DM and its complications have been associated with increased severity and mortality from COVID-19; likewise, there have been cases of elevated blood glucose in non-diabetic COVID-19 patients (Lim et al., 2021). In the UK, an online survey involving 2,364 adults reported an increased incidence of unhealthy dieting, lower levels of physical activity, and difficulty managing body weight during the COVID-19 lockdown (Robinson et al., 2021). Similar trends have been observed in the Middle East, North Africa, China, Spain, Poland, and Italy (Daniels et al., 2022). The COVID-19 pandemic and relative control measures could have long-lasting negative consequences on DM.

1.2.4 Diabetes in Ghana

Policymakers in Ghana are concerned about the rising prevalence of DM and the ensuing expenditures connected with the condition. The 2021 IDF Atlas report indicates that roughly 329,200 adults aged 20-79 live with DM in Ghana, marking roughly 17% increase in 2019's prevalence (281,100). If current trends continue, the number is estimated to increase to 439,000 in 2030 (Magliano and Boyko, 2021; Williams et al., 2019). The worrying part of Ghana's DM burden is that more than half of DM are undiagnosed, which means one in every two people with DM is unaware and may report later to health facilities with complications or even die. Additionally, the number of prediabetes in 2019 was five times higher than the actual cases of DM in that same year; consequently, DM prevalence is likely to quintuple

if Ghana does not intervene. Furthermore, the report indicates that four in every ten DM-related deaths occurred in the working population (under 60 years), reducing labour supply and productivity. Also, DM treatment cost per person increased by more than 520% between 2010 and 2019, which is higher than the average increase in Africa in the same period. Ghana has long recognised the DM burden and has launched several policy interventions (Ministry of Health, 2022a). However, implementation remains a challenge due to, but not limited to, insufficient financial and human resources.

1.2.5 The Socioeconomic Situation in Ghana and Implications for Diabetes

1.2.5.1 Macro-economic factors

Ghana's economic challenges, including rising inflation, Cedi depreciation, and high debt to gross domestic product (GDP) ratio, negatively affect DM control. The soaring global commodity prices compounded by the depreciation of the Cedi to the United States Dollar (USD) causes an increase in the cost of imported products, which includes DM medicines and supplies. Reports from the World Bank indicate that, as of July 2022, inflation has risen to 31.7% from 12.6% at the end of 2021 (Calderon et al., 2022a, 2022b; Kwakye et al., 2023). The reports indicated that Ghana imports about 40% of its fertilisers from Russia, a proportion that would have increased due to the supply chain destruction caused by the Russia and Ukraine wars, increasing food production costs and, subsequently, food costs. With the current Cedi depreciation, Ghana will need to give more Cedis to purchase the same number of medicines and supplies; the increasing prices could transcend to patients and households who buy DM medicines and food out of pocket.

Additionally, Ghana's debt-to-GDP ratio has sharply increased, indicating the unsustainability of government spending, including health spending. A World Bank report has classified Ghana as a high debt distress country, projecting that the country's debt to GDP is expected to reach 99.7% and 101.8% in 2023 and 2024, respectively, due to a widening government deficit, a considerable depreciation of the Cedi, and growing debt service cost (Calderon et al., 2022a). According to the report, Ghana's debt servicing in 2022 is estimated to take over 70% of the country's GDP, leaving little for financing social and health programs, including DM care. Amid the macroeconomic instability, Ghana secured about US$3 billion in a 36-month extended credit facility programme from the International Monetary Fund (IMF) in May 2023 to support the country in tackling the financial crisis (International Monetary Fund, 2023). In the country's 2015 IMF program, the government had to revise its public spending by reducing hiring and pay rise, cancelling subsidies on utilities and petroleum products, clamping down on tax evasion and streamlining policy exemptions (International Monetary Fund, 2019). Despite the positive economic effect, these changes caused financial hardship to individuals and households, including DM

patients. The government is on a similar trajectory with its 2023 IMF extended credit facility program. Specifically, the domestic debt exchange programme, where government bondholders and retirees tender financial investments for new ones with later maturity at lower average coupons (Ofori-Atta, 2022). This means that households depending on interest from government bonds and retirees may not have sufficient funds to sustain their cost of living and manage DM.

1.2.5.2 Urbanisation and obesity prevalence

Sociocultural factors such as urbanisation, a sedentary lifestyle, and poor food choices increase the DM burden in Ghana. Urban populations are more likely to be overweight and obese due to food consumption patterns and sedentary lifestyles (Ofori-Asenso et al., 2016; Yussif et al., 2024). Low physical activity levels and calorie-dense food consumption are the primary causes of overweight and obesity (World Obesity Federation, 2023; American Diabetes Association, 2024). Roughly 43% of adults in Ghana are either obese or overweight (Ofori-Asenso et al., 2016). The country's urban population increased from 23.1% in 1960 to 56.7% in 2021 (Ghana Statistical Services, 2021). Rapid urbanisation exposes many people to unhealthy lifestyles. Poor urban planning limits opportunities for physical activity due to few spaces for recreational/sports activities and a significant reliance on driving, among other forms of transportation, which reduce individuals' energy expenditure. The rise in unhealthy food consumption and sedentary lifestyle increases obesity prevalence and the risk of cardiovascular diseases and DM.

1.2.5.3 Health system-related issues

Unaffordable DM services and insufficient clinical expertise and technology are major health system factors that negatively impact the clinical management of DM in Ghana. The country uses the National Health Insurance Scheme (NHIS) to reduce cost barriers to healthcare. Theoretically, the NHIS is expected to pay for essential DM services and medicines (Government of Ghana, 2012a), but this is not always the case. Delays in NHIS claims payment influence accredited health facilities to discontinue service provision to insured persons or directly charge the insured for medicines and services, contributing to catastrophic expenditure for patients and their households (Kipo-Sunyehzi et al., 2020). Another challenge is that there are few DM-trained clinicians and few technologies to provide care. Generally, the doctor-to-patient and nurse-to-patient ratio in Ghana is worsening (Ministry of Health, 2018), partly due to clinicians migrating for greener pastures in high-income countries. The lack of medical technology, including diagnostic equipment, at primary and some secondary levels of care, coupled with few trained clinicians, limits DM service availability, especially in rural areas (Addo et al., 2020; Kushitor and Boatemaa, 2018; Ministry of Health, 2018). Patients may be referred to tertiary

health facilities in urban communities. However, the cost of transportation usually prevents them from seeking care, worsening DM treatment outcomes.

The prevailing macroeconomic situation and sociocultural and health system factors further exacerbate the DM burden, putting Ghana behind in achieving the Sustainable Development Goals (SDGs) and the WHO DM targets. The situation in Ghana justifies a need to understand the current system of DM treatment and develop cost-effective interventions to improve DM treatment outcomes and accelerate efforts toward achieving global targets.

1.3 Research Motivation

Developing cost-effective interventions to improve DM control in Ghana requires understanding the system of DM service delivery, patients' behaviours and treatment outcomes. Studies have demonstrated the potential of PH interventions to reduce DM-related morbidities, delay mortalities and reduce treatment costs to health systems and individuals. PH DM interventions include fiscal policies, legislative changes in, but not limited to, trade and agriculture, health promotion activities or changes to physical environments that can influence physical activity, diet and health-seeking behaviour (World Health Organisation, 2022a). The system of DM control is an interconnected ecosystem where patients interact with community cultures/lifestyles, health facilities with different resource capacities and various national health policies. Therefore, the effectiveness of an intervention does not solely depend on implementing but also on the behaviours and interactions of patients, health facilities and communities. These actors/policies and their actions have overlapping, unexpected, and indirect consequences on DM treatment outcomes, the health system, and the government. Understanding the dynamic interactions and feedback loop that transpire in Ghana's DM control system is important for designing and implementing contextual and effective interventions.

Real-time large-scale RCTs, cohort studies and economic evaluation methods have been used to generate evidence of the impact of interventions for DM control (Sandholzer-Yilmaz et al., 2022). However, RCTs and large-scale cohort studies can be challenging from an ethical, implementation time and cost perspective. Ethical issues, such as delaying life-saving interventions in human subjects, could constitute a breach of duty of care and lead to disapproval from ethics committees. In addition, large-scale RCTs and cohort studies are associated with high implementation costs that LMICs, including Ghana, may not afford, explaining the paucity of these studies in lower-resource settings. Although small-scale RCTs and cohort studies could be affordable, feasible and practical where ethics is not an issue, other considerations may limit their applications. For example, following patients through a life course to understand possible pathways and generate evidence can take a long time. Also, the challenge

of losing study participants to follow-up can threaten the study's validity and generalisability (Sterne et al., 2016).

Brailsford and colleagues (2017) have classified modelling and simulation approaches in the healthcare literature into qualitative, statistical analysis, mathematical modelling, statistical modelling, simulations and others. The term model covers various meanings in the context of medicine and research. In this study, model refers to the representation of an abstracted part of a real-world system, and modelling is the process of abstraction—usually involving a combination of tools, theories, approaches, and methods from multiple disciplines, including computer science, economics, mathematics, and PH. Not all models capture complex individual-level behaviours and the stochastic nature of clinical service delivery systems in a dynamic socioeconomic context (Mukonda et al., 2021).

SM is a viable approach compared to a mathematical or statistical modelling approach for modelling patients' self-management behaviours (SMB) and health service delivery for one main reason. SM provides an opportunity to construct a mathematical representation of the decision problem and context, representing the interaction between behaviour, health service delivery and the socioeconomic and health policy environment in a model (Petropoulos et al., 2024). The SM approach provides insights into the decision problem and serves as a tool for studying the decision problem and testing potential solutions, which aligns with the aim of our study. However, mathematical programming focuses on finding an optimal solution, assuming well-defined input variables and relationships (Petropoulos et al., 2023), which is not the case with patients' SMB.

Markov cohort model, system dynamics (SD), discrete event simulation (DES), microsimulation and agent-based modelling (ABM) are common SM used in DM intervention studies (Dadwani and Laiteerapong, 2020; Li et al., 2021; Mukonda et al., 2021; Twumwaa et al., 2022; Watson et al., 2014). In addition to the study problem and goal, system processes, data availability and aggregation level, and analysis unit, each approach has specific assumptions and structure and considers a problem from unique perspectives, which should be considered before applying a modelling approach in research. A combination of SM and CEA can be particularly useful for examining the health and economic benefits of PH interventions on population-level DM treatment outcomes, patient SMB, and government budget.

The motivation of this research is to search for and define PH interventions that improve the health and economic efficiency of T2DM control for patients and the government. We are motivated to build an ABM of T2DM treatment in Ghana and combine the model with CEA to generate evidence to support decision-makers in controlling DM within Ghana's PH system. This motivation has led to the following research questions and specific objectives, which we address in subsequent chapters using different research methods.

1. What is the state of DM service delivery in Ghana and DM interventions in Ghana and LMICs?
2. How do patients' behaviour influence health service delivery and DM treatment outcomes?
3. How have SM and economic evaluation methods (DAMs) been applied to evaluate PH DM interventions in LMICs?
4. What is an appropriate modelling approach for representing the system of DM treatment in Ghana?
5. What are the health and economic benefits of selected PH interventions to patients and the government?

The research questions collectively contribute to achieving the study's motivations. Question 1 improves understanding of the study context and the system of clinical DM service delivery. The question provides insight into DM interventions in Ghana and other LMICs. This understanding helps to appreciate the scope of the problem, how policy interventions have addressed the problem and what challenges remain. The literature review and clinicians' opinions addressed in Question 1 provided evidence of the importance of patient behaviour in DM treatment, which is further explored in Question 2. Question 1 introduced the application of SM in DM intervention studies, explored in Question 3 and informed PH interventions explored in Question 5. Specifically, Question 2 builds on Question 1 from a micro level, exploring the influence of patients' SMB on DM outcomes. Question 3 generates evidence of DAMs, when and how they have been used. The evidence and insights from Questions 2 and 3 helped address Question 4 by informing the selection of ABM for representing the decision problem/context. Question 5 uses insights from the ABM in Question 4 and CEA to examine the PH interventions we identified in Question 1. Insights and evidence from these questions combine to achieve the study's motivation of improving DM control in Ghana. Figure 1.1 highlights the relationship between the research questions.

The study's specific objectives are:

1. To describe the pathway to current DM service delivery in Ghana (RQ 1).
2. To describe interventions and barriers to DM control in Ghana and other LMICs (RQ 1).
3. To review the literature on patients' SMB and how it influences treatment outcomes (RQ2).
4. To review the literature on how DAM methodologies have been applied to investigate PH DM intervention in LMICs (RQ 3).
5. To assess the appropriate DAM methodologies to use in modelling DM treatment in Ghana (RQ 4).
6. To build and validate a simulation model of DM treatment outcomes (RQ 5).
7. To simulate and evaluate the health and economic benefits of PH DM strategies (RQ 5).

1.4 Thesis summary and structure

1.4.1 Thesis summary

The objectives of this research are in two forms: descriptive and prescriptive. The descriptive component (objectives 1 – 4) sought to understand the current practice with clinical DM treatment and how patients' behaviours contribute to DM treatment outcomes. The prescriptive component (objectives 5 – 7) aimed to prescribe how to improve DM treatment outcomes. Evidence from the descriptive study was used to inform the building of an ABM and the CEA in the prescriptive study, as shown in Figure 1.1. The subsequent paragraphs briefly describe how we answered the research questions.

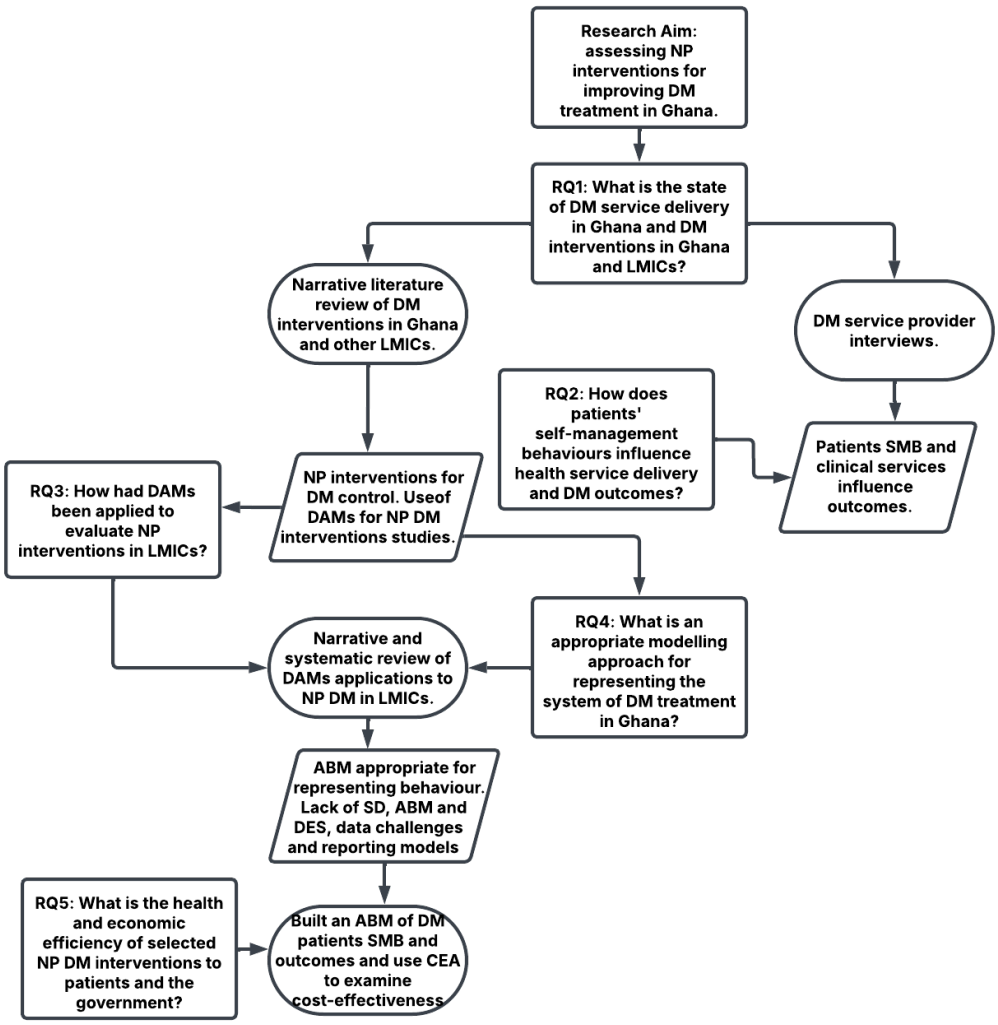


Figure 1.1 Link between research questions and activities (Author's own research).
Note: The cylindrical shapes represent research activities undertaken, and the rhombus (slanted square) shapes represent insights from the activity connected to them. DM= diabetes, DAMs= decision

analytical models, LMICs= low- and middle-income countries, ABM= agent-based models, DES= discrete-event simulation, SD= system dynamics models, SMB= self-management behaviour.

RQ 1: We conducted a non-systematic narrative review of published articles and NHIS policy documents to describe the pathway to clinical DM service delivery in Ghana. We conducted a narrative review of the literature on DM burden, policy and programme interventions in Ghana and other LMICs, focusing primarily on PH interventions because they could reduce the burden on health facility resources and the risk of DM in non-diabetes populations. Chapters 2 and 3 present the review findings. We employed a semi-structured qualitative interview approach to elicit DM service providers' perspectives on how clinical DM services are organised, delivered, and funded. The methodological approach allowed us to gather first-hand information and insights into DM management in PH facilities in Ghana, especially considering that COVID-19 might have resulted in changes to the system. We conducted 18 interviews with DM service providers in primary, secondary, and tertiary health facilities. We analysed the interview data using inductive and deductive methods. Chapter 6 presents the study in detail.

RQ 2: We used a non-systematic narrative review method to search and review the literature on health behaviour theories, HBM and TPB and how they explain patients' SMB. We explored factors influencing patients' SMB and the relationship between the behaviours and DM outcomes. The findings are presented in Chapter 3.

RQ 3: We first employed a narrative review approach to search and review the literature on SM and economic evaluation methods commonly applied in DM intervention studies. We then used a systematic review approach to specifically investigate the application of DAMs in DM intervention studies conducted in LMICs, identifying gaps in the modelling process and how to address the gaps to advance their adoption for DM studies in LMICs. The systematic review methodology and results are presented in Chapter 4.

RQ 4: We drew on an understanding of Ghana's DM service delivery system, service provider interviews and insights from the literature review on DAM approaches to decide on an appropriate modelling methodology. We focused on the features of the decision problem to be modelled using Salmon's (2011) assessment criteria and the ODD protocol from Railsback and Grimm (2019) to determine the appropriateness of ABM for representing patients' SMB and how they influence population-level DM treatment outcomes. Details are presented in Chapter 5 and Chapter 7.

RQ 5: We built an ABM of DM patients' SMB and clinical service delivery in PH facilities in Ghana. The model improves understanding of factors influencing cohort-level treatment outcomes–good, moderate, and poor BGC–and is used to investigate PH interventions for improving DM control. The model-building processes involved consultations with clinicians. Policymakers and international policies informed the selection of PH interventions. We simulated 1) the effect of a 20% SSB tax, 2) an annual 10% increase in the proportion of active NHIS-insured patients for five consecutive years, and 3) a 10% increase in the availability of DM medicines. Details on the simulated interventions and their effect on BGC are in Chapter 7. Using health outcomes from the ABM experiments, we estimated the cost-effectiveness of the interventions from a government perspective; the results are presented in Chapter 8.

1.4.2 Thesis structure

This section overviews the nine chapters of the thesis (Figure 1.2) to conclude this chapter.

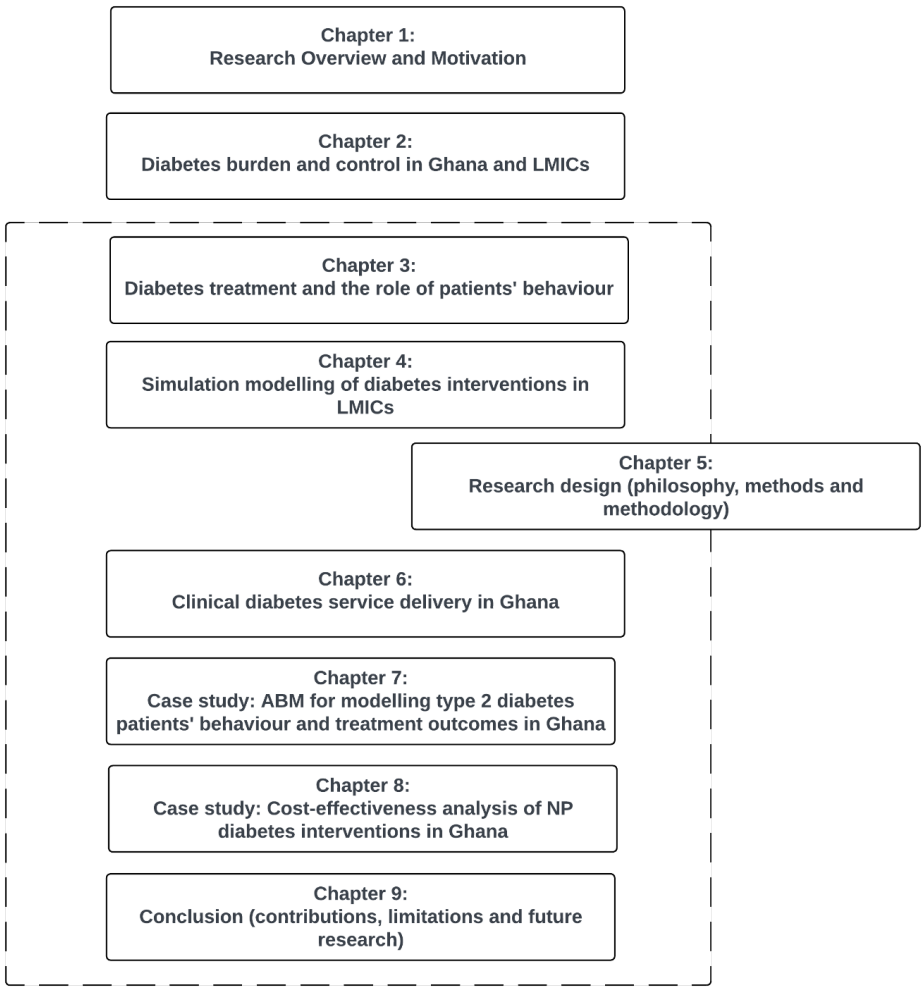


Figure 1.2 Thesis structure (Author's own research).
Note: Chapter 5 serves as an overarching chapter to the entire thesis.

Chapter 1 describes the research background and motivation and outlines the study objectives and research questions.

Chapter 2 presents a review of DM policy interventions in Ghana and other LMICs. It discusses the progress of countries have made towards implementing global DM policy recommendations. It also reviews DM intervention studies to provide insights into interventions that could be effective in Ghana. The chapter reveals Ghana's DM policy implementation challenges, which could hinder the country from achieving global targets.

Chapter 3 is based on a narrative literature review; it presents a discussion of DM intervention, focusing on PH interventions. The chapter also discusses the role of the patients' SMB in the treatment process and highlights health behaviour theories that could explain SMB. The chapter improves understanding of how PH interventions could influence DM treatment outcomes.

Chapter 4 describes common DAMs applied in DM intervention studies based on a narrative literature review. It also presents a systematic review of the application of DAMs for comparing the health effects and economic consequences of DM PH interventions in LMICs, the challenges, and how to improve their adaption. The chapter enables the identification of an appropriate modelling approach and economic analysis method to apply to DM service delivery and treatment in Ghana.

Chapter 5 discusses the philosophical assumptions underpinning the research and the methodology used to address the research questions. The chapter provides a foundation for understanding the approaches taken in Chapters 6 – 8.

Chapter 6 presents the results of a qualitative study, specifically interviews with DM service providers within the Ghana PH sector. The chapter describes the DM service delivery system and the challenges that clinicians and patients encounter in the treatment process. It also highlights the changes to service delivery resulting from COVID-19 and its related control measures. The chapter improves understanding of the service delivery pathway, which informed the modelling study.

Chapter 7 describes an ABM that represents T2DM patients' SMB and the clinical DM service delivery system. It presents the parameters, principles, and assumptions used to build the SM and the methodologies used to build model confidence. The chapter also presents the outcomes of experiments we conducted to understand the health impact of PH DM interventions and to support policy decision-making.

Chapter 8 presents the CEA of the interventions explored in the ABM experiments. It compares the health outcomes (proportion of patients with poor BGC and admissions) and the costs (direct medical and intervention costs) of PH interventions. The chapter provides insights to support policy decision-making on DM control in Ghana.

Chapter 9 concludes the thesis by discussing its main contributions and limitations and considering future research in the field.

2 Diabetes Burden and Control in Ghana and Low- and Middle-Income Countries

2.1 Introduction

This chapter provides a detailed description of the research context, which was briefly introduced in Chapter 1. It discusses the disease burden in Ghana and the country's DM programmes and policies. Additionally, it outlines the pathway for clinical DM service delivery in primary healthcare (PH) facilities in Ghana, reviewing the challenges associated with service delivery and their implications for DM control. Furthermore, the chapter presents a literature review of international policy interventions to which Ghana is a signatory, as well as implementation trends in Ghana and other low- and middle-income countries (LMICs). This addresses Research Question 1: What is the state of DM service delivery in Ghana, and what are the DM interventions in Ghana and LMICs? To gather relevant data, we searched the websites of the Ghana Health Service, the Ministry of Health, and the WHO for NCD policy documents. Additionally, we conducted searches on Google Scholar, PubMed, and Web of Science for published literature on Ghana's NCD burden, using search phrases such as DM and Ghana.

2.2 Diabetes burden in Ghana and other LMICs

Although DM burden is rising globally, the rate of rise is higher in LMICs than in high-income countries. According to the IDF 2021 Atlas report, more than 80% of the world's 463 million adults aged 20 to 79 living with DM are in LMICs, and the prevalence keeps increasing yearly (Magliano and Boyko, 2021). The report estimates DM prevalence to be 7.8% in high-income countries and 8.4% in LMICs. Although prevalence rates differ significantly within and between nations, they are usually influenced by similar variables, including but not limited to age, gender, ethnicity, changing diets, and sedentary lifestyle. The effects of DM on individuals and societies can also vary depending on the resource capacity for diagnosis, treatment, and prevention. In LMICs, poor healthcare access, illiteracy, cultural stigmas associated with chronic illnesses, and lack of awareness of DM contribute to low rates of DM diagnosis and poor treatment outcomes. Hence, the actual prevalence of DM in LMICs may be higher than reported.

Like other LMICs, Ghana's DM prevalence is increasing. NCDs, including DM, have a long history in Ghana, causing significant morbidity and mortality across socioeconomic strata, with those in lower strata experiencing worse health outcomes (Ministry of Health, 2022a). The disease prevalence varies

depending on the sub-population and diagnostic criteria. Surveys conducted in Ghana have reported the prevalence to range from 3% - 7% of the population. The majority are T2DM in persons aged 20 – 79 years, implying reduced productivity due to time lost to hospital visits and DM-related illnesses (Asamoah et al., 2017; Gatimu et al., 2016). Also, there is a significant prevalence of prediabetes, pending diagnosis soon if current trends continue (Magliano and Boyko, 2021; Ofori-Asenso et al., 2017). Prediabetes (also termed impaired fasting glucose, impaired glucose tolerance or intermediate hyperglycaemia) is characterised by elevated blood glucose levels above the normal range but below the threshold for a DM diagnosis.

DM-related mortality and morbidity in Ghana are steadily increasing. A retrospective study of hospital records found a positive linear trend in DM-related mortality and hospital admissions over 31 years in a referral hospital (Sarfo-Kantanka et al., 2016). According to the study, DM admission rates rose significantly during the review period (1983–2014), increasing from 2 to 15 per 1,000 patients—a more than 600% increase. This rise has significant implications for hospital resource utilization and the quality of care. A higher number of inpatients without a proportional increase in clinicians may reduce the time available for each patient. Furthermore, the inpatient mortality rate tripled (from 8 to 30 per 1,000 inpatients), with the highest impact observed among the elderly and patients with poor blood glucose control (BGC) or organ-related complications. The evidence suggests that improving BGC and reducing DM-related complications, such as ketoacidosis and hyperosmolar hyperglycaemic state, could lower DM mortality and improve treatment outcomes.

The worrying part about Ghana's DM burden is that the majority of cases are undiagnosed, implying that the reported burden may be underestimated. A meta-analysis of DM studies across Africa indicated that the average undiagnosed DM prevalence is 3.85% (95% CI: 3.10% – 4.60%) and that the prevalence is notably higher in Western Africa (4.72%, 95% CI: 2.64% – 6.80%), including Ghana than in other parts of the continent (Dessie et al., 2020). Studies among residents in Ghana have reported the prevalence of undiagnosed DM to range between 4.5% and 7.1% (Amoah, 2002; Nyavor et al., 2017), which aligns with that reported among African countries. According to the local studies, the prevalence could be explained by the population's inadequate knowledge of DM causes, symptoms, and prevention. Undiagnosed DM increases the risk of complications as patients remain unaware of their condition unless prompted by severe illness before seeking healthcare. The condition also increases patients' risk of mortality and high treatment costs. Considering the significant burden of undiagnosed DM, Ghana could consider scaling up its capacity for DM diagnosis and treatment.

2.2.1 Economic factors influencing diabetes burden in Ghana.

Ghana faces rising inflation, cedi depreciation, and a high debt-to-gross domestic product (GDP) ratio, which negatively impacts DM control. Inflation is the widespread increase in the prices of goods and services due to a decline in the purchasing power of money. According to reports from the Ghana Statistical Services, the annual inflation rate stood at 40.4% in October 2022, and the figure is projected to increase further in the following months (Ghana Statistical Service, 2022a). The report indicated that the year-on-year food inflation in the same month stood at 43.7%, and that of non-food products, including DM medicines and supplies, stood at 37.7%. The country's food inflation is reported as the highest in Africa (Calderon et al., 2022a). The rising inflation rate reduces DM patients' ability to afford healthy meals and medications, reducing treatment adherence and worsening BGC.

Ghana's economy is predominantly input-driven, and therefore, the significant depreciation of the cedis has resulted in a substantial increase in prices of pharmaceuticals, food, and medical supplies, among other imported products (Dzawu, 2022). The situation caused apprehension among residents, especially traders involved in importation. The Pharmaceutical Importers and Wholesalers Association of Ghana announced, in October 2022, their decision to demand cash payments at point-of-service for all medicines (Multimedia Group, 2022). According to the association, the decision will affect NHIS and its subscribers the most since the scheme primarily operates on a credit basis, where hospitals and pharmacies supply insured patients with medicines first and then receive payment from NHIS later. The association explained that the pharmaceutical industry is on the verge of collapse due to the constant depreciation of the cedis against the USD and long-standing debts the NHIS owes them. Many DM patients access medicines through the NHIS; therefore, reverting to out-of-pocket (OOP) payments will limit their ability to afford them, consequently reducing medicine adherence and increasing the risk of poor BGC.

Additionally, the rising debt-to-GDP ratio reduces funds available to the government for national development. Debt to GDP is a measure of the gross debt of the government as a proportion of its GDP, indicating how much of GDP is used in servicing government debts and what remains to national allocation. A World Bank report revealed that Ghana's debt stood at 78.4% of GDP in November 2022 and was estimated to reach 99.7% in 2023 (Calderon et al., 2022b). According to the report, the situation is worsened by major credit agencies downgrading Ghana's long-term debt credit rating. Thus, the country's ability to access the bond market to cover its medium-term financing needs has been downgraded, affecting its capacity to pay off foreign debt. Ghana has secured an IMF programme to revive its economy. The programme is postulated to possibly include a debt restructuring policy—an arrangement involving negotiations with creditors to help Ghana pay its outstanding debt. According

to the World Bank report, the global economic crisis has stunted the aid extended by multilateral institutions to indebted countries through the Debt Service Suspension Initiative. Also, mechanisms to bring together multilateral and private creditors under the Common Framework to speed up the debt restructuring process for countries in or at high risk of debt distress have been less promising. As a result, the IMF's release of funds to Ghana may be delayed, leaving residents and DM patients in financial hardship.

Furthermore, utility and transportation costs in Ghana have risen substantially, increasing the cost of living and negatively affecting medicine storage and the health-seeking behaviour of patients. The Ghana Statistical Service reported that the 2022 inflation rate on housing, water, electricity, gas and other fuels had increased by 69.7% compared to the rate in 2021 (Ghana Statistical Service, 2022a). Supply-chain distortions on the global market due to COVID-19 and the Russia-Ukraine war and increased prices of products on the international market explain fuel price increases in many countries, including Ghana (Calderon et al., 2022b; Ghana Statistical Service, 2022a). The increasing fuel and transportation costs cause traders to increase the prices of goods and services, including medicines and food. Patients are likely to miss review appointments due to unaffordable transportation fares. DM medicines, such as insulin, must be stored in cool temperatures, requiring refrigerators. Coupled with the increase in medicines, food, and transportation, DM patients struggle with paying electricity bills and can be disconnected from power, making it difficult to properly store insulin.

2.2.2 Socio-cultural factors impacting diabetes burden in Ghana.

2.2.2.1 Physical inactivity

Ghana has a considerably high physical inactivity prevalence, posing a threat to preventing and controlling DM. Physical inactivity contributes to obesity and worsens the outcomes of DM. Obesity leads to increased body fat and the release of non-esterified fatty acids from fat tissue, which increase insulin resistance and are associated with T2DM. In a meta-analysis of 43 studies conducted between 1988 – 2016, among 48,966 adults in all regions of Ghana, the prevalence of overweight and obesity were estimated to be 25.4% (95% CI 22.2-28.7%) and 17.1% (95% CI = 14.7-19.5%), respectively (Ofori-Asenso et al., 2016). The study results mean that about a quarter of Ghana's adult population does not meet the WHO recommended level of physical activity, which is at least 150 minutes per week of moderate-intensity aerobic activity or at least 75 minutes at a vigorous intensity (World Health Organisation, 2020b). The lack of physical activity has negative implications for the population's health and DM prevention.

The high prevalence of physical inactivity in Ghana can be attributed to various factors, including urbanisation, sedentary lifestyles, and a lack of access to safe spaces for exercise. The urban population in the country surged from approximately 5.6 million in 1990 to about 18.5 million in 2020, indicating a rise in the proportion of people living in urban areas from 36% in 1990 to around 57% in 2020 (World Bank, 2024). While urbanisation enhances access to healthcare and education, it also increases sedentary lifestyles and congestion. Sedentary behaviour, characterised by prolonged sitting or lying down with minimal physical activity, is more prevalent in urban areas because of their transportation, infrastructure, environments, and screen time (Sallis et al., 2016). Urban residents often rely on cars and buses instead of walking or cycling, reducing energy expenditure. The few sidewalks, bike lanes, and parks further hinder active transportation or engagement in recreational activities. According to the study, many jobs in cities, particularly office and industrial occupations, involve extended periods of sitting or standing, making it challenging to incorporate physical activity into daily routines. Additionally, residents of urban areas tend to spend more time on smartphones, televisions, and computers, leaving limited time for physical activity, especially among the younger population. A multisectoral strategy to address physical inactivity, one that includes encouraging physical activity through community-based interventions, expanding opportunities for physical activity in classrooms and workplaces, and enhancing the infrastructure for active transportation and recreation, could help Ghana increase its residents' engagement in physical activity.

2.2.2.2 Unhealthy Diet

There is evidence indicating a significant intake of unhealthy food in Ghana. The Global Burden of Disease study found that many Ghanaians consume less nutritious foods, including foods low in whole grains, high in sodium, and lacking in fruits and veggies, contributing to mortality and disability (Institute for Health Metric and Evaluation, 2019). Studies conducted among residents in Ghana have found adults regularly consume sugary drinks, unhealthy snacks and a lot of fast food and high-calorie foods and little effort towards implementing policies to improve healthy diet consumption (Holdsworth et al., 2020; Laar et al., 2020). The frequent eating of fruits and veggies is known to help prevent diseases like heart problems, strokes, DM, and cancer (Aune et al., 2017; Li et al., 2014). However, evidence from a national survey suggests that both men and women generally consume few fruits and vegetables. Only 3% of women and 4% of men met the WHO target of five or more servings daily (Ghana Statistical Service and ICF, 2024).

Multiple factors contribute to the increased consumption of healthy foods in Ghana. These factors include, but are not limited to, suboptimal enforcement of food safety regulations, lack of nutrition education, and socio-cultural norms, as well as increased access to unhealthy foods and high cost of

healthy foods, contribute to the high consumption of unhealthy foods in Ghana (Adom, 2018; Laar et al., 2020; Mockshell et al., 2022). Fast food, sugary beverages, and processed meals are easily accessible and usually affordable in Ghana, making them a preferred choice for consumers. In contrast, consuming a balanced diet is challenging because lean proteins, fruits, and vegetables can be scarce and expensive. In certain Ghanaian cultures, foods high in fat, sugar, and salt are considered prestigious or traditional, leading people to prefer them. As a result, individuals from these cultures may encounter difficulties in transitioning to healthier diets. For example, the Asantes of Kyirapatre, in Ghana's Ashanti Region, refrain from killing and eating tilapia (Apatre) because of the belief that their revered ancestor, Okomfo Anokye, harboured a strong dislike for those fishes (Adom, 2018).

Traditionally, the Ghanaian health delivery system has focused on managing communicable diseases and maternal and child health. Laar and colleagues (2020) reported that the system is new to addressing unhealthy food consumption and other NCD risks. Not only are these efforts in their early stages, but they are also not sufficiently coordinated. According to Laar and colleagues, policymakers in the country recognise the need to create and implement regulations and provide the infrastructure required to enable the development of healthy eating environments, particularly to address the promotion and advertisement of unhealthy foods and beverages on social media and near educational institutions. The researchers found that policymakers perceive fiscal policy interventions such as subsidised healthy food prices and food labelling programmes as essential but less feasible due to factors including the power, influence, and resistance of food industries and the large informal and non-market food sources. In summary, tackling the issues related to Ghana's unhealthy food consumption demands a thorough and well-coordinated effort. Such initiatives are essential for encouraging the consumption of healthier foods and reducing the population's rising risk of DM and other NCDs.

2.2.2.3 Diabetes Awareness

Many adult Ghanaians know little about DM and how to prevent or manage the disease, making them less effective at managing DM. Government, private and non-governmental organisations, including the Ghana Diabetes Association and National Diabetes Management and Research Centre, lead DM awareness campaigns. For example, the MoH has collaborated with Sanofi, an IDF partner, to train 170 clinicians with current knowledge and competencies to effectively educate the public on DM, healthy lifestyles, and treatment (International Diabetes Federation, 2023).

In May 2022, WHO and the World Diabetes Foundation agreed to undertake a collaborative, integrated initiative focused on preventing and managing DM in Ghana and Uganda to support the attainment of global DM objectives (World Health Organization, 2023). Despite the operation of such institutions,

less than a quarter of the public knows of DM, and few DM patients know of the disease condition (Afaya et al., 2020a; Amissah et al., 2017; Bossman et al., 2021). Some Ghanaians believe DM is spiritual rather than a medical condition, encouraging them to seek alternative sources of care in churches, traditionalists, and herbalists (de-Graft Aikins et al., 2019). As mentioned earlier, the Ghana health system has largely focused on infectious diseases and maternal and reproductive health, which could explain the dearth of DM education campaigns.

2.2.2.4 Clinical diabetes care

The system of clinical DM service delivery in Ghana faces multiple challenges, which makes clinical DM delivery suboptimal, especially in the public sector. Most Ghanaians with DM do not receive regular care, and the majority of those who receive care experience complications and do not meet IDF-recommended targets for glycaemic control (Djonor et al., 2021; Kushitor and Boatemaa, 2018; Mobula et al., 2018; Sarfo-Kantanka et al., 2016). Limited medical equipment/technology, inadequate infrastructure, and a shortage of trained healthcare professionals influence DM control (Godman et al., 2020; Tagoe et al., 2023). Few primary healthcare facilities have diagnostics equipment and the expertise to detect and manage DM (Kushitor and Boatemaa, 2018), leading to misdiagnosis, incorrect diagnosis, and delayed treatment, which increase treatment costs and the risk of complications and death. Low-resource facilities can refer patients to high-resourced facilities. However, patients may not follow through with care because of financial constraints, long travel distances, mistrust in health providers, lack of knowledge of their condition and stigma (Afaya et al., 2020b). Consequently, patients default to treatment and become at risk of complications and death.

The government is taking initiatives to enhance clinical DM treatment, including the creation of DM clinics, coverage of DM care under the NHIS and the training of medical personnel in managing the disease (Godman et al., 2020). However, the insufficient funds and poor monitoring and evaluation of health policies and programmes make the initiatives ineffective at addressing the DM burden. For instance, the NHIS is challenged with insufficient funds, which causes delays in the payment of claims to service providers, resulting in a lack of medical supplies and medicines in health facilities and, consequently, a decrease in the quality of care provided (Alhassan et al., 2016; van der Wielen et al., 2018, 2018). Ghana needs to improve the implementation, monitoring, and evaluation of its initiatives to ensure they are cost-effective and appropriate for addressing its DM burden.

Overall, Ghana acknowledges the DM burden and has committed to several international policy interventions to control DM. The preceding section discusses recent and current policy frameworks that define the scope of NCD interventions, including DM prevention and control globally.

2.3 International Policy Interventions on NCD and Diabetes.

Global policy interventions for DM control, specifically, and NCDs in general, shape Ghana's responses to DM. This section discusses major global NCD and DM-specific policy interventions/targets that have defined and continue to define the scope of DM prevention and control.

2.3.1 The Millennium Development Goals

In early 2000, the United Nations (UN) launched the Millennium Development Goals (MDGs), primarily to reduce extreme poverty by 2015, focusing on eight development goals (with 21 targets) grouped into three broad themes (United Nations, 2016). The first theme concerns poverty, education, and gender equality; the second theme concerns maternal health, child mortality, HIV/AIDS, malaria, and other diseases; and the third theme addresses development through global partnership and environmental sustainability. The second theme includes other diseases, such as NCDs and DM.

The global development community achieved some success with the MDGs. However, these successes were uneven across countries. An MDG report demonstrated success in achieving some goals while recognising the uneven progress in MDG implementation across regions and countries (United Nations, 2016).

According to the report, the MDGs liberated about one billion people from extreme poverty, supported girls' education more than ever, protected our planet from pollution, facilitated new and innovative partnerships, and incited public opinion and immense value in setting ambitious goals. Despite these significant successes, many people remain in poverty and poor health. After the MDG end date, sub-Saharan Africa and Southern Asia experienced extreme poverty and high maternal mortality, and the elderly, women, and disabled people remained disadvantaged. Although the undernourishment rate fell in all regions worldwide from 2014 to 2016, the report indicated that it remained high in sub-Saharan Africa (23%) and many developing countries; there remain marked differences between rural and urban areas, as well as between rich and poor households in terms of child mortality rate and access to basic amenities.

The MDGs and Implications for NCD Control

MDG 5, improving maternal health and MDG 6, combating HIV/AIDS, malaria and other illnesses, addressed health behaviours that influence NCDs. For instance, malnutrition and maternal smoking are risk factors for cardiovascular disease and mortality in mothers and children. Thus, advancing goals 4

and 5 meant addressing NCDs. Discussions at the 2010 MDG Review Summit acknowledged NCDs as a fundamental development issue, positioning them for inclusion in the post-2015 development framework (International Institute for Sustainable Development, 2010). The post-2015 development framework contributed to shaping the development of the SDGs, in which NCDs are given considerable attention.

2.3.2 Sustainable Development Goals

The SDGs replaced the MDGs in 2016. With the overarching principle of leaving no one behind, the SDGs aim to address the disparities in development among countries, aiming to end poverty, advance prosperity, and ensure a peaceful and healthy planet (United Nations, 2020). The SDGs contain 17 goals summarised into five themes: people (goals 1-6), prosperity (goals 7-12), planet (goals 13-15), peace (goal 16) and partnership (goal 17).

Before the start date of the SDGs, discussions at the third UN conference on financing for development, held in Ethiopia in July 2015, led to the development of the Addis Ababa Action Agenda, a comprehensive policy framework to realign all financial flows (official development assistance, public, private, domestic, and international) toward sustainable development (United Nations, 2015). The agenda echoes countries' primary role in their development and the need for poverty eradication and inclusive, equitable and sustained growth. At the conference, Ghana and other nations admitted that incentivising behaviour and advancing science and technology are necessary steps toward the SDGs. Ghana needs to explore how to incentivise adherence behaviours and leverage science and technology to prevent and sustainably control DM and other NCDs.

The SDG 2020 Report indicated that the world had made some progress until the onset of the COVID-19 pandemic (United Nations, 2020). For instance, there were improvements in tuberculosis control, maternal and child health, HIV, and immunisation. According to the report, under-five mortality had reduced significantly, and many lives have been saved through immunisation, increased access to electricity, and an appreciable effort to protect marine life and address the challenges of rapid urbanisation. Aside from SDG 3, there was no significant improvement in all other goals at the end of 2019. The COVID-19 onset has reversed progress and exacerbated existing challenges, making the realisation of SDGs much more difficult.

The SDGs and Implications for Diabetes Control

SDGs directly address the DM burden through universal health coverage (UHC) (SDG3.8) and NCDs (SDG3.4). The concept of UHC means providing "financial risk protection, access to quality essential healthcare services and access to safe, effective, quality and affordable essential medicines and vaccines for all" (United Nations, 2020). The term ‘coverage’ in UHC describes who gets what services at what performance level and the degree of fairness in distributing health services. UHC does not imply that all health services are free to access; instead, nations must decide what to cover, considering available resources. Advancing UHC could improve access to affordable DM services and medicines, reducing the incidence of treatment non-adherence, which increases the risk of morbidities, healthcare costs and premature deaths. SDG 3.4, which aims to reduce premature NCD-related mortality by one-third and promote mental health and well-being, addresses DM.

DM, cardiovascular diseases, chronic respiratory diseases, and cancer are the main NCDs with devastating impacts on lives, national economies, and health systems. About seventy-one per cent of global mortality results from NCDs, and more than three-quarters of these deaths occur in LMICs, especially among 30–69-year-olds who constitute the working population (World Health Organisation, 2020). Moreover, managing NCDs comes with substantial financial consequences for countries. Results of macroeconomic simulations suggest that DM will lead to an output loss of US$1 trillion out of a total lost output of US$47 trillion from mental health and the four NCDs mentioned above between 2010 and 2030, and that the loss could sufficiently relieve 2.5 billion people from poverty for many years (Bloom et al., 2012). LMICs are expected to bear a large share of the economic burden as their economy develops. Consequently, LMICs, including Ghana, must prioritise NCD prevention and control to improve health and save money.

Limited financial resources for health and a lack of commitment to health contribute to poor health outcomes in LMICs. The 2001 Abuja Declaration expressed African Union countries' commitment to allocating at least 15% of their annual budget to health and admonished donors to increase support (World Health Organisation, 2011). In Ghana, the percentage of the government budget allocated to health declined from 7.6% in 2022 to 6.7% in 2023, which did not meet the 15% target (UNICEF, 2023). The problem in LMICs, particularly in Africa, is that available resources are insufficient to meet the demand for health. With COVID-19 and economic crises in donor countries, donors may reduce financial support to LMICs until their economies recover and grow, further reducing LMICs' financial resources for health.

2.3.3 Global Action Plan for the Preventions and Control of NCD

The 66th World Health Assembly high-level meeting on the prevention and control of NCDs established the Global Action Plan for the Prevention and Control of NCD 2013–2020 (NCD-GAP) to advance global NCD-related targets (World Health Organisation, 2013a). The policy has six objectives: (1) setting the agenda for NCD, (2) increasing capacity to accelerate national response, (3) reducing modifiable risks, (4) strengthening health systems, (5) increasing research capacity, and (6) monitoring and evaluating progress. NCD-GAP end date has been extended from 2020 to 2030 to align with the SDGs.

The 2020 evaluation of the NCD-GAP involving 194 countries found that there has been significant progress in (2) and (3), but general performance on the other objectives (primarily objective 4: strengthening health systems using national NCD management protocol availability as an indicator remains low (World Health Organisation, 2020c). According to the evaluation report, besides having a national NCD policy (objective 1), HICs performed better on all other objectives than LMICs. For instance, as of 2019, no LMIC provided drug therapy and counselling at the primary level while about two-thirds of HICs provided such services.

2.3.4 Package of Essential Noncommunicable Disease Interventions

The Package of Essential Noncommunicable Disease Interventions (PEN) is a set of cost-effective NCD interventions for primary care (World Health Organisation, 2020d, 2013b). PEN includes essential medicines and technologies and validated tools for assessing gaps in NCD service provision and supporting the implementation, monitoring and evaluation of NCD interventions. The policy was first published in 2010 and updated as the WHO "best buys" policy in 2017 and WHO PEN in 2020.

The "best buys" consist of eighty-eight interventions and recommendations on cardiovascular diseases, cancer, DM, chronic respiratory disease, and their risk factors (World Health Organisation, 2017a). WHO recommends increasing excise taxes on tobacco/alcohol products, inscribing warnings on their packages, comprehensive bans on their advertisements, promotions, and sponsorship, reducing alcohol sales hours, elimination of exposure to second-hand smoke, and public education on tobacco, which are part of the "best buys". It emphasises the potential of non-financial factors, including low multisectoral involvement, tax evasion, non-enforcement of regulations, and weak primary care system, to adversely influence the feasibility of interventions in countries. Section 2.4 presents “best buy” policy implementation patterns in Ghana and similar economies.

2.3.5 The WHO Global Diabetes Targets, 2022

In the 75th World Health Assembly in 2022, the WHO announced global targets for DM to improve and monitor DM responses within national NCD programmes in member states (World Health Organisation, 2022b). According to the Assembly, the targets aim to lower the risk of DM and ensure everyone with DM has access to equitable, all-inclusive, affordable, and quality care. The targets to be achieved by 2030 include: 1) 80% of people living with DM being diagnosed; 2) 80% of diagnosed cases receiving treatment and having good control of glycaemia; 3) 80% of people with diagnosed DM and receiving treatment having good control of blood pressure; 4) 60% of DM patients receiving treatment who are 40 years or older receiving statins and 5) 100% of people with T1DM who are diagnosed and receiving treatment having access to affordable insulin and blood glucose self-monitoring.

Ghana may not achieve these targets due to its challenges, including, but not limited to, a weak health system, inadequate health resources, and an increasing DM burden. The country needs to identify and scale up cost-effective and sustainable interventions to achieve the targets. Simulating PH interventions' health and economic effects could support decision-making and resource allocation for achieving these targets sustainably and effectively.

2.3.6 WHO Obesity targets

Obesity increases the risk of developing DM and other NCDs and leads to complications in individuals with DM. Nations have committed to the goal of preventing any increase in adult obesity prevalence from 2010 to 2025, specifically to maintain their obesity prevalence at the 2010 level (World Obesity Federation, 2023). However, as highlighted in the 2020 World Obesity Report, global obesity rates continue to rise, with the most significant increases and highest numbers observed in LMICs and most countries are less than 10% likely to achieve the 2025 target (World Obesity Federation, 2023).

According to the report, more than 132,000 DM cases in Ghana in 2016 were linked to obesity and overweight. The report projects that the country's adult obesity prevalence, which was 3.5% in 2010, may reach 7.9% by 2025. Given the current trends, Ghana is unlikely to achieve the 2025 target of maintaining 2010 obesity prevalence. With the ongoing increase in obesity prevalence, it is anticipated that the burden of DM will also escalate.

2.4 Application of NCD Policy Interventions in Low-and Middle-Income Countries

Most countries, including LMICs, have adopted the 'best buys' to control and prevent NCDs; however, implementation patterns vary across countries. The WHO NCD Progress Monitor, first published in 2015, tracks how countries implement the WHO 'best buy' policies and identifies barriers and leverage points for effective NCD management. According to the monitor, LMICs, especially African countries, have been performing poorly in implementing the 'best buys' policies; they were among the fourteen countries that did not make any progress and the twenty countries that achieved just one of the ten progress indicators (World Health Organisation, 2015a, 2017b). Table 2.1 shows NCD implementation trends in Ghana and neighbouring countries with similar DM prevalence among 20–79-year-olds. There is a tendency to think that countries' income levels are associated with the degree of implementation. Therefore, it is inappropriate to compare Togo and Guinea, which are low-income countries, to Ghana and Nigeria, which are lower-middle-income countries (per the 2020 World Bank classification). However, the WHO report on global health spending in 2020 indicates otherwise (World Health Organisation, 2020e). Specifically, the report indicates a weak correlation between countries' income levels and investments in NCDs.

As shown in Table 2.1, Ghana has the highest percentage of deaths from NCDs, from 42% in 2015 to 45% in 2022, indicating an increasing burden of these diseases. Over the years, all four countries have consistently performed poorly in unhealthy diet reduction measures. From 2015 to 2022, Ghana has not set (or reported) time-bound national NCD targets and indicators based on WHO guidance (target 1) and does not have a functioning system for generating reliable cause-specific mortality data on a routine basis (target 2). Additionally, the country has recently failed to implement measures to reduce unhealthy diets (targets 7a–7c) and physical activity (target 8). Considering that unhealthy diets and physical inactivity are risk factors for T2DM, Ghana can control the disease burden by implementing these measures.

Table 2.1 Trends in WHO Best Buy Implementation in Selected African Countries (Author's own research, compiled from WHO NCD Progress Monitors 2015, 2017, 2020).

Targets	D	P	1	2	3	4	5a	5b	5c	5d	5e	6a	6b	6c	7a	7b	7c	7d	8	9	10
Ghana																					
2015	42	20	ND	M	PA	FA	M	M	PA	FA		PA	M	PA	M	DK	DK	DK	FA	M	ND
2017	44	21	M	M	PA	FA	M	PA	PA	FA	M	PA	FA	FA	M	M	M	FA	FA	FA	M
2020	43	21	M	M	PA	M	M	PA	PA	FA	PA	M	M	NR	M	M	M	FA	M	FA	DK
2022	45	22	M	M	PA	M	M	M	FA	FA	FA	M	M	NR	M	M	M	FA	M	FA	M
Nigeria																					
2015	24	20	PA	M	M	FA	M	PA	M	M		PA	PA	PA	M	M	M	ND	M	ND	M
2017	26	21	FA	M	M	M	M	M	PA	FA	NR	PA	M	PA	M	DK	DK	PA	M	M	M
2020	29	22	FA	M	M	M	M	M	PA	FA	M	PA	M	FA	M	M	M	PA	M	M	M
2022	27	17	FA	M	M	FA	M	M	FA	FA	M	PA	M	FA	M	M	M	FA	M	M	M
Togo																					
2015	30	20	FA	M	PA	FA	M	PA	PA	FA		PA	M	FA	M	M	M	M	FA	PA	M
2017	37	22	FA	M	PA	M	M	PA	PA	FA	M	PA	M	PA	M	M	M	M	M	PA	M
2020	38	24	FA	M	PA	M	M	PA	PA	FA	FA	PA	M	PA	M	M	M	M	M	PA	M
2022	41	24	FA	M	M	FA	M	PA	PA	FA	FA	PA	M	PA	M	M	M	M	DK	M	M
Guinea																					
2015	31	21	M	M	PA	FA	ND	PA	PA	FA		PA	PA	PA	M	M	M	DK	M	M	M
2017	31	20	M	M	PA	M	M	PA	PA	FA	M	PA	M	M	M	M	M	PA	M	PA	M
2020	35	22	M	M	M	M	NR	PA	PA	FA	M	PA	FA	FA	M	M	M	M	M	PA	M
2022	33	25	M	M	M	FA	M	PA	PA	FA	M	PA	FA	FA	M	M	M	M	M	PA	M

Note: D= percentage of death from NCDs, P= probability of premature mortality from NCDs DK= Do not know, NR= No response, ND= no data, PA= Partial achieved, FA= Fully achieved, M= missed, not achieved. Areas with missed targets are shaped red to easily identify unachieved targets. Targets 1= national NCD targets, 2= mortality data, 3= risk factor surveys, 4= national integrated NCD policy/strategy/action plan, Targets 5 are associated with tobacco demand-reduction: 5a=increased excise taxes and prices, 5b= smoke-free policies, 5c= large graphic health warnings/plain packaging 5d= bans on advertising, promotion, and sponsorship, 5e= mass media campaigns (introduced from 2017). Targets 6 are associated with the reduction of harmful use of alcohol: 6a= restrictions on physical availability, 6b= advertising bans or comprehensive restrictions, 6c= increased excise taxes. Targets 7 are associated with unhealthy diet reduction: 7a= salt/sodium policies, 7b= saturated fatty acids and trans-fats policies, 7c= marketing to children restriction, 7d= marketing of breast-milk substitutes restrictions, 8= public education and awareness campaign on physical activity, 9= guidelines for the management of cancer, cardiovascular diseases, DM and cardio-respiratory diseases, 10= drug therapy/counselling to prevent heart attacks and strokes.

From Table 2.1, Ghana appears to have retrogressed from achieving nine WHO 'best buy' targets in 2017 to five targets in 2019, indicating reduced efforts to control the disease burden. A stakeholder engagement in Ghana revealed that the country developed NCD policies during the 19th century, but implementation has been challenging (Tindana et al., 2020). Stakeholders found inefficient programme management, limited funding, low community awareness, expensive medication, and lack of structured screening initiatives to inhibit optimal control. The media hardly adheres to laws regarding the advertisement of alcoholic beverages and tobacco. Ghana fairly adheres to national regulations on labelling the content of processed foods but not alcohol regulations, as these regulations are challenging to enforce because they are scattered in many legislations, and people are less aware of them (Hayford et al., 2015). The NHIS provides some relief from the high NCD treatment cost, but there are concerns about high OOP expenditure on health. Overall, Ghana has shown varying degrees of success in achieving NCD targets, with notable achievements in certain areas, partial achievements in others, and some targets remaining unmet.

2.5 Ghana's Diabetes Policy Interventions and their Implementation Challenges

The Ghanaian government has introduced several initiatives and policies to address its NCD burden with mixed success. This section describes the key ones that have led to the current landscape, first considering more general UHC and NCD policies and then current programmes.

2.5.1 Ghana NCD and UHC Policies

Ghana has designed several policies to address the NCD burden. Key ones include:

- Regenerative Health and Nutrition Strategic Plan 2007-2011(Ministry of Health, 2007)
- National Policy for Prevention and Control of NCDs 2012 (Ministry of Health, 2012)
- National Health Policy (Ministry of Health, 2020a)
- Universal Health Coverage Roadmap 2020 – 2030 (Ministry of Health, 2020b)
- National Policy Non-Communicable Diseases 2022 (Ministry of Health, 2022a).

These policies aim to prevent NCD risk factors, manage the disease prevalence through PH interventions and strengthen the health system for effective and efficient service delivery. For example, the Regenerative Health and Nutrition Strategic Plan 2007-2011 addressed NCD risk by promoting preventive health through improved health behaviours, including healthy eating, regular physical

activity, water intake, sufficient rest, and a clean environment (Ministry of Health, 2020). The plan sought to raise awareness, build capacity, train stakeholders and create an enabling environment, partnerships, and networks to promote healthy living. Similarly, the National Health Policy emphasises using evidence-based, cost-effective interventions to promote health, and strengthen the health system for early detection, effective diagnosis and improved treatment.

Past policies have contributed to some success, but limited funding and less priority for NCDs hinder further progress. A before-and-after assessment of the Regenerative Health and Nutrition Strategic found that unhealthy lifestyles (such as smoking, poor diet, and alcohol consumption) declined, but alcohol consumption increased (Tagoe and Dake, 2011). Policymakers and implementation officials have cited a lack of awareness and challenges in operationalising the National policy, insufficient funding and weak intersectoral collaboration as barriers to effective implementation of the policy (Nyaaba et al., 2020). The 2022 NCD Policy acknowledges the seeming neglect of NCDs in Ghana, attributing this to limited funding and low prioritisation. According to the Minister of Health, the 2022 policy prioritises funding and multisectoral collaboration, particularly with the Ministry of Finance, to advance NCD control (Ministry of Health, 2022a).

2.5.2 National NCD Programmes

2.5.2.1 Community-Based Health Planning and Service

Ghana introduced the Community-Based Health Planning and Services (CHPS) initiative in 1999 to address unequal geographical access to healthcare by moving primary care from district-level facilities to convenient community locations and addressing local health needs (Ghana Health Service, 2016, 2005). Nurses reside in communities (community-built clinics), where they plan and implement health programmes and run clinics. CHPS has improved access to reproductive health services, but the policy provides few NCD services, primarily offering blood pressure and blood glucose checks, which are insufficient to meet community demands (De-Graft Aikins et al., 2014).

Challenges of CHPS

Several community- and health system-related factors affect the optimal operation of CHPS. An exploratory study involving 60 health providers in CHPS compounds and community members found that negative attitudes among health providers, high attrition rate, and provider absenteeism reduced community members' utilisation of the services (Kweku et al., 2020). According to the study, service providers identified a lack of community ownership of CHPs, insecurity of CHP compounds, and late

reporting of health issues by community members as key challenges to service delivery. Additionally, broader health system challenges–including late referrals, unavailable essential logistics, and the long distance between CHPS compounds and communities–contribute to the programme's suboptimal operation (Ministry of Health, 2020b).

2.5.2.2 National Health Insurance Scheme

Ghana implemented the NHIS in 2004 to increase access and reduce healthcare costs, particularly for the poor and vulnerable populations. The National Insurance Act (Act 852) legally mandates the National Health Insurance Authority (NHIA) to operationalise the NHIS (Government of Ghana, 2012b). According to a report from the NHIA, the scheme offers a comprehensive healthcare package that covers inpatient and outpatient care, diagnostics and medicines. The NHIS benefit package does not include PH interventions. It is funded predominantly by the National Health Insurance Levy (2.5% levy of goods and services) and the Social Security and National Insurance Trust contributions (2.5% of monthly contributions by formal sector employees and some self-employed individuals (National Health Insurance Authority, 2018). The authority uses the funds to subsidise premiums for informal sector workers and pay premiums for vulnerable groups (identified as the 'poorest' or 'core poor'), children under 18, Social Security and National Insurance Trust pensioners, and non-SSNIT pensioners aged 70 and pregnant women. The report indicates that the NHIA invests surplus NHIS funds and uses investment returns to support the scheme's operations. The scheme's enrolment hovered around 48% of the population in 2010 and covered 36% of the population in 2018; the majority covered were exempt from premium contributions (Ministry of Health, 2020b; National Health Insurance Authority, 2018).

The NHIA, health service providers and NHIS subscribers are the main NHIS policy actors. Figure 2.1 shows the key roles/activities of these actors.

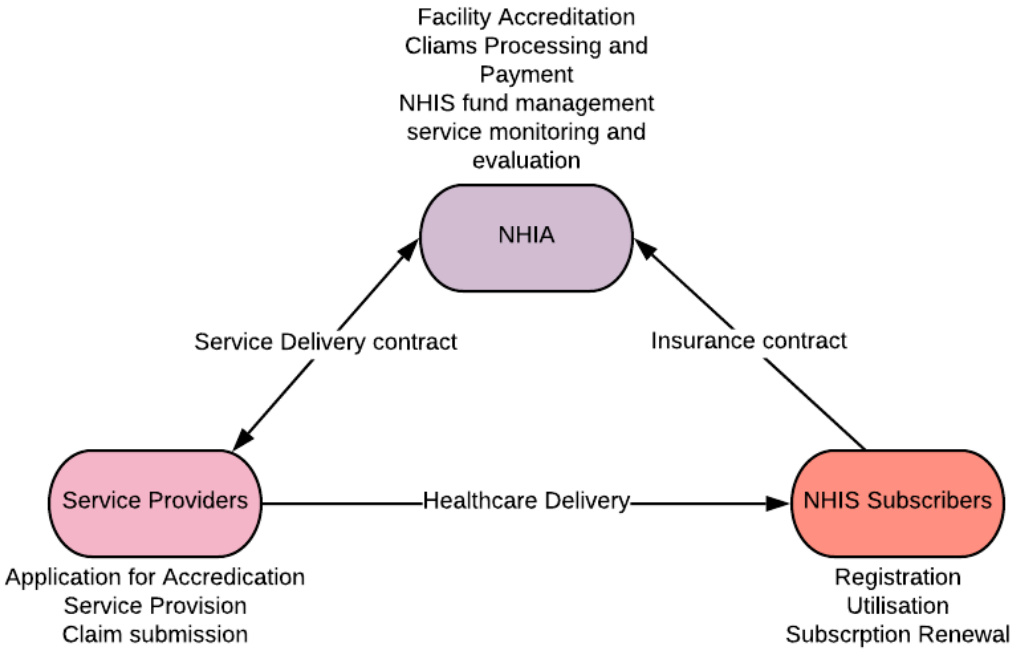


Figure 2.1 Key actors of the NHIS policy and their primary roles (Author's own research, compiled from National Health National Insurance Act (Act 852) and the National Health National Insurance Authority Report 2018).

NHIS subscribers undergo three main phases under the scheme: registration, utilisation and subscription renewal (National Health Insurance Authority, 2020). During registration, the NHIA collects subscribers' details and biometric information, performs a needs assessment to ascertain premium-exempt persons, issues insurance cards, and assigns the insured a preferred primary service provider. After registration, new subscribers, except for pregnant women and under-five-year-olds, wait three months before service use. Members who fail to renew subscriptions beyond three months of expiry are subject to a one-month waiting period. Subscribers can renew their insurance in NHIA offices or electronically (as of December 2018) by dialling a short code on their mobile phones (National Health Insurance Authority, 2018). According to the report, subscribers present their NHIS card at utilisation points for verification, after which health providers deliver services under the NHIS benefit package. Subscriptions are renewed annually at a fee at NHIS offices or by a mobile short code.

Health service providers under the NHIS engage in three key activities: application for accreditation, service provision and claims application. Service providers first obtain accreditation from the NHIA and the Health Facility Regulatory Agency (HEFRA). HEFRA is legally mandated to register, license and monitor all healthcare providers (Government of Ghana, 2011). NHIA accredits healthcare providers with an HEFRA license, and the accreditation entails quality assurance procedures, including physical inspection of the health facilities' environment (Lamptey et al., 2017). According to Lamptey and colleagues, the quality assurance standards vary by facility type—hospital, pharmacy, clinic—and

service provision level—tertiary, secondary, or primary. Facility types include public and private hospitals, licensed chemical sellers, i.e., persons engaged in the retail of over-the-counter drugs, CHPS, Christian Health Association of Ghana facilities, dental and eye clinics, diagnostic and health centres, laboratories, maternal homes, pharmacies, and physiotherapy.

The NHIA is responsible for fund management, service monitoring, and evaluation of public and private insurance (Government of Ghana, 2012b). Health providers submitted claims manually until 2010, when the NHIA introduced claim processing centres and an electronic claim (National Health Insurance Authority, 2018; Nsiah-Boateng et al., 2017a). Service providers have sixty days to submit claims, and the NHIS has twenty-eight days to reimburse them. NHIS provider payment mechanisms consist of capitation, which is used to reimburse outpatient services in primary care, and diagnostic-related groupings used for inpatient and specialised services (National Health Insurance Authority, 2018).

Challenges of the NHIS

Low enrolment and actors' behaviour influence the effective implementation of the NHIS. Studies have reported that the behaviour of health service providers, NHIA, and subscribers (in Figure 2.1) contributes to the experiences users have with the scheme, which affects their decision to remain actively enrolled (Alhassan et al., 2016; Awoonor-Williams et al., 2016; Debpuur et al., 2015; Fenny et al., 2015; Kipo-Sunyehzi et al., 2020; Suchman, 2018; Wang et al., 2017). Unprofessional behaviours of service providers, including verbal abuse and long waiting times, especially for patients using NHIS, reduce their satisfaction with the scheme. Some patients misuse services by frequently visiting health facilities for minor ailments and attempting to collect medicine for uninsured relatives. These behaviours increase service utilisation, thereby raising NHIS costs and could reduce health service quality and NHIS enrolment.

The NHIS faces financial threat, and its sustainability is questionable. The vast NHIS premium exemption group and the rising cost of medicines and supplies threaten the scheme's financial sustainability (Alhassan et al., 2016; Wang et al., 2017). Moreover, value-added tax compliance and SSNIT membership remain low, given the country's large informal sector and poor law enforcement. Additionally, the rates at which funds flow for NHIS payments are woefully slow. The NHIA first deposits government allocations, VAT and SSNIT contributions into a national consolidated fund, with disbursement subject to complicated paperwork and delays. These funds could be disbursed directly to service providers. Also, cumbersome calculations, long waiting times, and unresolved claims delay processing and payment (Wang et al., 2017). Delayed claim payment challenges healthcare facilities' ability to provide quality healthcare. The need for innovative and sustainable strategies to fund the

NHIS and redesign the scheme's service package is urgent, considering Ghana's commitment to advancing universal health coverage under the SDG.

2.5.2.3 Health Technology Assessment

Ghana has shown interest and organised a Health Technology Assessment (HTA) at a national level to address health issues. HTA is a systematic process of assessing the characteristics, consequences, and implications of health technologies or interventions to support decision-making (World Health Organisation, 2015b). The first nationwide HTA initiative was led by the MoH and supported by the International Decision Support Initiative (iDSI) in 2016. The study addressed the high cost of antihypertensive drugs covered by the NHIS and provided evidence for updating the 2017 Standard Treatment Guidelines (Doherty et al., 2017; Hollingworth et al., 2020). In October 2019, the MoH inaugurated a national steering and technical committee for HTA institutionalisation. The committee consists of development partners and public and private sector representatives responsible for advising on the governance, assessment methods, and decision-making process for HTA (Koduah et al., 2023). The importance of HTA to the healthcare ecosystem cannot be overemphasised. Especially now that Ghana is transitioning from foreign aid, HTA will support Ghanaian policymakers in setting priorities fairly, making better decisions, and effectively allocating scarce resources. HTA could provide insights to guide the alignment of benefit packages and funding structures of the NHIS to ensure sustainability.

Challenges of Health Technology Assessment

Data availability, technical capacity, and institutional collaboration are the main challenges of HTA implementation in Ghana and other LMICs. To conduct a rigorous assessment of health interventions, researchers require contextual, relevant data on clinical efficacy, costs, service utilisation, epidemiology, health outcomes, equity and access, which are often unavailable in LMICs (Hollingworth et al., 2020). The Demographic and Health Survey and other large data sources exist; however, there is wide variability in data quality, form, and accessibility (Wagenaar et al., 2017). For instance, the NHIS generates rich data on health service utilisation and cost; however, access is generally restrictive (Hollingworth et al., 2020). Academic institutions need to train researchers, critically assess HTA studies and collaborate with government organisations on HTA projects (Hollingworth et al., 2020). Such training programmes often involve collaborations with international organisations, such as the iDSI, and academic institutions. Ghana needs to strengthen its capacity for sound HTA and improve data quality and access.

2.6 Summary of the Diabetes Burden and Policy Interventions

Ghana needs to address the rising DM burden to put the country on track for achieving SDG 3. The government acknowledges the problem and has committed to various global policies/targets, national policy initiatives and programmes. However, policy and programme implementation are hampered by multiple interconnected factors, including but not limited to insufficient funding, patient and service provider behaviour, inadequate and less-skilled health workforce, and poor intersectoral collaboration. The country needs to re-examine existing policies/programmes or design sustainable ones that effectively address the DM burden and are financially sustainable and feasible (Nyaaba et al., 2020).

While the previous section has explored the national and global DM intervention landscape, it is apparent that these interventions directly or indirectly influence the pathway to clinical DM service delivery. Therefore, understanding the current clinical service delivery pathway in Ghana is crucial for identifying gaps and leverage points where interventions could significantly impact DM control. The following section describes the clinical DM service delivery pathway, highlighting the key stakeholders and the challenges in the process.

2.7 Pathway to clinical diabetes service delivery in Ghana and associated challenges

This section describes the pathway to clinical DM service delivery in PH facilities in Ghana, from a literature review, to improve understanding of the context and partly address Research Question 1: *What is the state of DM service delivery in Ghana?* It describes key procedures, the major actors involved, challenges, and implications for DM control.

Figure 2.2 shows the pathway for DM patients receiving care in PH facilities in Ghana. Patients and health providers are directly involved in the care processes, highlighted in Figure 2.2. Each procedure is described in the subsequent paragraphs.

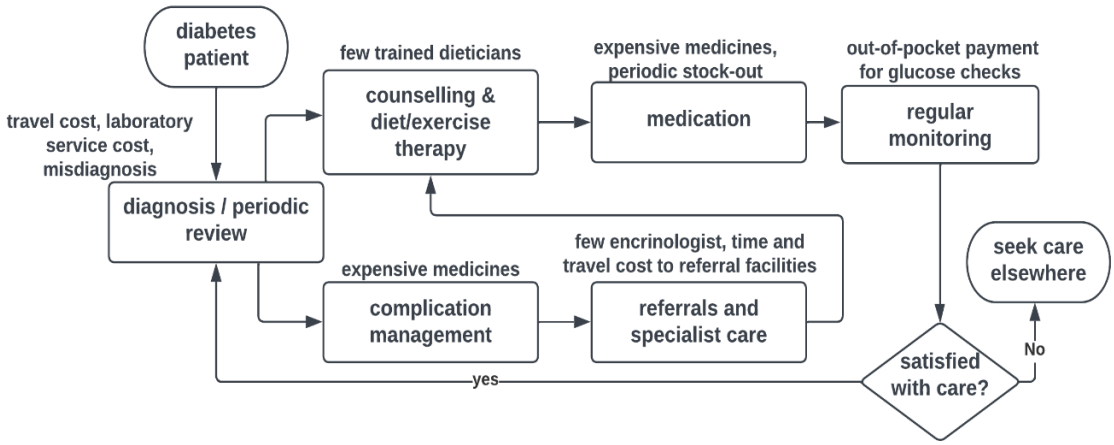


Figure 2.2 Pathway to clinical diabetes service delivery in Ghana's Public health Sector (Author's own research, compiled from literature review with references in Section 2.7).
Note: Procedures are nonsequential and are represented in rectangular shapes.

2.7.1 Diagnosis

DM, particularly type 1, is often misdiagnosed. Diagnosis requires careful estimation of plasma glucose levels and often retesting on a different day to confirm previous results (American Diabetes Association, 2024; Ministry of Health, 2023). Clinicians and laboratory technicians are responsible for diagnosis. Accurate diagnosis is important to inform appropriate interventions.

The prevalence of misdiagnosed DM in Ghana is unknown; most studies reporting on misdiagnosed DM are case studies. DM is misdiagnosed because its symptoms are similar to malaria and typhoid, which are commonly reported in Ghana. For instance, Ameyaw (2017) reported a misdiagnosis in an eighteen-year-old female who presented symptoms of unexplained weight loss, amenorrhea, vomiting, body weakness and severe abdominal pain at a regional hospital in Ghana. The patient was diagnosed with ectopic pregnancy after a positive urine pregnancy test. Persisting symptoms after clinical intervention resulted in a surgical incision into the abdominal cavity, which was normal. Then, the doctor checked the patient's blood sugar level, which was excessively high (33.3 mmol/L). At this point, all clinical interventions to save the patient's life were unsuccessful. Misdiagnosis delays appropriate medical intervention and may result in complications, increasing treatment costs and mortality risk.

2.7.2 Counselling on lifestyle modification

The Ghana Standard Treatment Guidelines (STG) stipulates that DM patients be referred to dieticians/diet nurses for education and diet modification plans (Ministry of Health, 2010). However,

not all patients receive such services because there are few dieticians/diet nurses (as shown in Figure 2.2). Changes in diets and physical activity engagement can delay the incidence and progression of T2DM (American Diabetes Association, 2024; Brouns, 2018; Kolb and Martin, 2017). Patients are counselled by nurses and physicians who have inadequate knowledge of the nuances of DM. Mogre et al. (2019) found that about nine out of every ten nurses sampled in northern Ghana did not know the recommended daily caloric intake of carbohydrates for DM patients. Nutritional counselling from untrained nurses can be misleading and detrimental to DM control. Ghana needs to train more healthcare providers to provide case-specific dietary and exercise advice to DM patients.

2.7.3 Medication

The high cost and persistent shortage of DM medicines contribute to medication non-adherence among DM patients, increasing the chances of poor treatment outcomes. The NHIS pays for some anti-DM medicines, including first- and second-generation sulphonylureas, thiazolidinediones, metformin and insulin, but not the cost of relatively newer drugs like DPP4 inhibitors, GLP-1 agonists, amylin mimetics, and insulin analogues, which are relatively expensive for patients to purchase out of pocket (National Health Insurance Authority, 2023; Sarfo-Kantanka et al., 2017). NHIS pays a fixed amount for insulin, and when the market price of insulin increases, service providers may require patients to pay the difference out of pocket (Bimpeh, 2016). Quaye (2015) found that more than two-thirds of the DM management cost in four NHIS-accredited hospitals was spent on drugs. The uninsured bear the total medicine costs, which can be financially burdensome. Korsah et al. (2023) reported instances in which patients went several days without insulin because they cannot afford the drug. Moreover, insulin is not always available in PH facilities, particularly in rural-based facilities. Patients in rural areas travel long distances to obtain free insulin or pay out of pocket for expensive, non-generic types (Bimpeh, 2016). Erratic supply and unaffordable DM medicines lead to non-adherence and DM complications, which consequently increase DM management costs for patients and NHIS. The NHIS is expected to pay the cost of diagnosis for DM, but it has not done this in all cases. Okoroh et al. (2018) found that between 6 and 18% of households insured under the NHIS make OOP payments and incur catastrophic healthcare costs. Multiple diagnoses and misdiagnoses increase the DM burden by delaying appropriate interventions, increasing the risk of complications, and raising costs for the NHIS and patients.

2.7.4 Regular monitoring

DM patients cannot afford regular blood glucose monitoring, which is part of standard care (Figure 2.2). Djonor et al. (2021) found that 46.6% of the 268 DM patients interviewed did not have a blood glucose monitor. Among them, 32.4% cited financial constraints as the reason. Mogre and colleagues

(2019) interviewed one hundred and eighty-seven DM patients and found that only one performed self-monitoring of blood glucose daily for seven days. Patients lack the requisite knowledge and skills to perform and interpret blood glucose tests, fear the procedure, and experience pain from frequent finger-pricking to draw blood, which contributes to low self-monitoring of blood glucose (Ong et al., 2014). According to Mogre et al., government subsidies on glucometers, test strips and syringes could reduce the financial burden imposed on families and patients and improve glucose monitoring, self-care and DM treatment outcomes.

2.7.5 Periodic clinical reviews

Periodic clinical reviews are an important part of DM care, but patients miss them due to transportation costs, laboratory costs, and a lack of appreciation for their importance. During reviews, service providers assess patients' medication adherence, drug side effects, and potential complications and make necessary treatment adjustments to improve patient outcomes (Ministry of Health, 2023). Missing review appointments prevents service providers from intervening in the treatment process, which could lead to elevated blood glucose levels and DM complications. Patients miss periodic reviews because they cannot afford transportation to the health facility and the cost of services and medicines, especially those not covered by the NHIS (Korsah and Agyeman-Yeboah, 2023). Consequently, doctors are unable to provide adequate care, leading to complications and poorly managed DM.

2.7.6 Complication management

More than half of DM patients have comorbidities that increase their risk of DM complications, further increasing the financial cost of treating DM, as shown in Figure 2.2. DM complications are grouped into macrovascular and microvascular complications. The former includes peripheral arterial disease, coronary artery disease, and stroke, and the latter includes diabetic nephropathy, neuropathy, and retinopathy. Complications can be diagnosed during periodic medical reviews. Depending on the severity of the complications, the healthcare resource capacity, and the treatment protocols, clinicians decide whether to manage patients' health needs or refer them for specialist care (Ministry of Health, 2023). More than two-thirds of DM patients visiting an endocrine facility between 2011 and 2015 suffered from hypertension (Sarfo-Kantanka et al., 2017). Poor health-seeking behaviour and non-adherence to medicines increase the risk of complications (Mogre et al., 2019). Comorbidities and DM complications reduce patients' productivity and quality of life and double the financial cost of treatment because of the high cost of medicines. Quaye found that medicines for treating complications constitute about 47% of the total financial cost of DM (Quaye et al., 2015). Patients buy out of pocket for

medicines that are not covered by the NHIS (Sarfo-Kantanka et al., 2017). In situations where patients and families cannot afford medicines, patients are at risk of dying.

2.7.7 Referrals and specialist care

In addition to a poor referral system, Ghana has few trained DM specialists who cannot meet patient demand, leading to delayed care and, consequently, poor treatment outcomes. The ADA recommends that a team of specialists, including an endocrinologist, diet therapist/nutritionist, physiotherapist, and clinical psychologist, provide care to DM patients with complex needs that cannot be met within the skill competencies of general practitioners (American Diabetes Association, 2019). However, Ghana struggles to follow the recommendation because of a lack of inadequately trained DM service providers. Referrals can be made to the few high-resourced facilities. As indicated in Figure 2.2, there are a few endocrinologists in Ghana; the available few are in three NHIS-accredited referral hospitals in three major cities: Accra, Cape Coast and Kumasi (Sarfo-Kantanka et al., 2017). Transportation costs, time, and OOP payment for services discourage patients from following through with referrals (Amoah and Phillips, 2017). Improving the supply and geographical distribution of certified DM specialists in health facilities could improve service delivery and reduce DM management cost for patients.

In conclusion, patients and service providers face challenges along the clinical DM service delivery pathway, including issues related to the availability and cost of medicines and services, service provider expertise, and patients' adherence to treatment regimens. The COVID-19 pandemic and its related control measures could have exacerbated the challenges or resulted in changes in the service delivery pathway in Ghana. In addition to findings from the literature, we conducted an exploratory study to increase our understanding of the situation regarding clinical DM service delivery (Chapters 5 and 6 present the methods and results of the exploratory research, respectively).

2.8 Chapter Summary

This chapter has addressed key aspects of Research Question 1: *What is the state of DM service delivery in Ghana and DM interventions in Ghana and LMICs?* We have outlined the current DM burden in Ghana, the global and national policy landscape, and the challenges in implementing these policies. We have described interventions and barriers to DM control in Ghana and other LMICs. The review of global policy interventions and their implementation in LMICs, including Ghana, has revealed common barriers such as insufficient funding, inadequate health workforce, and poor intersectoral collaboration. The review has also highlighted targets and PH interventions that Ghana could explore to control the disease burden, which we further investigate in Research Question 5.

Furthermore, the pathway to clinical DM service delivery in Ghana has been described, highlighting patients at the centre of the pathway and significant challenges such as misdiagnosis, medication shortages, and limited access to specialist care. These findings set the stage for further investigation into the role and behaviour of patients in DM management, as outlined in Research Question 2 and presented in Chapter 3. The complex interplay of factors influencing DM control in Ghana, from policy implementation to clinical service delivery, underscores the need for a comprehensive, systems-based approach to addressing this growing health challenge.

3 Treatment and the Role of Patients' Behaviour

3.1 Introduction

This chapter provides a comprehensive description of DM control strategies and SMB We present a non-systematic narrative literature review of PH DM interventions and their effectiveness at controlling the disease, addressing the second part of Research Question 1*: "What is the state of DM service delivery in Ghana and DM interventions in Ghana and LMICs?"* highlighted in Chapter 1. We used SUPRIMO, a University of Strathclyde academic literature search engineer, to find peer-reviewed studies. We also searched the American Diabetes Association website for literature. The chapter discusses SMB, factors influencing it and how SMB influences DM treatment outcomes, addressing Research Question 2: *"How does patients' behaviour influence health service delivery and DM treatment outcomes?"*

3.2 Diabetes Interventions and Blood Glucose Control Estimation

Clinical and PH interventions are two broad classifications of DM interventions. The former usually employs drug therapy and clinical procedures, whereas the latter takes a population-wide PH approach focusing on improving SMB in patients and influencing healthy lifestyles in at-risk populations. SMB is "the day-to-day management of chronic conditions by individuals over the course of an illness." (Grady and Gough, 2014, p. e26), which largely influences the effectiveness of DM interventions. They include medicine adherence, health-seeking, diet, and physical activity.

BGC in DM could be monitored through point-based estimates (fasting or random blood glucose tests) or an average over time (glycated haemoglobin tests). The former provides a snapshot of blood glucose levels and is used by clinicians to provide immediate care in acute conditions. A point estimate fluctuates due to stress, changes in diet and illnesses (American Diabetes Association, 2024). Despite being affordable and taking less time to conduct, a point-estimate measure could change rapidly in a short period and, therefore, may not represent a patient's overall control of DM over time. The glycated haemoglobin test measures the average blood glucose levels, usually over a period of 120 days. Red blood cells have a lifespan of 120 days, and since glucose attaches itself to them, the test can capture variations over 120 days (American Diabetes Association, 2024; World Health Organisation, 2011). Although the glycated haemoglobin test is generally preferred (World Health Organisation, 2011), its results may be inaccurate in DM patients with rapid red blood cell turnover or blood disorders such as anaemia.

The Ghana DM treatment standards recommend using fasting blood glucose tests for DM diagnosis and monitoring purposes, especially where the glycated haemoglobin test is inaccessible (Ministry of Health, 2023). The protocol suggests a follow-up test to confirm DM if a point estimate is used for diagnosis. A point estimate, preferably fasting blood glucose, is to be used in routine reviews to assess BGC. The glycated haemoglobin test is to be conducted twice or three times per year to assess overall control and treatment progress (Ghana DM treatment guidelines, 2023).

3.2.1 Pharmacological Diabetes Interventions

Pharmacological interventions can delay the progression of DM complications, relieve patients' symptoms and control blood glucose levels. DM medicines include sulfonylureas, biguanide, thiazolidinediones, insulin, and several types of inhibitors—alpha-glucosidase inhibitors and DPP-4 inhibitors (American Diabetes Association, 2024; Ministry of Health, 2023). T1DM requires medicines, but T2DM can be treated with a healthy diet and adequate physical activity. Metformin is usually prescribed for T2DM, where lifestyle modification is insufficient for achieving blood glucose targets. Metformin is accessible, efficacious, and less costly than newer forms of DM medicines; Ghana's NHIS also covers it.

Aside from efficacy and clinical conditions, national and global guidelines, clinicians must consider cost, acceptance, convenience, and carer /family support when prescribing DM medicines (American Diabetes Association, 2018; Ministry of Health, 2023). The guidelines recognise that DM medicines can cause weight gain and that patients may struggle to maintain a healthy weight. Prescribing an expensive original brand due to its benefit to a patient on a low income is unsustainable because the patient cannot afford it. Similarly, insulin injections in frail patients with no carer or support could result in non-adherence due to the difficulty of correctly titrating insulin and the pain of continuously pricking the skin. Occasionally, trade-offs must be made as it is challenging to balance efficacy, cost, convenience, and acceptability in a patient's prescription. These trade-offs could influence medicine non-adherence, among other unhealthy SMB.

Pharmacological interventions have little impact on undiagnosed and at-risk populations, who form a significant proportion of Ghana’s DM burden (Ministry of Health, 2023; World Health Organisation, 2017a). Clinicians prescribe medicines and perform surgical procedures on patients who have been diagnosed and are receiving treatment. Carers and patients’ close contact may be enlightened on DM due to their close relationship with patients. Until they are diagnosed, people living with and those at risk of DM remain without intervention (World Health Organisation, 2017a).

3.2.2 Public Health Interventions for Diabetes

PH interventions usually target lifestyle to reduce disease risk and strengthen health systems. They include health promotion campaigns, insurance coverage and fiscal policies. PH interventions can reduce T2DM incidence and improve patient treatment outcomes by influencing healthy lifestyles and health-seeking behaviour. The WHO recommends that PH interventions reach people where they live and spend most of their time, leverage existing community programmes and features, and use activities that do not require additional resources for their implementation (World Health Organisation, 2017a). Policymakers can leverage community resources such as parks and social groups for physical activity intervention. By doing so, they reduce the challenge related to resources and funding for programme implementation.

PH interventions can be sensitive to socioeconomic and cultural factors. Implementing an intervention that has been successful in high-income countries may fail in low-resourced countries due to differences in food choices, the nature of jobs, and lifestyle. For instance, obesity is associated with good health and wealth in Nigeria and Ghana, whereas in European countries, it is undesirable and associated with poor health (Ofori-Asenso et al., 2016; Templin et al., 2019). Nevertheless, Ghana can take cues from the implementation in other countries, especially those from low-resource settings with similar socio-cultural backgrounds, and adapt interventions to meet its economic, social, and cultural context. Therefore, we reviewed PH DM intervention studies, focusing on the content and application of the interventions. We present the review under three main groups: education, fiscal policies, and insurance policies.

Categories of PH Diabetes Intervention

3.2.2.1 Diabetes education

Interventions focused on DM education can be characterised by the information transmission modalities: phone /text message or in-person sessions. Phone conversations and text messages do not necessarily require patients and clinicians to be in a designated physical space, as information can be transmitted virtually. In-person educational sessions may be organised in consultation rooms or other physical spaces in hospitals or communities.

DM education programmes using phone or text message.

There are mixed results on the effect of text message/phone-based DM education on BGC and SMB. Studies that demonstrate the effectiveness of text messages and mobile phone-based DM education for improving BGC are mostly RCTs conducted in high-income countries (Alamer et al., 2020; Aminuddin et al., 2021; Asante et al., 2020; Fang and Deng, 2018; Haider et al., 2019; Kirwan et al., 2013; Ostrovsky and Ehrlich, 2018). The messages or phone calls often focused on medicine intake, diet and physical activity, and follow-up time varied, with a minimum of 4 weeks. Asante et al., for instance, examined how to reinforce health self-management through mobile phone calls placed by DM specialist nurses to T2DM patients receiving care in a tertiary facility in Ghana. The experiment lasted for 12 weeks. The intervention group (30 patients) received about 16 calls lasting an average of 12 minutes in addition to usual care, while the control group (30 patients) received standard care only. The researchers found a significant reduction in mean blood glucose (glycated haemoglobin) in the intervention group compared to an increased mean blood glucose in the control group. Fang and Deng (2018) also reported a reduction in fasting and random blood glucose and glycated haemoglobin (HbA1c) among 129 DM patients in China who received text messages and information on an online news platform over 12 months.

Other RCTs, such as those by Van Olmen et al. (2017, 2013) and Arora et al. (2013), found no significant improvement in blood glucose outcomes from text message- or phone call-based education. These studies also focused on multiple SMB factors, including medicine intake, diet, physical activity, and follow-up time, which varied, with the least being six weeks. The TEXT4DSM study is a large RCT with 480 DM patients each from an ongoing DM education programme in Cambodia, the Philippines, and the Democratic Republic of Congo. The study evaluated the effectiveness of short messages on BGC in DM patients (Van Olmen et al., 2013). According to the study, the intervention arm received weekly automated messages and phone calls from trained educators to discuss their self-management and treatment concerns. At the end of two years, there was no significant change in HbA1c levels in the intervention and control groups. Adjusting for differences in country, time, and the ongoing intervention in the analysis did not change the overall finding that text messages had an insignificant effect on blood glucose levels, DM knowledge and service use. A meta-analysis of seven RCTs conducted in Africa (three studies involved DM patients in Ghana) found no significant reduction in blood glucose due to text messages and other mobile health interventions (Aovare et al., 2023).

From the reviewed literature, intervention design, implementation, and contextual factors could explain the inconsistency in the intervention effect. Including text messages in an ongoing DM education study could be a source of bias in Van Olmen et al.'s study. Implementation challenges, such as participants not reading messages, switching phone numbers, and network connectivity, could explain the different

results among countries. The different results among studies could also be associated with context-specific characteristics, implying that country-specific DM interventions or those adapted to fit the sociocultural context of a country may be appropriate. Investigating the effectiveness of DM intervention within the Ghanaian health system and among the Ghanaian DM population could provide representative results for health policy and practice.

DM education through mass media campaigns

Television and radio-based campaigns influence health behaviours. People exposed to mass media campaigns can either enforce or undermine the desired change by spreading their understanding of the message within their close contacts. Where the majority of a person's close contacts are exposed to a mass media campaign, changes in group behaviour become the norm, influencing unexposed group members to behave as such (Stead et al., 2019).

There is a consensus in the health literature that mass media campaigns increase DM knowledge. However, it is unclear how mass media campaigns influence BGC (Stead et al., 2019; Sugden et al., 2017; Tabassum et al., 2018). Stead and colleagues (2019) conducted an umbrella review and found that mass media has a mixed effect on the uptake and cessation of smoking in adults. The authors reviewed 36 papers, most of which were conducted on tobacco, physical activity, and sexual health in high-income countries and LMICs. Stead et al. (2019) also found that mass media campaigns strengthened intentions to quit smoking but had a mixed effect on youths' intentions to start smoking tobacco. According to the authors, these outcomes may vary in subgroups, which is consistent with Tabassum et al.'s findings from a narrative review of mass media campaigns for health behaviour changes (2018). Specifically, Tabassum and colleagues found that mass media campaigns are most effective when well-targeted at a subgroup and the desired behaviour is incidental rather than habitual. Also, access to resources needed for behavioural change, such as counselling, is crucial in persuading exposed individuals to act on mass media campaign messages (Tabassum et al., 2018).

Ghana has employed mass media campaigns to disseminate health messages, but these campaigns are rarely evaluated for effectiveness and cost-effectiveness. Mass media campaigns in Ghana include radio and television advertisements and billboards. An example is the "Good Life, Live it Well" campaign, launched in 2010 by the Ghana Health Service (GHS) and USAID, which aimed to address multiple health issues and promote healthy lifestyles (USAID, 2016). Another mass media campaign that has gained public attention is "You Only Live Once" (YOLO), which premiered in 2015 and was developed by National Population Council in collaboration with the Ghana Health Service, Ghana Education Service and National Youth Authority (Daily Guide, 2021). YOLO is a teen television series that explores several health and social issues affecting the youth. There is evidence to suggest that mass

media campaigns improved health outcomes and behaviours related to national health insurance enrolment (Kansanga et al., 2018), malaria (Yaya et al., 2018), sexually transmitted diseases (Asamoah et al., 2017) and perceptions of social media for health (Bannor et al., 2017) in Ghana. We found no evidence of the cost-effectiveness of mass media campaigns, although such evidence could influence policy decisions on mass media campaigns to control DM.

Based on the literature reviewed, mass media campaigns appear useful for increasing DM awareness in Ghana. More than 50% of Ghanaians watch television or listen to the radio at least once a week (Ghana Statistical Service et al., 2015). Consequently, television and radio-based campaigns could reach a significant proportion of the population. However, a possible challenge with using television and radio campaigns is that habitual/lifestyle behaviours may be challenging to maintain once campaigns are over. Moreover, competing environmental factors, such as marketing and easy access to high-calorie unhealthy foods, could hamper long-term behaviour change. There is a need for further research and evaluation to determine the effectiveness and sustainability of mass media campaigns for health behaviour change.

DM Education Programme

DM education programmes could be structured and unstructured. The former has predefined intervention outcomes, a target population and a set of duration. Structured education programmes are facilitated by a team of experts inside or outside health facility premises. Unstructured education programmes are discussions on self-management between clinicians and patients when patients seek care. Unstructured DM education usually occurs in consultation or waiting rooms, and their content, duration and frequency are unplanned.

There is evidence suggesting that structured DM education improved DM control and SMB (David et al., 2021; Heller et al., 2014; Jiang et al., 2021; Pérez-Escamilla et al., 2015; Speight et al., 2016; Thanh and Tien, 2021; Yorke and Atiase, 2018). The UK Dose Adjustment For Normal Eating (DAFNE) programme, an RCT involving 169 adults with T1DM, found that structured education on flexible intensive insulin treatment, diet, and insulin adjustment can improve glycemic control and quality of life (Heller et al., 2014). The programme included a five-day structured DM self-management session for groups of six to eight outpatients at a designated centre. In Australia, the OzDAFNE programme, which modified the DAFNE programme to reflect Australia's food choices, found a noticeable reduction in HbAIc, weight, frequency of hypoglycemia and an improvement in quality of life in 145 T1DM patients (McIntyre et al., 2010). Speight and colleagues (2016) conducted a follow-up study to examine whether the intervention effect that McIntyre et al. found persisted over time, given an increase in the programme's coverage. Using an uncontrolled before-and-after design, the authors randomly selected

506 T1DM patients who participated in the OzDAFNE programme and collected clinical data before and 6–8 months after the intervention. The researchers found that the incidence of hypoglycemia, DM-related distress and diabetic ketoacidosis requiring admission was reduced by half. There was a significant improvement in BGC. Structured DM education has shown positive results in low-resource countries. In Vietnam, Thanh and Tien (2021) found, through RCTs, that the intervention significantly improved DM knowledge and glycemic and blood pressure control in T2DM.

In Nigeria, David et al. (2021) found similar results to those in Vietnam when they examined the effect of pharmacist-led care on BGC in T2DM through a parallel single-blinded RCT of 54 outpatients with uncontrolled DM attending a tertiary hospital. Unlike Speight et al. and Thanh and Tien's study, which included one structured education programme, there were two structured education sessions (baseline and three months after) in David et al.'s study. There were 54 patients in the intervention arm, which was moderated by a pharmacist, lasted for 30-45 minutes, and was organised in a consulting room in a hospital. The intervention cohort received phone call reminders on lessons and review appointment dates every six weeks. The control group also received phone call reminders of review dates plus usual clinical care. After three months of implementation and three months of follow-up, the authors found a significant decrease in blood glucose in the intervention group and a significant increase in the control group. The proportion of patients with controlled DM (HbA1c < 7%) in the intervention group was twice that observed in the control group. However, when fasting blood glucose (fbg) was used, the change was insignificant in both groups. Overall, the authors reported that patients who received the intervention were twice as likely to have good BGC as those who did not.

Based on the literature review, the modalities for delivering structured DM education are similar across countries. However, the contents of the programme, particularly those of dietary choices, are modified to fit each country's socio-cultural and economic context. For instance, McIntyre et al. reported that "the dietary elements of DAFNE have been adapted to Australian food choices and nutritional analysis, but the core curriculum is consistent with the UK programme". Moreover, these countries have sufficient financial resources to support programme implementation and large-scale RCTs for programme evaluation. In low-resource countries, study results were measured shortly after implementing the intervention, a period when knowledge obtained through the programme could be retained. A long follow-up period would provide insight into the lasting impact of the intervention on BGC. Low-resource countries, including Ghana, may not afford longitudinal empirical studies. However, these countries could leverage SM approaches to evaluate the long-term impact of DM education programmes.

In summary, education programmes could increase individuals' awareness and motivation to live healthy lifestyles. The approach needs to be carefully designed and contextualised. Text messaging and

phone call-related interventions should consider the frequency, technical/connectivity challenges, cost, and burden to the sender (clinicians) and receiver (patients). Structured education programmes improved glycemic control, but there is little evidence of their effectiveness and cost-effectiveness in Ghana.

3.2.2.2 Fiscal policies for diabetes control

Fiscal policies are revenue-generating legal instruments and expenditure measures that change the prices of commodities and services, influencing consumers' behaviour. The WHO and UN recommend that countries use fiscal policies to influence health behaviours (World Health Organisation, 2022a, 2017a, 2017c). Revenue-generating policies impose taxes on commodities, which increase prices and may reduce consumption. Expenditure measures, including vouchers and coupons, subsidise prices, encouraging consumption. Ghana could take lessons from countries that have implemented health-related fiscal policies to guide the implementation of the country's recent SSB tax policy.

Tax-based fiscal policies for diabetes.

Hawkes et al. (2015) developed a theory of change to explain the primary mechanisms through which food policies influence health outcomes and behaviours (Figure 3.1). The theory explains the relationship between food preferences, social and informational environments, access, and affordability in determining dietary behaviours.

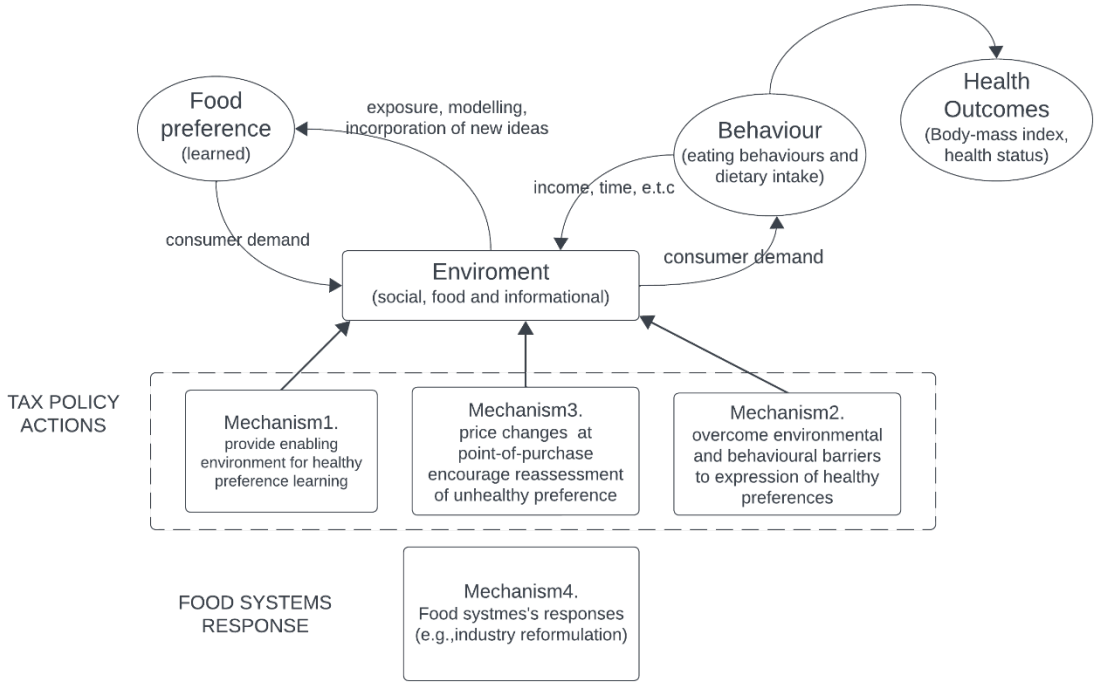


Figure 3.1 Framework of the theory of change and mechanisms of food-policy actions on health behaviour (Adapted from Hawks et al. 2015).

According to the theory, food taxes operate through three of the four mechanisms shown in Figure 3.1. Price increases encourage consumers to reconsider their unhealthy food preferences (mechanisms 1 and 3). Taxes encourage people to develop healthy preferences, especially when combined with educational campaigns (mechanism 2). The food environment could change as companies respond to taxes by reformulating their products to reduce sugar/calorie content (mechanism 4).

Through the mechanisms shown in Figure 3.1, SSB taxes have proven effective at reducing consumption and obesity in many countries (Andreyeva et al., 2022; Itria et al., 2021; Nakhimovsky et al., 2016; Teng et al., 2019). Nakhimovsky et al. found in middle-income countries that SSBs' price elasticity–how demand for SSBs changes in response to a price change–ranged from -0.6 to -1.2, indicating reduced demand with an SSB tax. Tax-induced decreases in SSB consumption ranged from 5 to 39 kilojoules per person per day, with a 10% increase in SSB prices, and milk was a likely substitute. In Andreyeva and colleagues' meta-analysis, SSB taxes were associated with increased prices of taxed beverages (with a tax pass-through rate of 82%) and a 15% reduction (95% CI, 20% to 9%) in SSB sales. The price elasticity of demand was estimated at -1.59 (95% CI, −2.11 to −1.08). Teng and colleagues' work included studies worldwide. They found that a 20% SSB tax had a more significant impact than a 10% SSB tax. Although a 10% caused a 1.9% (95% CI: -2.1% to 6.1%) increase in total untaxed beverage consumption in four jurisdictions, this increase was not statistically significant. It is

unclear what the effect of Ghana's 20% SSB tax will be on DM, obesity, and overweight prevalence is, which requires research attention.

SM studies have shown that taxes on unhealthy foods and products could reduce consumption, consequently reducing obesity and the DM burden. In South Africa, Manyema et al. (2014) investigated how a 20% tax on SSBs would affect DM outcomes. The authors built a Markov model using nationally representative data on SSB consumption and price elasticity, energy intake and expenditure equations, DM risk and disability weights, and DM cost estimates. The model conceptualised SSB consumption to directly reduce body mass index, reducing T2DM incidence. A deterministic sensitivity analysis was performed to examine the effect on disease burden due to changes in tax, DM parameters, and cost-related parameters. The authors found that the tax policy reduced SSB intake, especially among 20–24-year-olds. Over 20 years, the tax intervention prevented over 150,000 T2DM cases, averted several DALYs and resulted in significant healthcare savings.

The South African model outcomes are similar to those observed in India (Basu et al., 2014) and Germany (Tönnies et al., 2021). Tönnies et al. investigated the impact of a 50% increase in SSB, red meat product, and tobacco taxes on the prevalence of T2DM in 2020 and 2040. The authors used the Markov model and the German Diabetes Risk Score to forecast prevalence under routine practice, assuming that DM incidence rates remain unchanged over the simulation period. Price elasticity data were used to estimate the reduction in age-specific risk scores, and differential equations were used to estimate the decline in DM incidence and prevalence rates. The researchers found that combined taxes on SSB, red meat, and tobacco products over the simulated period could substantially decrease DM prevalence by more than half a million in 2040 (equivalent to a 6% relative reduction). However, they highlighted that raising taxes alone may not be adequate to attenuate the future DM burden.

Morocco, South Africa, Nigeria and Ghana are among the few African countries that have implemented an SSB tax (Kenmure and Loewenson, 2023). Nigeria increased the prices of all alcohol products and SSBs by 10 Naira (N) per litre (US$0.006 per litre at the 2024 rate) in 2021 to combat rising levels of obesity and NCDs and generate revenue for the government following the financial impact of the COVID-19 pandemic (Adedeji and Lucero-Prisno, 2022). In South Africa, the government proposed a 20% per litre tax on SSBs in 2016 to compel manufacturers to reduce the sugar content in drinks (Stacey et al., 2021). Manufacturers contested with the decision, arguing it would reduce revenue and lead to job losses. In contrast, health and academic experts argued in favour of the health and economic benefits of the policy. In 2018, the government enacted the SSB tax, the Health Promotion Levy, but at a reduced rate of 10% (Stacey et al., 2021). In Morocco, the government implemented a soda tax in 2019 and then, in 2020, an SSB tax based on the sugar concentration in a drink. The policy was uncontested by

stakeholders, probably because of the multisectoral involvement and several awareness campaigns that led to its adoption (Belkhadir et al., 2020).

In December 2022, Ghana passed a 20% excise duty tax on SSBs, including fruit and vegetable juices (Republic of Ghana., 2022). Before the policy introduction, Singh et al. (2023) found that government officials and other stakeholders perceived SSB tax mainly as a medium for revenue generation, which could be used for health. Government officials expressed concerns about potential increases in illicit trade and negative economic effects. The officials perceived that close ties between politicians and the beverage industries would obstruct effective implementation. Similar stakeholder concerns have been reported in other countries (Eykelenboom et al., 2019). Singh et al. recommended research to provide evidence of the value of health taxes for improving health in Ghana.

The reviewed studies demonstrate that the benefits of SSB taxes on health, both broadly and in relation to DM specifically, may be modest, accrue over several years or may not be observed due to mediating factors, including poor tax implementation. Combining an SSB tax policy with other mass media campaigns could increase its impact on health. Countries must explore their populations' consumption patterns to inform which foods, when taxed, could maximise health effects. Moreover, Ghana can leverage SM methodologies for their flexibility in exploring potential long-term tax effects in a short time compared to RCTs and cohort studies.

3.2.2.3 Insurance and co-payment policies for diabetes control

Insurance and co-payments subsidise health services and medicine costs, increasing access to medication, improving adherence and reducing the financial burden of healthcare on households (Guindon et al., 2022; Mann et al., 2014; Sinnott et al., 2013).

In a meta-analysis of seven studies (all conducted in the US populations) involving a total of 199, 996 people, Sinnott and colleagues found an 11% (95% CI 1.09–1.14) increase in the odds of medication non-adherence among publicly insured individuals, particularly when they were required to co-pay for medicines, especially for DM, hypertension, and hyperlipidaemia medicines. Mann and colleagues also found similar results in a meta-analysis when they compared adherence in patients with uncapped medicine coverage and those without. The researchers found from three studies conducted in the US that among individuals aged 65 or older with hypertension, hypercholesterolemia, and DM, having medical insurance increased the chances of following recommended medications by 19–136% compared to those without coverage.

Guindon et al.'s (2022) umbrella review included studies from non-US countries, including Canada. The authors examined 20 reviews investigating the association between medicine insurance or cost-sharing on the one hand and medicine use, health service use and health outcomes on the other hand. They found that the lack of prescription medicine coverage or the presence of co-payments decreased medication adherence. There was a 0.4% decrease in adherence for every USD increase in co-pays and an average of 3% decrease in adherence per year of co-payment increase. Seven studies reporting on own-price elasticities of medicine showed that a 10% price increase resulted in a 2–6% decrease in usage.

In Ghana, the NHIS increases health service utilisation and reduces OOP payments (Alhassan et al., 2016; Aryeetey et al., 2016; van der Wielen et al., 2018). Aryeetey and colleagues used structured questionnaires and interviews to gather data from 34 health facilities before and after NHIS implementation. They used the WHO General Service Readiness indicator to guide data analysis. They found a 64 % and 51 % increase in the total outpatient and inpatient visits, respectively, after NHIS implementation, with varying health service demand (inpatient or outpatient services) in different parts of the country. Medicine availability generally improved in all health facilities after policy implementation. Approximately 2.4% of service provider claims were not reimbursed, contributing to providers' dissatisfaction with the scheme, as Alhassan et al. (2016) identified.

Wielen and colleagues found results similar to those of Aryeetey et al. when they used data from the Ghana Living Standards Survey 2012 – 2013. The authors employed propensity score matching and controlled for individual-level differences while estimating how NHIS coverage affected health service use among rural residents aged 50 and above. They found that insured persons were 6% and 9% more likely to use inpatient and outpatient services, respectively, than those uninsured. Among the insured, non-poor individuals and females used outpatient services more than their counterparts.

Cross-sectional studies have found a positive effect of NHIS coverage on DM management (Mobula et al., 2018; Tagoe et al., 2023). Interviews with 18 DM service providers revealed that the NHIS covers insulin, metformin, and glibenclamide. However, other medications, such as those for treating diabetic retinopathy, are not covered, leading to increased patient costs, which raised concerns (Tagoe et al., 2023). Mobula and colleagues collected data from the medical records of 1226 T2DM patients attending five health facilities of varying resource capacity. The authors also gathered medicine-related data by administering questionnaires to patients. The data analysis revealed that medicines not covered by insurance, long durations of DM and an increasing number of medicines prescribed per patient, among other factors, were associated with poor BGC.

Based on the review, the literature on taxes generally is based on SSB price elasticity: price increases lead to reduced consumption, which may not always be the case if there are untaxed, unhealthy alternatives. Considering that not all unhealthy foods are taxed simultaneously, the design and form of tax policies must be carefully considered to avoid increased consumption of unhealthy, untaxed substitutes. Fiscal policies combined with mass media campaigns could be an effective approach compared to implementing each strategy individually. Ghana must monitor and evaluate its SSB tax for compliance to ensure effectiveness. Moreover, the evidence on NHIS coverage and DM burden in Ghana is predominantly from cross-sectional studies, which may not represent the current situation. The overall health policy environment and health system, including NHIS operations and services, keep changing and may affect the results of cross-sectional studies.

3.2.3 Summary of diabetes interventions

PH interventions take a population-wide approach by modifying lifestyles from a social, economic, or cultural perspective using policies and programmes. Although PH interventions have effectively controlled DM in other countries, their application in LMICs, particularly Ghana, is limited. Education, insurance coverage and SSB tax policies could improve DM control, as shown in other countries. Extrapolating the results from studies in different countries to Ghana can be challenging, considering that differences in lifestyle, culture and health system capacity influence the application and effectiveness of interventions. Therefore, context-specific insights into the impact of PH interventions on DM are useful for policy decision-making for effective DM control in Ghana.

3.2.4 Interventions Considered in Simulations for Improving Diabetes Outcomes in Ghana

Based on insights from the literature review, we considered several interventions that could potentially positively impact T2DM control in Ghana.

Intervention 1: Increasing coverage of the NHIS

Based on the literature review, expanding insurance coverage among DM patients could increase access to medicines and health services, improving BGC at the population level. The NHIS could help Ghana meet the WHO DM target of 100% access to DM medicines. At the national level, coverage reached 57% in 2023 (Ministry of Health, 2023). NHIS covers DM medicines and clinical services; however, less than half of the country's population is actively insured. As detailed in Chapter 2, the NHIS covers

the cost of metformin, insulin, consultation, inpatient services, and laboratory examination of blood glucose, making medicines and services affordable to patients.

Uninsured patients' risk being unable to afford medicines or health services if they lack sufficient funds. The WHO global DM targets acknowledge the need to increase access to DM medicines by targeting access to affordable insulin and blood glucose self-monitoring for all T1DM (World Health Organisation, 2022b). Chapter 2 details the WHO Global DM Targets.

Increasing insurance coverage among DM patients under the NHIS would increase the affordability of DM medicines and clinical services, which could improve treatment adherence and BGC at the population level. In Chapter 6, we present details on the proportion of the increase in NHIS coverage explored in the simulation studies.

Intervention 2: Increasing access to DM medicines

The WHO recognises the challenge of accessing DM medicines and seeks to address the problem in its 2030 Global DM targets. In Ghana, the persistent shortage of insulin is reported to contribute to medicine non-adherence in DM patients (Kushitor and Boatemaa, 2018; Masters et al., 2014; Mobula et al., 2018). The government of Ghana acknowledges the persistent shortage of DM medicines, which contributes to non-adherence and poor DM control, and is addressing it (Ministry of Health, 2017b). Aryeetey et al.'s study shows an association between expanding insurance coverage and medicine access. The authors found increased medicine availability, especially for those covered by insurance, post-NHIS implementation.

Logically, the full benefit of expanding insurance coverage may not be realised if medicines are not covered or unavailable to insured patients. Although the NHIS pays for DM medicines, they must be available in health facilities and community pharmacies before patients can buy them through the scheme. The availability of insulin and metformin in health facilities in Ghana ranges from 2.3% to 100%, with higher availability in urban areas than in rural areas (Kushitor and Boatemaa, 2018).
Ensuring 100% availability of DM medicines may be unrealistic for the Ghana government, considering that supply chain factors, including the availability of pharmaceuticals in the global market, are beyond their control. Consequently, we explored a 10% increase in the proportion of times patients found DM medicines in the simulation studies.

Intervention 3: 20% SSB tax

The literature indicates that an SSB tax could reduce the consumption of unhealthy food and improve DM outcomes (Basu et al., 2014; Jevdjevic et al., 2019; Manyema et al., 2014). Similarly, Ghana's 20% SSB tax could reduce the burden of obesity, overweight, and DM by reducing the consumption of unhealthy foods. The tax imposition on SSB would generate revenue for the government.

At the time of this study, no data had been collected on changes in dietary consumption associated with the introduction. Consequently, we assume Ghana's SSB tax effect based on evidence from LMICs, specifically from India and South Africa ((Basu et al., 2014; Manyema et al., 2014).

Intervention 4: Increase NHIS coverage and the effect of a sugar-sweetened beverage tax.

The motivation for this experiment is that the government could invest the revenue generated from the tax in increasing NHIS coverage. The literature review indicates that SSB taxes generate revenue for the government. In the study by Singh et al. (2023), it is evident that policymakers in Ghana perceive that revenue generated from the SSB tax could be invested in NHIS and other health-related interventions. Therefore, we explore the combined intervention for its health and economic efficiency for patients and the government.

3.3 Patients' Self-management Behaviour

While the previous section has explored various DM interventions, the effectiveness of these interventions ultimately depends on patients' SMBs. Even the most well-designed interventions can fail if patients do not adhere to treatment regimens or adopt recommended lifestyle changes. Therefore, understanding patients SMBs is crucial for developing and implementing successful DM control interventions. The following section delves into the complexities of patient SMB, examining the theories explaining health-related actions and the multifaceted factors influencing treatment adherence and outcomes. This understanding will provide valuable insights into modelling patients' SMB and how interventions can be tailored to effectively address the challenges of DM management in Ghana.

Patient behaviours primarily influence BGC in DM treatment. The DM treatment regimen is complex and lifelong and demands behavioural changes, including continuous medicine intake and a healthy lifestyle. As highlighted in Chapter 1, DM patients meet clinicians a few times a year to review treatment progress. Much of the time, patients are on their own, self-managing the condition. Adherence refers to the degree to which a person's behaviours align with agreed-upon advice from a healthcare

practitioner (WHO, 2003). Poor adherence to long-term therapies, including DM care, worsens health conditions, increases healthcare expenditure, and could jeopardise treatment effectiveness. Good adherence, however, could slow the progression of DM complications.

Although good adherence and a healthy lifestyle have been associated with good BGC and reduced health service utilisation (Capoccia et al., 2016; Khunti et al., 2017), it is evident that many patients have trouble adhering to treatment guidelines (Krass et al., 2015). The WHO asserts that adherence interventions and healthy SMB may have a far bigger effect on population health than any change to a particular medical intervention because they reduce risk factors and prevent adverse health outcomes (WHO, 2003). About one-third of DM patients are not adherent to medication, with depression and cost being major determinants of non-adherence (Iglay et al., 2015). In Ghana, good medicine adherence proportions among T2DM patients range from 38.5% to 84.5% (Afaya et al., 2020b; Amaltinga, 2017; Bruce et al., 2015; Osei-Yeboah et al., 2018; Peprah et al., 2022). Moreover, few people in Ghana eat healthily and regularly exercise. According to the 2010 National Demographic and Health Survey, 15 to 49-year-olds ate fruits and vegetables about 3 days a week. Obesity prevalence almost doubled while overweight prevalence tripled between 1993 and 2014 in Ghana (Amugsi et al., 2017), indicating increased unhealthy diet consumption and less physical activity engagement in the population.

Multiple interacting factors influence patients' SMB. Thus, it is logical to explore SMBs using various theories, methods, and perspectives to improve understanding of the concept. Health behaviour theories provide a conceptual framework for improving understanding of how health behaviours are formed. The Health Belief Model (HBM) and the Theory of Planned Behaviour (TPB) are commonly applied in the PH literature for their ability to explain health behaviours (Munro et al., 2007). Therefore, we explored the two behavioural theories in the following section, examining the tenets and how they could explain DM patients' SMBs.

3.3.1 Health Behaviour Theories in Chronic Disease Management

Health behaviour theories attempt to explain and predict health behaviours from patients' perspectives. Since DM is a chronic disease, its treatment is influenced not only by biological factors but also by patients' social, psychological, and economic conditions. We review two commonly applied health behaviour theories, the HBM and the TPB, in the preceding paragraphs to provide context to their application to explain SMB in chronic disease patients.

Health belief model: origin and features

HBM was developed in the 1950s by Hochbaum, Rosenstock, and Kegels to explain and predict people's intent to participate in health programmes and adopt health behaviours. The model was later applied to explain medicine adherence. According to the HBM, attitudes, beliefs and perceptions towards a health condition mainly determine engagement in health behaviours. The model's main constructs are perceived susceptibility, perceived severity, perceived advantages, perceived barriers, cues to action, and self-efficacy. Perceived susceptibility is an individual's opinion of vulnerability/risk associated with a health problem, while perceived severity describes how seriously an individual perceives their disease condition. Perceived barriers pertain to potential obstacles to behaviour change, and perceived benefits refer to the value/ efficacy of engaging in healthy behaviours. Self-efficacy is an individual's perception of his or her ability to successfully carry out a health behaviour. Demographic and social factors can modify an individual's perception of health. Additionally, HBM explains that an internal or external cue (e.g., feeling unwell or a mass media campaign) can trigger people to engage in health behaviours.

Practical application of the Health Belief Model

The HBM has been applied to improve understanding of DM risk and SMBs and to inform the design of interventions to address the burden (Amare et al., 2022; Darvishpour et al., 2018; Khosravizadeh et al., 2021; Marsim et al., 2021; Shabibi et al., 2017; Willis, 2018; Yue et al., 2015). In predicting behaviour, the factors influencing intentions/behaviour are measured with survey tools/questionnaires and then path analysis and regression models are used to combine the influencing factors (Amare et al., 2022; Darvishpour et al., 2018; Yue et al., 2015). In these studies, HBM was found to have moderate to high predictive ability. The model has also been adopted as a framework to conceptualise barriers and facilitators of health behaviours in several disease conditions (Khosravizadeh et al., 2021; Marsim et al., 2021; Shabibi et al., 2017; Willis, 2018).

Theory of planned behaviour: origin and features

Icek Ajzen developed the theory of reasoned action in the 1980s to predict intentions to engage in a behaviour over which individuals can exert self-control (Ajzen, 1991). The theory of reasoned behaviour asserts that individuals act on their intentions if they reasonably flow from their beliefs about the behaviour in question. Attitude and subjective norms predict intentions to perform behaviour. Attitudes are founded on beliefs about the expected outcome of a given behaviour, whereas subjective norms are based on beliefs about how others think an individual should behave. The theory of reasoned action was extended to TPB to explain behaviours over which individuals have no control by

introducing the construct of perceived and actual behavioural control (Ajzen, 2002). TPB suggests that attitude, subjective norms, and perceived behavioural control can predict behavioural intention, which can predict actual behaviour when combined with actual behavioural controls.

Practical application of the Theory of Planned Behaviour

Like the health belief model, the TPB has been applied to explain and predict treatment adherence and risk behaviours such as smoking, diet, and physical activity engagement. Studies that applied the theory to predict behaviour generally 1) identified the targeted behaviour, 2) classified its predictors under the model's constructs, 3) measured the predictors through self-reported/objective approaches using questionnaires and then 4) used statistical methods including regression and structural equation modelling to investigate the relationship among predictors and the targeted behaviour (Akbar et al., 2015; Cooke et al., 2016; Riebl et al., 2015; Ritchie et al., 2021). These studies found that intention could predict health behaviours. TPB-based behavioural interventions in low-resourced settings have effectively changed health behaviours (Paul et al., 2023). The theory has been adopted as a conceptual framework to improve the understanding of health behaviours of individuals living with chronic disease (Pourmand et al., 2020; Prapavessis et al., 2015).

Application of HBM and TPB to DM patients' self-management behaviour.

Section 7.4.3 in Chapter 7 described how we applied HBM and TPB to conceptualise patients' SMB. Briefly, perceived barriers (HBM) and perceived behavioural control are similar; they represent the challenge of unavailable and unaffordable DM medicines, resulting in non-adherence. We conceptualise perceived severity and cues to action (HBM) such that patients who experience poor BGC seek healthcare regardless of not having an appointment. We conceptualised discharged patients to have high perceived susceptibility and perceived severity (HBM) and therefore assumed they lived healthy lifestyles and adhered to medication if they had medicines. We used the understanding of subjective norms in TPB to conceptualise inpatient behaviours, such as the patients following treatment regimens while admitted.

3.3.2 Factors influencing patient self-management behaviours.

Several factors, including those highlighted in Figure 3.2, impede the ability of DM patients living in low-resourced settings to adhere to medications, live healthy lifestyles and seek care as recommended by health providers. In this section, we discussed the factors influencing SMB of chronic disease patients under WHO's five dimensions of adherence to improve understanding of the study context.

Provider and health system-related factors

Poorly coordinated services, unprofessional clinician behaviours and communication gaps among health provider-related factors influence patients' satisfaction with clinical services and SMB (Abate et al., 2021; Kwakye et al., 2024; Polonsky and Henry, 2016). Poor communication among health providers and a poor referral system jeopardises care quality, continuity, and timeliness. A change in prescriber or facility, probably due to referral, may require new providers to have adequate patient history. Service providers find it challenging to deliver effective care when referrals are accompanied by limited patient history. Patients may see providers as controlling and not trustworthy, especially when patients feel excluded from care decisions. They may have challenges trusting new or multiple service providers, which could affect SMBs.

Diabetes and medicine-related factors

The complexity of DM treatment regimens, compounded by co-morbidities and physical and emotional stress, often leads to unhealthy SMB (World Health Organisation, 2003). DM patients usually have co-morbidities, making their treatment regimens even more complicated in terms of the number of prescriptions and the mode and timing of administration. Insulin injections can be painful and associated with adverse events and fatigue, which could influence patients to default on treatment (ÅgårdRanjbar and Strang, 2016). When injecting insulin, which requires good eyesight and steady hands, physical limitations, such as being bedridden or shivering due to hypoglycemia, might be a hindrance. Patients may be asymptomatic even when blood glucose is poorly controlled; the absence of unfavourable symptoms enhances patients' perception of low severity and susceptibility to DM, which could lead to non-adherent behaviours.

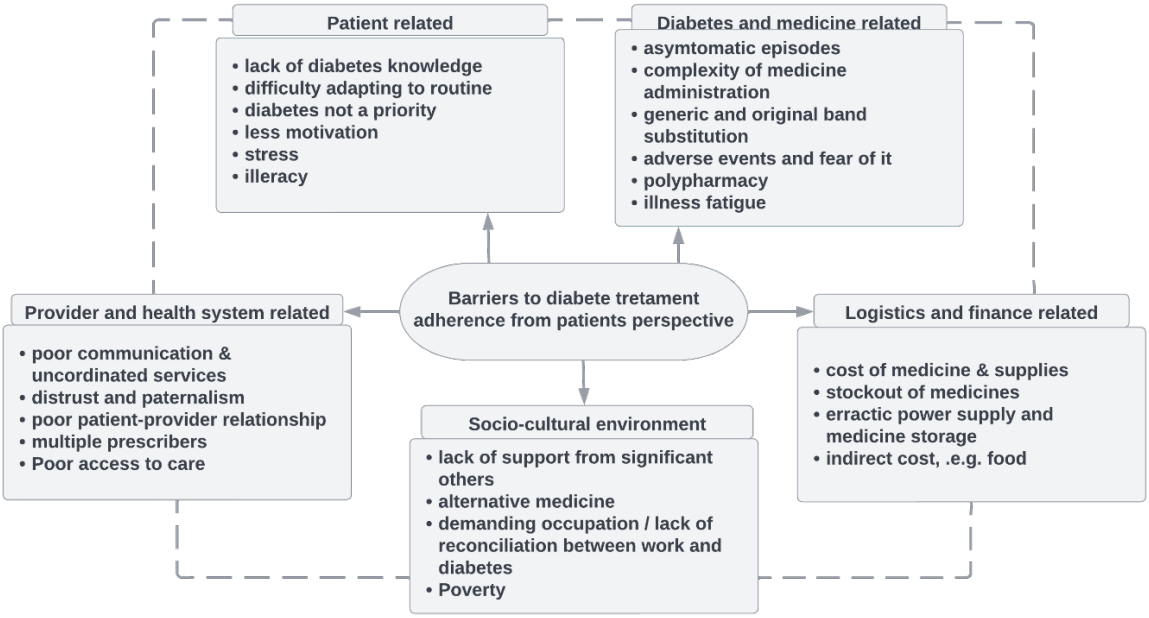


Figure 3.2 Factors influencing treatment adherence in diabetes patients (Author's own research, compiled from a literature review with references in Section 3.3.2).

Patient-related factors

Inadequate knowledge of DM, poor health literacy, and the chronic nature of DM contribute to patients' challenges in maintaining healthy SMB (Abate et al., 2021; Ågård et al., 2016; Dhar et al., 2017; Fan et al., 2016; Kwakye et al., 2024; Nielsen et al., 2017; Xie et al., 2020). Patients may be unaware of the importance of medication adherence and may change their doses based on their poor understanding and feelings. They could have incorrect beliefs regarding drugs and lack the motivation to take medicines daily for the rest of their lives, considering the chronic nature of DM. Poor health literacy worsens the knowledge gap and can cause problems in understanding written prescriptions. DM management requires that patients sustain healthy lifestyles and follow treatment regimens/routines for a lifetime, which can be challenging. Patients may forget to take medicines or attend review appointments because of busy work schedules and difficulties balancing their profession with DM.

Socio-cultural environment

Lack of support from family, financial constraints and social influence contribute to unhealthy SMB (Abate et al., 2021; Ågård et al., 2016; Dhar et al., 2017; Kwakye et al., 2024; Suglo and Evans, 2020; Xie et al., 2020). The lack of emotional, financial, and physical support from family and significant others influences patients to be non-adherent to treatment. Poverty prevents access to medicines and healthcare. Even with insurance, poor patients encounter challenges with co-payments and insurance

premiums. Poverty influences patients to abandon orthodox medicines for traditional medicines and faith healers, which could increase their risk of DM complications. Some traditional medicines are not tested and approved by authorities and could be inefficacious and harmful. Usually, T2DM patients have developed unhealthy lifestyles over their lifetime and may have difficulty sustaining healthy lifestyles. Their household, friends and community culture often influence their lifestyle, making it easy to follow the dominant unhealthy lifestyle in their communities.

Logistics and finance-related factors

Financial barriers, combined with persistent medicine stock-outs and inadequate storage conditions, significantly hinder patients' ability to adhere to treatment and maintain healthy SMB (Abate et al., 2021; Dhar et al., 2017; Kwakye et al., 2024; Song and Lee, 2021; Suglo and Evans, 2020). Patients may not be able to afford medicines and care if they are uninsured or if such services/medicines are not covered by insurance. Generic brands of medicines, which are more affordable than original brands, are usually prescribed in Ghana's PH facilities, but the medicines are persistently out of stock in pharmacies and hospitals. DM medicines, particularly insulin, require storage under cold temperatures to protect their efficacy. However, this is not always possible due to Ghana's erratic power supply. Patients risk contaminated medicines under unfavourable temperatures. The high cost of travel to health facilities, sweeteners, glucometers, and testing strips associated with DM management discourages patients from adhering to treatment and recommended SMBs.

In sum, factors relating to patients, DM treatment, clinicians and the socio-cultural and economic environment influence SMB. Interventions targeted at these factors could influence healthy SMB and improve DM treatment outcomes.

3.3.3 The Relationship between Self-management Behaviour and Diabetes Outcomes

The SMB of people with chronic diseases has been studied at length. However, the main problem is how to improve SMB amidst the multidimensional and contextual factors influencing it. While some factors beyond patients' control influence SMBs, other influential factors are within patients' control. For example, reducing salt, saturated fats, and SSB consumption and increasing physical activity levels are largely within patients' control. In this section, we discuss patient-related factors and how they influence SMBs and DM treatment outcomes to improve understanding of the study context.

Socioeconomic factors to self-management behaviours (a)

Evidence suggests a positive association between socioeconomic characteristics, such as insurance, and SMB among patients in LMICs, including Ghana (Addo et al., 2018a; Afaya et al., 2020b; Peprah et al., 2022). As shown in Figure 3.3, improving health literacy and increasing insurance coverage improve medicine adherence and encourage healthy lifestyles. Insurance coverage influences attendance of outpatient appointments and medication adherence in Ghana (Addo et al., 2018b; Aryeetey et al., 2016).

The WHO defines health literacy as achieving a level of knowledge, personal skills, and confidence to take steps to improve one's own and the community's health by modifying one's lifestyle and living conditions (Dodson et al., 2015). It involves empowering people by improving their attitude, motivation, and ability to use health information and services. In Ghana, Amoah et al. (2017) used path analysis within structural equation modelling to analyse responses from 779 rural and urban residents in the Ashanti region regarding how social participation and health literacy affect health and well-being. The authors found that about 60% of the study participants had inadequate health literacy; health literacy is significantly associated with income, residence, education, and age. Health illiteracy has been associated with medicine non-adherence and readmission among DM patients in Ghana (Atinga et al., 2018).

Lifestyle modification is recommended for DM control. Healthy diets and regular moderate to high-intensity exercise increase insulin sensitivity, improving BGC (American Diabetes Association, 2024). As discussed in Chapter 2, very few Ghanaians engaged in regular physical activity. The prevalence of overweight and obesity in DM patients (46%) in Ghana is significantly higher than the national prevalence (43%), indicating poor physical activity engagement among DM patients (Ofori-Asenso et al., 2016). Mogre and colleagues (2020) found among 230 DM patients attending three DM clinics in Ghana that diet modification and physical activity are generally attitudinal and not a matter of cost or lack of knowledge. In sum, insurance increases patients' ability to afford DM care, and health literacy promotes healthy attitudes and lifestyles.

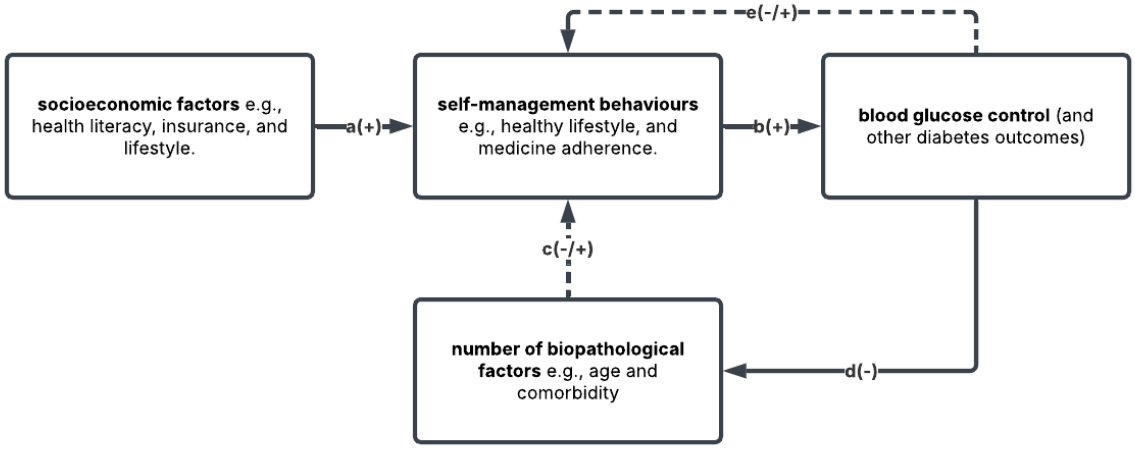


Figure 3.3 Association between patients-related factors and BGC outcomes (Author's own research, compiled from a literature review with references in Section 3.3.3).
Note: (+) means a positive association, improving the input variables (from the arrow) could lead to improvement in the output variables (to the arrow). (-) means a negative association, improving the input variables could lead to reducing the impact/incidence of the output variables. The dotted arrow means mixed evidence, could be positive or negative, on the association between variables.

Self-management behaviour to BGC and other DM outcomes (b)

SMB, especially lifestyle and medicine adherence, are known to have a positive linear association with BGC among T2DM (American Diabetes Association, 2024; Ministry of Health, 2023).

According to the American Diabetes Association (2024), there are multiple potential biological pathways for the therapeutic effect of SMB on BGC: 1) exercise improves insulin sensitivity, which in turn improves glucose metabolism; 2) before insulin therapy, adequate physical activity effectively delays DM progression by causing skeletal muscle contraction, which increases blood glucose absorption into body cells; 3) physical activity reduces intra-abdominal fat, which causes insulin resistance. The Association explained that excessive consumption of alcohol, high-calorie diet, and SSB increases the risk of T2DM and poor BGC outcomes. However, increased consumption of yoghurt, cheese, milk, fruits and vegetables improves DM control. Seeking care and attending clinical appointments allow clinicians to monitor treatment progress and provide timely interventions to reduce complications and discomfort associated with DM treatment.

Biopathological factors to self-management behaviours (c)

There is mixed evidence on the association between biopathological factors (e.g., age and co-morbidity) in patients on the one hand and SMB on the other hand. In Ghana, older patients were found to be more

likely to take medicines and adhere to dietary recommendations than younger ones (Afaya et al., 2020b). Older and co-morbid patients tend to be self-aware of their health and more adherent to treatment regimens, knowing that they are immuno-compromised. Co-morbidity and frailty in older DM patients and forgetfulness due to the busy schedules of the youth could explain the SMB of older and young patients (Peprah et al., 2022; Sefah et al., 2020). Frailty reduces the physical and emotional ability to engage in SMB, such as injecting insulin and exercising (Peprah et al., 2022). Ageing is reported to cause difficulty in remembering to take medication among chronic disease patients in Ghana (Addo et al., 2018b; Boima et al., 2015).

Biopathological factors (age/co-morbidity) and BGC and other DM outcomes (d)

Age and co-morbidity indirectly correlate with BGC and other DM outcomes. Specifically, ageing and co-morbidities compromise the body's insulin sensitivity and immune system, contributing to poor BGC and reduced recovery rate from acute complications (American Diabetes Association, 2024; Ministry of Health, 2023). The majority of T2DM patients in Ghana have co-morbidities such as hypertension, obesity, and hyperlipidaemia are common co-morbidities (Kazibwe et al., 2024; Peprah et al., 2022). Poorly managed co-morbidities considerably increase the risk of macrovascular and microvascular DM complications, including stroke, peripheral vascular disease, coronary artery disease, retinopathy, nephropathy, and neuropathy (American Diabetes Association, 2024).

Persistent poor BGC increases the risk of microvascular, macrovascular, and cardiovascular diseases in DM patients Zhou (American Diabetes Association, 2024; Ministry of Health, 2023). However, the opposite—having controlled DM reduces the incidence of acute complications and delays the progression of microvascular and macrovascular complications. Regarding age, BGC does not affect ageing because ageing is irreversible. However, the inverse (ageing affecting BGC) is possible.

BGC and other DM outcomes to self-management behaviours (e)

T2DM is usually asymptomatic in patients with good to moderate BGC. Consequently, such patients may have low perceived severity, forget to take medicines, or miss clinical review appointments (Berkoh et al., 2022; Bruce et al., 2015; Owiredua et al., 2018). The opposite could apply in patients with uncontrolled blood glucose. Persistent poor BGC leads to admission, which increases patients' perception of DM severity, encouraging them to adhere to recommended SMB (Atibila et al., 2022). Poor BGC could render patients physically weak, making it difficult for them to engage in physical activity, self-monitoring, and correct insulin injection.

In sum, DM patients' SMB largely influences BGC through various pathways and should be given considerable attention in DM intervention policies. Multiple factors affect patients' ability to maintain healthy SMB, some of which patients can modify when given adequate support.

3.4 Chapter Summary

This chapter has partly addressed DM interventions, which is part of Research Question 1: "*What is the state of DM service delivery in Ghana and DM interventions in Ghana and LMICs?"* We have outlined two broad categories of DM interventions: pharmacological and PH, focusing on PH interventions. Our review focused on the study design, the intervention's medium of delivery, the effectiveness of DM control and implementation challenges. The review on PH interventions has revealed key considerations when implementing interventions, such as the duration of the interventions, logistics, socio-cultural context and patients' behaviour. It also highlighted the application of SM methods for examining PH interventions, which we further explored in Research Question 3, presented in Chapter 4.

Furthermore, the chapter has also addressed key aspects of Research Question 2*: "How do patients' behaviour influence health service delivery and DM treatment outcomes?"* We have described patients' SMB using the HBM and TPB. We have outlined factors influencing patients' SMB, describing how these behaviours influence DM outcomes. The review has revealed common patient- and system-related factors influencing behaviour and, consequently, DM outcomes such as lifestyle, co-morbidity, insurance coverage and availability of medicines. The review evidenced the complexity and mutual influence of patients' SMBs and DM control, further underscoring the need for a comprehensive, systems-based approach to addressing the DM burden.

4 Simulation modelling of diabetes interventions in LMICs

4.1 Introduction

Having examined the complexities of DM interventions and patients' SMB in Chapter 3, it becomes clear that understanding and predicting the outcomes of various interventions is challenging because outcomes emerge from heterogeneous patients' interactions and their mutual influence on the service delivery system. Researchers have turned to SM to address this challenge and better inform policy decisions. Chapter 4 explores various SM approaches and their application to DM interventions in LMICs, providing a foundation for the methodological choices made in the thesis.

This chapter presents a systematic review addressing Research Question 3: *How have decision analytical modelling (DAM) methods been applied to evaluate DM interventions in LMICs?* We conducted the review at the initial stages of the overall research. Afterwards, we considered five decision analytical models commonly used in the health literature: SD, DES, Markov cohort models, microsimulation, and ABM, for their application to PH DM interventions in LMICs.

Section 4.2 was published as an additional file to the paper: Twumwaa, T. E., Justice, N., Robert, V. D. M., & Itamar, M. (2022). Application of decision analytical models to diabetes in low-and middle-income countries: a systematic review. BMC Health Services Research, 22(1), 1397.

Section 4.2.1 consists of the last two paragraphs of the Introduction section of the above-mentioned paper. Section 4.3.2 includes the methods and study selection section of the paper. Section 4.3.3 has been amended from the paper's discussion section to clarify the research gaps. Each gap is supported by evidence from relevant parts of the paper's results section. The summary (section 4.3.4) has been taken from the Conclusion section of the paper.

Given the importance of individual-level behaviour to the decision problem, we found ABM more appropriate than other SMs for modelling DM patients' treatment behaviour and treatment outcomes. The rationale for choosing ABM is further elaborated in Chapter 6. This chapter focuses on the application of the aforementioned DAMs for modelling DM treatment behaviour and interventions among populations in LMICs. We only included sections of the paper above-mentioned above that are relevant to the thesis. The chapter begins with an overview of modelling approaches, highlighting the

differences among the models to improve understanding of the appropriateness of each approach for representing patient treatment behaviour. It then follows with a systematic review focusing on how the overviewed SM approaches have been combined with economic evaluation methodologies to study PH intervention studies in LMICs. The chapter concludes by identifying and discussing the gaps in the literature regarding SM applications that are relevant to this research.

4.2 Overview of Simulation Models in Health Service Research

SMs are built to represent decision problems, considering decision variables, objectives, constraints, and uncertainties. They provide a systematic approach to analysing decision scenarios, enabling decision-makers to better understand the potential outcome of alternatives. Researchers and decision-makers can study "what-if" scenarios and evaluate the effects of various policies on system behaviour using SM, avoiding potential risks and costs associated with real-world experiments (Almagooshi, 2015). In the subsequent paragraphs, we reviewed commonly applied SM approaches in the health literature to provide an understanding of when and where these approaches are suitable for exploring decision problems. Table 4 summarises the key characteristics of the SM approaches reviewed in the subsequent paragraphs.

These modelling approaches are particularly relevant to our research questions outlined in Chapter 1. Specifically, they are relevant to Research Question 3: *"How have decision analytical modelling (DAM) approaches been applied to evaluate DM interventions in LMICs*?" Understanding these different modelling techniques provides a foundation for answering this question. Moreover, these approaches will inform our method selection for addressing Research Question 4: *"What are the health and economic benefits of selected PH interventions to patients and the government?*" By understanding the strengths and limitations of each approach, we can select the most appropriate method for modelling DM interventions in the Ghanaian context.

4.2.1 Markov Models

Markov cohort model, Monte Carlo, and fundamental matrix are examples of different Markov modelling approaches (Boucherie and Van Dijk, 2017; Briggs et al., 2006; Briggs and Sculpher, 1998). Monte Carlo uses probabilities and random numbers to simulate the pathway for several people starting at a particular state. In a fundamental matrix, transition probabilities and utilities/costs associated with all states remain constant; hence, the expected utility/cost can be calculated with a matrix (1). This review focused on Markov cohort models, as they are commonly used in healthcare decision analysis. Markov cohort models represent the pathway of an average person from a population with similar

characteristics rather than representing individual-level variability. Probabilities are assigned to events or to the proportion of the modelled cohort expected to experience those events, in order to simulate transitions between states. The consequences of being in a state, called utilities or cost, are assigned to each state. Time is modelled in cycles—equal time intervals accumulating to the overall time horizon considered for analysis. At initialisation, the hypothetical population is distributed among starting glucose control states: good, moderate, and poor. During the simulation, individuals in a particular state are divided into other states by transition probabilities, resulting in a new distribution for the next cycle. The assumption of a "memoryless" property, meaning that transition to another state is independent of the previous states, restricts their application, as this would oversimplify BGC states where progression to another state is dependent on the previous state.

4.2.2 System Dynamic Simulation

SD uses systems processes and feedback loops to investigate complex interactions and their effect of structure, policies, and time delays on organisational success (Bala, 2017; Sterman, 2001). SD is a top-down approach to analysing complex systems through buildups and feedback, usually displayed in causal loop diagrams, to determine system structure and behaviour. In a top-down approach, the behaviour of a group of entities is assumed from the onset and modelled 'as a whole' whereas in a bottom-up approach, group behaviour emerges from the interactions of individual entities. A causal loop diagram (collection of a system's feedback loops) is a visual representation of system structure and a qualitative assessment of system behaviour. Causal loops are transformed into stock-flow diagrams to quantitatively determine the net effect of feedback loops on system behaviour. Stocks (buildups of flow rates due to differences in inflows and outflows) and flows (quantities added or subtracted from stock) are the building blocks that describe a system's state at a time. SD assumes continuous variables and models time continuously.

4.2.3 Discrete-event Simulation

DES focuses on changes in a system's state triggered by the succession of distinct events over time (Baril et al., 2019; Fishman, 2013; Ullrich and Lückerath, 2017). Thus, DES is built on queues/queueing systems. Entities are static or dynamic objects, explicitly defined and managed through process listing—allocating them to resources that perform activities or provide services. DES comprises these concepts: work items, resources, routing, buffer, scheduling, sequencing, and performance. *Work items* represent individuals/items who enter the modelled system to seek services, such as DM patients (work items) accessing outpatient care (services/activities). *Resources* are materials or human resources required for producing services. In the case of the preceding example, healthcare providers and medical

equipment are resources. Healthcare resources are required for each DM patient (work item) seeking service(s), and services are delivered in order. The collection of services and the ordering of their performance is termed routing. A *buffer* is a finite or infinite list of works pending services. *Scheduling* describes patterns of resource availability, such as the number of doctors on a rota per month. When a queue/waiting list is infinite, sequencing describes how limited resources provide services, using rules such as 'first-come-first-serve' and elderly persons first. DES can model open- or closed-loop systems. Work emanates from outside the system in open-loop systems, and their arrival time is unknown and uncontrolled by the modelled system. The opposite is true for closed-loop systems.

4.2.4 Microsimulation Modeling

Microsimulation models operate from an individual level using a bottom-up approach. Microsimulation modelling (MSM) is like Agent-Based Modelling (ABM) in that both techniques use a bottom-up approach to model interactions and simulate transitions between states (Bae et al., 2016; Figari et al., 2015). When MSM is run, individual entities are run through mechanistic processes such as a DM progression pathway. Entities in MSM and ABM can be heterogeneous with distinct characteristics, and in both modelling approaches, individual entities can interact (Bae et al., 2016). MSM can represent entities' behaviour by abstracting from a pool of behaviour, but the entities themselves cannot make autonomous decisions. In DM studies using microsimulation, individual patients could have attributes such as body mass index, prescriptions, age, and BGC state. However, microsimulation does not represent how the individual patient decides to take medicines, interacts with health facilities (decision to seek care and how seeking care influences blood glucose), adapts and changes behaviour following acute blood glucose complications, and how these interactions and behaviours contribute to emerging cohort-level behaviours/outcomes.

4.2.5 Agent-Based Modeling

ABM is a bottom-up modelling approach characterised by system behaviour and patterns emerging from interactive and autonomous agents' decisions. Typically, an ABM system consists of the environment, agents, and interactions among agents and between agents and the environment (Macal, 2016). Agents can be single or grouped autonomous and heterogeneous entities whose behaviours are defined by rules and commands. Thus, ABM can abstract reality from the micro-, mezzo-, or macro-level, depending on the study problem. Transitions between states are modelled from a bottom-up approach using rules, inferences, and probabilities (Macal, 2016). Unlike MSM, where aggregation of individual characteristics amounts to population characteristics, individual-level attributes may not sum

up to an ABM's population/system-level features since some characteristics/behaviours emerge from non-linear interactions between autonomous agents and entities.

There are currently diverse views on the definition of ABM and no clear distinction between MSM and ABM in the modelling literature. There is consensus that both approaches model bottom-up, micro-level, and multiple agents. However, it is unclear how both approaches differ in features and capabilities. Macal (2016) identifies four definitions of ABM. Briefly and in no order: definition 1) emphasises individual agents with different characteristics, 2) autonomous individual agents who can react to environmental stimuli, 3) individual agents can interact among themselves and with their environment, and 4) autonomous and interactive individual agents learn and adapt to changes in their environment during simulation.

Table 4.1 Characteristics of selected simulation models applied in DM intervention studies (Author's own research, compiled from a non-systematic literature review with references in section 4.2).

Distinguishing features	**Markov Cohort models**	**SD**	**DES**	**Micro-simulation**	**ABM**
Elements of system structure	Decision nodes, chance nodes, pathways	Stocks and flows	Work, resources, route	Entities and environment	Entities and environment
Nature of system structure	Fixed over time	Fixed over time	Fixed over time	Changes with time	Changes with time
Modelling perspective/ approach	Macro-level; uses details of a group average	Macro-level; does not model micro-level details	Micro-level: passive entities move through a queueing system	Micro, meso or macro-level: passive entities	Micro, meso or macro-level; autonomous entities.
Entities	Homogeneous (group average)	Homogeneous	Homogeneous	Heterogeneous	Heterogeneous
How time is usually modelled	Discrete	Continuous	Discrete	Discrete	Discrete
How experiments are usually performed	Experiment by changing transition probabilities	Experiment by changing flows	Experiment by changing processes, e.g., schedules, and work-route	Experiment by changing. entities' environment, e.g., key model parameters and input data	Experiment by changing agents' behaviour rules
What causes changes in the system behaviour	Transition probabilities	Feedback loops	Delays and the occurrence of sudden events	Interactions and individual traits	Interactions and agents' traits and behaviour

4.2.6 Hybrid Simulation Designs

Hybrid models combine multiple modelling methods to describe complex systems. For example, combining ABM and SD gives both a bottom-up and top-down paradigm for simulating complex adaptive systems. Morgan et al. (2017) and Swinerd and Mcnaught (2015) proposed mixed method designs for hybridising DES and SD in particular (Table 4.2) but could be used to combine other models.

Table 4.2 Hybrid model designs (Compiled from Swinerd and Mcnaught, 2015 and Morgan et al., 2017).

Swinerd and Mcnaught hybrid model design	Model Description/Explanation	Morgan et al. hybrid model designs
Integrated	There is a base model, and elements of a second model are used to enrich the base model. The model is built as a single unit, and the problem dictates the need to incorporate elements of a second model. With this description, Swinerd and Naught identify two forms of SD and ABM hybrid model designs: 1. Rich internally structured agent: SD model built within an ABM agent. 2. Stock agent: a component in SD is used to influence an aggregate parameter in ABM.	Enrichment
	Elements from two or more modelling approaches are combined to form a new model. Interaction between the two models occurs at a fixed time step.	Integration
Interfaced	Two or more modelling approaches from different paradigms are combined while relaxing paradigm restrictions. For instance, an ABM aggregate measure is used to influence parameter(s) in SD.	Interaction
Sequential	A first modelling approach informs a second modelling approach; these approaches complement each other. Both models run separately, exchanging information in consecutive runs.	Sequential
	Multiple modelling approaches produce two potential representations of the same system, allowing for comparison.	Parallel

Note: Model descriptions/explanations match the designs on the left (Swinerd and Mcnaught's) and right (Morgan et al.'s). Enrichment and integration designs by Morgan et al. constitute Swinerd and Mcnaught's Integrated design. Morgan et al.'s parallel design does not correspond to Swinerd and Mcnaught's hybrid designs.

4.3 Application of decision analytical models to diabetes in LMICs.

The previous section has provided an overview of SM approaches commonly applied in health service research, highlighting when and where they are appropriate for representing decision problems and systems. With this understanding of the SM approaches, we present a systematic review investigating how they have been applied to explore DM interventions in LMICs in the next section. The review will further improve our understanding of the context, challenges, and gaps in implementing the methods.

4.3.1 Introduction

Decision analytical models (DAMs) overcome these challenges by using mathematical and logical relationships to abstract real-world phenomena for investigation. DAMs are most useful when there is a lack of data due to a rare event, legal circumstances, time constraints, or technical, ethical, and financial challenges that prevent real-life studies. LMICs can benefit from their use to prioritise interventions and policies as they enable comparatively cheap, convenient, and risk-free experiments that are impossible in reality (Briggs et al., 2006). DAMs can offer an opportunity to perform "what-if" scenarios to predict and explore PH DM interventions in LMICs before these interventions are implemented, saving policymakers the cost and time that would have been invested in trial and error.

Despite the benefits of DAMs, their application to DM in LMICs is limited. Most DAMs for T2DM are built among high-income populations and then generalised to LMICs, which could be misleading considering that the differences in culture, ethnicity, and health system capacities influence DM control. For instance, DM develops ten years earlier and at a lower body weight in Africans and Asians than in Europeans (Spanakis and Golden, 2013). There is a need to consolidate the literature on DAM applications, particularly their methodology, to DM in LMICs to identify gaps in their adoption and advance their use.

Whereas studies have appraised the application of DAMs to study DM interventions (Dadwani and Laiteerapong, 2020; Gillett et al., 2012; Mukonda et al., 2021; Watson et al., 2014; Yi et al., 2010), few have focused on PH DM interventions in LMICs. This study adds to this research. Mukonda and colleagues' review of computer simulation models for T2DM in LMICs, like our present study, reports on model-based economic evaluations to support decisions in T2DM care to assess their quality and validity. However, unlike Mukonda and colleagues, we focus on DAMs for PH interventions and consider both T1DM and T2DM. Therefore, we conducted a systematic review focused on five types of DAMs: systems dynamics, agent-based models, microsimulations, DES and Markov models, hereafter referred to as DAMs, to 1) investigate how DAMs have been applied to examine PH policy

interventions in LMICs, 2) assess what gaps exist in the modelling procedures according to the Consolidated Health Economic Evaluation Reporting Standards (CHEERS) checklist, and 3) determine how to advance their adoption for DM research in LMICs. The next section briefly summarises the approach to the systematic review and the identified research gaps.

4.3.2 Methods of Conducting the Systematic Review

Methods

We qualitatively reviewed peer-reviewed articles that examine DAMs of the natural progressions of T1DM and T2DM and assess the effect of PH interventions on these populations. The qualitative review was designed and presented using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009).

Information sources and search strategies

A combination of search terms for DM and the four modelling approaches (indicated below) was used to search titles and abstracts of papers in PubMed and Cochrane databases from inception to 8th August 2022. The search was limited to peer-reviewed articles published in English. The researcher (ETA) conducted the search and removed duplicate papers. Two researchers (ETA and Dr. Nurnabi Sheikh) screened abstracts of 60 papers (Figure 4.1), each researcher independently screened 30 papers. A disagreement on one paper (i.e., Mash et al., 2015) was resolved through discussions with one of the study supervisors, Professor Robert Van Der Meer. The paper was excluded because a diabetes education programme, the intervention, was assessed in clustered RCTs, while the microsimulation model focused only on estimating the cost-effectiveness of the intervention.

> (((diabetes) OR (type 1) OR (type 2) OR (NIDDM) OR (IDDM) OR (DM)) AND ((Diabetes Mellitus [MeSH Terms]))) AND ("agent-based" OR "system dynamic" OR "discrete event" OR "microsimulation" OR "Markov model")

Eligibility criteria

Table 4.3 summarises the inclusion criteria applied. We included studies that met the following criteria: 1) use any of the four DAMs, 2) examine PH interventions among persons living with T1DM or T2DM or at risk of T2DM (as defined in the papers), and 3) conduct the study in an LMICs population per World Bank 2020 classification or initialise the modelled population with data from LMICs.

Exclusion criteria

Studies were excluded where 1) DM control was secondary to a primary disease/medical condition, e.g., preventing DM in people with schizophrenia, because in such studies, the model was designed with a particular focus on the primary disease and 2) they focus on pharmaceutical interventions and the pathological disposition of DM. Studies were excluded if the epidemiological data—DM prevalence, obesity and blood glucose distribution—used to initialise the modelled population originated from developed countries. DM prevalence and risk are higher in most developed countries; therefore, using data from such countries would likely misrepresent the disease burden in LMICs. All qualitative studies, literature reviews, abstracts only, non-English language papers, and methodological papers were excluded. For instance, we excluded Kazemian et al.'s study (2019) titled "Development and validation of PREDICT-DM: a new microsimulation model to project and evaluate complications and treatment of type 2 diabetes mellitus" because the paper focused on the design, development and validation of the model for the United States population.

Table 4.3 Inclusion and exclusion criteria applied in the study (Adopted from Twumwaa et al., 2022).

Parameter	**Inclusion criteria**	**Exclusion criteria**
Population	T1DM and T2DM patients LMICs.	Gestational DM, non-diabetics DM is secondary to a primary condition, e.g., DM in schizophrenia patients.
Intervention	DAMs that examine PH population-based DM interventions for T1DM and T2DM	Medicine, medical technology, and medical procedure-related interventions. Adopts an existing developed model.
Study design	Markov, microsimulation, system dynamics, discrete-event, agent-based modelling studies with a component of economic evaluation: benefit, cost or cost-effectiveness analysis.	
Evidence / Time frame	Peer-reviewed articles Published in English From inception to 8th August 2022.	Models that examine or advance methodological approaches

Note: LMICs = low- and middle-income countries; DAMs = decision analytical models

Data Collection Process

We used a data extraction tool containing relevant information from the methods section of the CHEERS checklist (Husereau et al., 2013) needed to answer the research question to collect data from selected articles. The checklist is recommended to standardise and improve the reporting of economic evaluations of health interventions; it provides guidelines for model-based economic evaluation. We then summarised data under categories using NVivo 12.0 and presented the summary in Excel.

Data Items

Pieces of information were extracted from the selected articles and organised under themes to answer the study questions. We collected and organised data under five themes: "study details", which included data items such as author(s), title, publication date and place; "DM details", consisting of the following data items: the type and DM state modelled, interventions and outcomes reported. "Model design" included model choice, parameterisation, and calibration, uncertainty analysis and validation. "Limitations" gathered information on study limitations reported in reviewed publications, and "economic evaluation" gathered details on the type of evaluation conducted, perspective adopted, interventions assessed, and outcomes reported.

Study selection

Figure 4.1 highlights the process of article identification, screening, and selection. Our initial search resulted in 811 articles, and no relevant article was retrieved from searching the reference list of selected articles. Overall, we screened the full text of 23 studies and then included 17 studies in the qualitative review. Details of the included studies are in Appendix A.

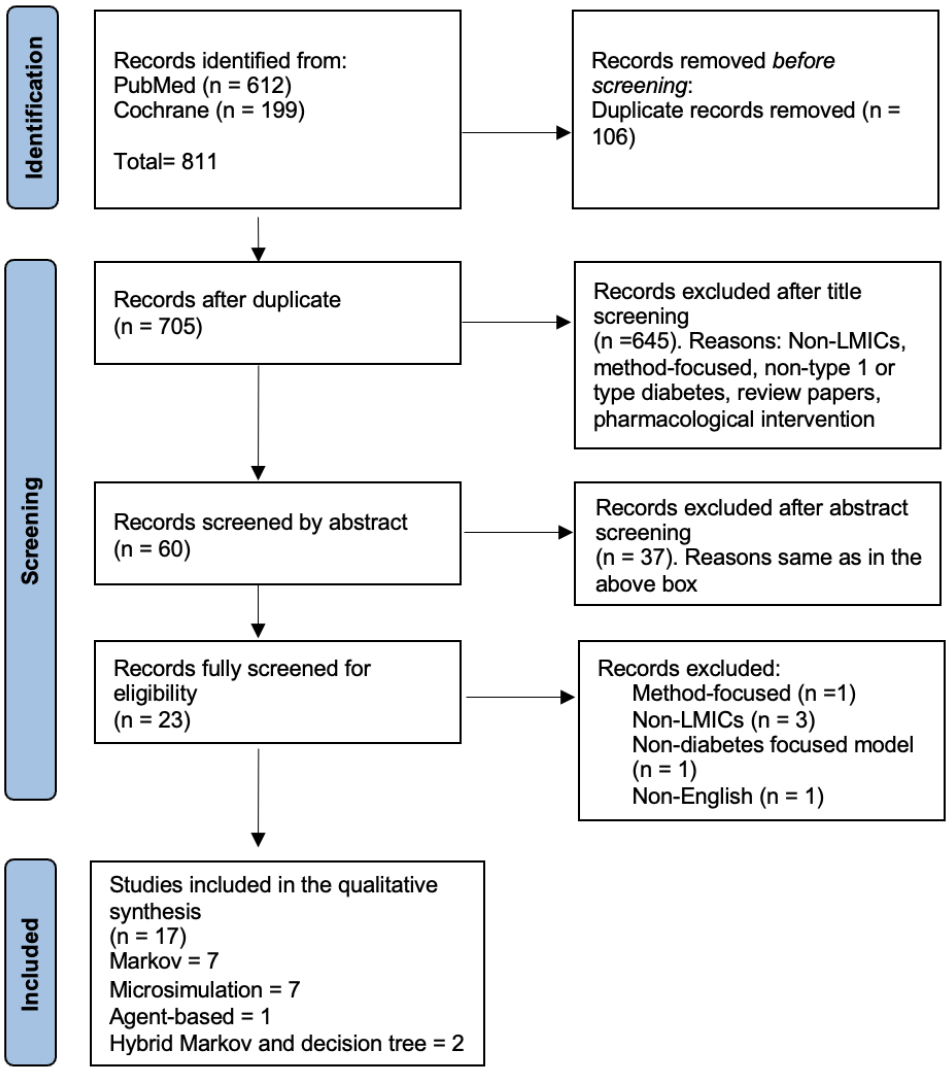


Figure 4.1 Article selection process (Adopted from Twumwaa et al., 2022).

Additional literature search

In addition to the literature available in PubMed and Cochrane (the results of which have already been published), we searched the African Journals Online, EMBASE, and AfricArXiv databases. Using the same search terms, ETA restricted the search to journal articles from their inception until August 2022—matching the cutoff date used in the published results—to ensure consistency. ETA screened the titles and abstracts of the search results. The table below presents the findings. Three studies were eligible for inclusion in the qualitative synthesis; however, they had already been identified and included in the qualitative synthesis of the published paper.

Table 4.4 Results for additional database searches

Database	Number of papers identified	Number included in abstract screening	Number of papers included in quatitative synthesis
African Journal Online	1	1	0
EMBASE	1195	45	3 eligible studies: Feldhaus et al, 2021; Kaur et al., 2022; Wang et al 2019 but had already been included in the systematic review
AfricArXiv	31	31	0

4.3.3 Gaps in Research Identified from the Systematic Review

The systematic review identified multiple research gaps. First, most studies were conducted in Asian sub-populations, particularly China and India (12 studies, 71%); only a few modelled DM interventions in the African population, including Ghana, where the burden is increasing at a higher rate than other LMICs. Appendix A details studies included in the review. These studies mentioned limitations with data as a challenge to modelling, which could explain why there are few modelling studies in Africa. The dearth of studies exclusively from Africa somewhat indicates the scarcity of DAMs in research in the region. Health data may be unavailable or scattered across different sources and forms that are not readily usable in a model, requiring modellers to combine or transform available data through mathematical methods to estimate and calibrate model parameters.

The reviewed studies obtained data to parameterise models from plausible assumptions, previous simulation studies, published cohort studies and data recorded in clinical trials, national surveys, and registers. Healthcare data sources exist in Africa; however, the levels of detail and quality are often insufficient. Except for one study (Chao et al., 2014), which used primary data from a DM prevention programme, all studies reported that local epidemiological and clinical data (e.g., DM state transition probabilities and risk equations) and cost data were mostly unavailable, unreliable or insufficient for modelling purposes, leading them to use data from international studies. Consequently, confidence in the validity of outcomes/results from models using such data sources could be questioned. The situation is daunting, given the expected escalation of the DM burden, and it highlights the need for more data collection/generation structures on the continent. Although the outcomes of models built for Asian populations could be generalised to African populations, the approach could be misleading, considering that the differences in culture, ethnicity, and health system capacities influence DM control.

In the absence of sufficient and quality data in LMICs, especially in Africa, calibration techniques are used to adjust the parameters of existing models to reflect different population characteristics. The objective of (re)calibration is to enhance the representativeness or predictability of a model that otherwise might under- or over-estimate model outputs. Calibration approaches reported in the reviewed studies include Markov Chain Monte Carlo —a standard Bayesian posterior computation approach (Robert et al., 2018) and adjusting the Risk Equations for Complications of Type 2 Diabetes (RECODe) with local data. RECODe was specifically designed for Americans; however, the equation can be adjusted with local data to represent context-specific epidemiology. The International Society for Pharmacoeconomics and Outcomes Research also produced protocols for adapting a validated model to a specific context/population (Daniel Mullins et al., 2014). During such an adaptation process, it is essential that baseline characteristics of the modelled cohort are adjusted to reflect local epidemiological data and possibly the transition probabilities between states. Also crucial for the adaptation are context-specific cost, health state preferences, and utility data. The requirement of context-specific data brings us back to the challenge of reliable/robust DM data in LMICs and how the situation limits the application of DAMs for DM in the region. Modellers could obtain model data from various sources: ongoing clinical trials or existing data through systematic review and meta-analysis, routine data collection, expert opinion, and observational studies. Among these data sources, researchers have suggested using data from observational studies in LMICs compared to RCTs despite concerns about selection bias affecting data quality (Baik et al., 2010). As a result, observational studies, which are easier to conduct in LMICs, could fill in the data gaps required to implement DAMs.

Second, despite the increasing application of SM, particularly Markov cohort models and microsimulations, in this field, their use is still ad hoc and rarely explicitly documented in published studies. Few of the reviewed studies included an explicit statement explaining the reason for choosing one modelling method over the others to answer their research questions. The choice of SM method should be based on the research problem/system to be modelled, the research objective and data availability. Three studies mentioned that the benefit of microsimulation over Markov models was mainly to represent complex relationships, individual-level dynamics, and histories (Basu et al., 2015; Sanjay Basu et al., 2016; Basu et al., 2019). One study (Luo et al., 2019) that investigated how individual-level factors influence PH outcomes found ABM beneficial in capturing interactions and feedback between individual-level behaviour and population-level parameters. The assumption of a "memoryless" property, meaning that transition to another state is independent of the previous states, is a fundamental characteristic of Markov modelling but also a drawback (Briggs et al., 2006) as this would be a simplification for DM where progression to another DM state is dependent on the previous state. Given the substantial patient variability and interconnected risk in DM, complexity is almost unavoidable (Yi et al., 2010). Another challenge with using Markov cohort models in a CEA is the likelihood of skewed estimates of the incremental cost-effectiveness ratio resulting from "uncaptured"

patient heterogeneity (Willis et al., 2013). Unlike Markov cohort models, microsimulation models individual characteristics through time, thereby representing patient variability and overcoming the Markov assumption. Individual-level characteristics can affect how they move through the model and can also be utilised to modify the likelihood of future occurrences. Microsimulation allows modellers to assign the risk of events, considering a patient's unique demographic characteristics, risk factors, and event history. Microsimulation is not constrained to "mutually exclusive" health states, as is the case with Markov-based models. However, the challenge with microsimulation compared with a Markov cohort model is the heavy computation and data required (Yi et al., 2010).

In addition to data challenges, currently, LMICs lack the technical capacity to build heavy computational models. Collaborations between international and local academic and research institutions could help increase modelling expertise in LMICs. Knowledge exchange initiatives can build capacity in LMICs to advance DAMs. An example is the Mount Hood Diabetes Challenge Network (Palmer et al., 2018), which facilitates the sharing of ideas and skills among DM simulation modellers through workshops, hackathons, and conferences. Modellers could be encouraged to document the rationale for using specific modelling approaches, which would inform researchers in the field about the different applications of each approach. Also, a comprehensive framework for selecting modelling approaches could be developed for future research.

Last, few studies reported on how their models were validated despite model validation improving models' fitness for purpose, especially when adapting parameters or existing models developed from other populations. More than half of the reviewed studies (11 studies, 45%) did not report model validation procedures, and few discussed how applicable their model was in other LMICs, which could reduce confidence in models and their outcomes. Validation involves comparing model components, such as structure, input, outcome, and assumptions, with reality to increase confidence in the model outcomes. Validation techniques include face validation (expert assessment of model behaviour and processes), internal/verification (check coding accuracy), cross (compare model outputs with outputs of similar models), external (compare model output with actual data), and predictive validity (compare model output with prospectively observed data). Multiple techniques can be used to increase confidence in models. Four of the six reviewed studies that reported validating their models conducted external validity using historical data from national surveys and literature reviews (Abu-Rmeileh et al., 2013; Basu et al., 2015, 2014; Ben et al., 2020). The remaining two studies (Javanbakht et al., 2018; Luo et al., 2019) combined all four validation techniques: 1) face validation through expert consultation, 2) internal validity through sensitivity analysis and manually checking codes for errors, 3) cross-validation via comparing model outputs to outputs of similar published models, and 4) external validation using actual data from national/international surveys and registers. Some reviewed studies used data from the United Kingdom Prospective Diabetes Study (UKPDS) Outcomes Model and RECODe to estimate

transition probabilities and risk equations for predicting DM complications. It is worth noting that both were developed for the United Kingdom and United States populations, respectively. Even though these models had undergone external validation, it is unclear if they had also been validated for the LMIC populations of interest. Tarride and colleagues (Tarride et al., 2010) identified some drawbacks to using UKPDS data: 1) the majority of UKPDS participants were of European descent, and considering that DM progresses differently in different ethnic groups, there is a challenge with generalising data to varied ethnic groups; 2) Technology and treatment regimens have advanced since the study was conducted (1977–1997). Such developments, including new medicines and disease incidence, could affect the transition between DM states, affecting the model's applicability; and 3) Differences in culture, lifestyle, demographics, health systems, and available health technology mean that the rate of DM progression in a United Kingdom population is different from LMIC populations, affecting the application of the model to LMICs. These issues highlight the need for extensive model validation and reporting on the validation process to increase model representativeness, transparency, and confidence in model processes and outcomes, consequently increasing model adoption.

4.3.4 Summary of the systematic review

DAMs have been increasingly applied in LMICs to evaluate interventions to control DM, which may contribute to better decision-making about the best use of limited resources and improving patient outcomes. However, there is a need to advance the use of DAMs to evaluate PH DM policy interventions in LMICs, particularly DAMs that use local research data, because 1) such models are a good representation of DM burden in LMICs, and 2) they could be effective at estimating intervention effects on the local population. Additionally, given that data limitation is a major concern in model-based assessments, especially in non-Asian LMICs, clinical and observational research on DM is undoubtedly necessary. Finally, reporting input data, calibration, and validation that underlie DAMs of DM in LMICs needs to be more transparent and credible.

4.4 Application of Economic Evaluation Methods to DM interventions in Ghana

We searched the literature for the application of economic evaluation methods to DM interventions in Ghana. The aim was to 1) identify the application of the methods to inform our analysis, 2) the scope of evidence on the economic efficiency of PH interventions for DM, and 3) to update our literature review of DAM but with a focus on Ghana.

We searched the health literature for studies conducted among residents of Ghana. We searched the Web of Science (all Databases) for literature until 17th September 2024 that contained the terms (Ghana) AND (diabetes) AND (cost) in the abstract. We found 38 studies: one duplicate, two protocols, and 13 that were not focused on Ghana or DM. Among the remaining 22, only three were cost-of-illness studies on DM management (Amon et al., 2024; Pei, 2015; Quaye et al., 2015).

Four studies were literature reviews on DM burden, policy and programme (Aikins et al., 2010; de-Graft Aikins et al., 2012; Kazibwe et al., 2024; Ofori-Asenso et al., 2016). Fifteen studies used interviews and surveys to investigate adherence and service delivery pathways and outcomes (Adinortey et al., 2019; Effah Nyarko et al., 2019; Eghan et al., 2009; Salifu and Hlongwana, 2020; Tagoe et al., 2023; Wilson et al., 2024; Yorke et al., 2023) and DM burden, patients' experience, quality of life and coping strategies (Ababio et al., 2017; Abdulai et al., 2022; Aikins, 2005; Amin et al., 2023; Berkoh et al., 2022; Korsah, 2015, 2010; Kratzer, 2012).

Of the three cost-of-illness studies, Quaye examined direct medical costs, service costs and the financial protection that NHIS offered households. Pei examined direct and indirect medical costs. There have been considerable changes to Ghana's economy, including the rising cost of living, medicines, and utilities, between 2015 when Quaye (data collected in 2009) and Pei published their studies, implying that their results may not represent the present burden. Amon et al. (2024) collected self-reported cost data from T2DM patients in 2022. None of the three studies provided evidence of health outcomes associated with the cost estimates, and neither did they compare interventions.

Our findings from the Ghana-specific literature indicates a paucity of studies comparing the health and economic outcomes of DM interventions in Ghana. Evaluating the cost and health efficiency of PH interventions could inform the government of the additional costs they are likely to bear should they implement PH interventions, giving them evidence to support decision-making on resource allocation.

4.5 Chapter conclusion

This chapter has addressed Research Question 3: "*How have decision analytical modelling been applied to evaluate DM interventions in LMICs?"* We have provided an overview of common SM approaches applied in PH intervention studies: Markov Models, SD, DES, Microsimulation, ABM, and hybrid models, focusing on when and where these approaches are suitable for exploring decision problems. The review revealed that ABM is an appropriate approach for representing the heterogeneity and complex SMB at the individual patient level.

Furthermore, we have presented a systematic review of how DAMs have been applied to DM PH interventions in LMICs. The review has highlighted the paucity of DAM applications in African countries, including Ghana, and identified key methodological gaps: insufficient and quality data as well as poor documentation and reporting of DAM methodologies. These findings set the stage for investigating an appropriate modelling approach for representing the system of DM treatment in Ghana, as outlined in Research Question 4, and describing the overall research approach and methodologies used in this thesis, presented in Chapter 5.

5 Research Design

5.1 Introduction

The chapter describes the research design, which includes the general plan of how we went about answering the research questions, the sources of data and how the data was collected and analysed, as well as ethical issues encountered. The chapter begins with a description of the research problem, where we rationalise the appropriateness of critical realism for the study's nature and context, highlighting the study's ontology, epistemology, and axiology stance. The chapter discusses the research methodology used to address the research questions. We provide reasons for choosing a mixed-method approach to address the research questions and explain how evidence from each method within the thesis is combined to achieve the overall research aim. The chapter concludes by presenting the research plan, ethical considerations, and a note on ethics approval.

5.2 Philosophical Assumptions

Research is a systematic exploration through experimentation and theoretical investigation to gain new insights and knowledge about various aspects of human beings, culture, and society (Saunders et al., 2019). Throughout the research process, scholars rely on different epistemological assumptions about the limits of knowledge, ontological assumptions about the fundamental nature of reality, and axiological assumptions about the researcher's values and how they influence the research process (Burrell and Morgan, 2017). Adopting a coherent research design and philosophy provides direction, maintains consistency, and improves the validity of the research; it guides result interpretation and helps address values and ethical considerations in the research (Saunders et al., 2019). Consequently, we adopted a thought-through and consistent set of assumptions to design and guide the research, ensuring coherency.

5.2.1 Critical Realist Perspective

A paradigm serves as a framework that guides the entire research process–a lens through which researchers view and interpret the world, helping them understand and investigate complex phenomena. It encompasses the researcher's worldview, assumptions, beliefs, and methodologies, collectively shaping the inquiry approach. Primarily, the research paradigm represents a set of fundamental assumptions about the nature of reality (ontology) and the way knowledge is acquired (epistemology). These assumptions lay the groundwork for selecting research methods, data collection techniques, and

data analysis strategies. Three main research paradigms are commonly recognised in PH research: positivism, interpretivism, and critical theory. Each paradigm offers a distinct philosophical stance and approach to conducting research.

Positivism remains the dominant paradigm in PH research despite numerous academic criticisms. The paradigm is rooted in the natural sciences and assumes, on ontological grounds, that reality is objective and can be observed and measured. It emphasises quantitative data collection methods and seeks to uncover universal laws governing human behaviour. Regarding epistemology, positivist researchers are assumed to be independent of the research they conduct and cannot influence or be influenced by their studies. Randomisation and blinding are adopted to ensure a sense of objectivity. Although positivism considers social context, it tends to convert social variables into measurable physical terms (Park et al., 2020), such as how age, income status, and sex affect medicine adherence.

Interpretivism, on the other hand, asserts that reality is subjective and socially constructed. It recognises the importance of individual experiences, meanings, and social contexts. Interpretivist researchers adopt qualitative methods to explore the richness and complexity of human behaviour. They emphasise in-depth interviews, participant observation, and content analysis to capture research participants' nuances and diverse perspectives, thereby generating detailed, context-specific understandings rather than generalisable theories.

Numerous questions about healthcare and health services are inconsistent with the positivist paradigm. The disparity between the primarily mechanical notion of healthcare and the complex social aspect of healthcare continues to impede innovation in healthcare and health service delivery studies. The lived experiences, perceptions, and beliefs, which are subjective and anchored in specific historical and social contexts, are insufficiently addressed by the positivist paradigm (Park et al., 2020; Saunders et al., 2019). Adding an interpretivist point of view to positivism could provide a thorough picture of the complicated system of DM treatment/care. However, the two paradigms are incommensurable due to their divergent ontology, and a researcher cannot be both a positivist and an interpretivist simultaneously. To address the conflict between positivism and interpretivism, researchers must embrace a different philosophical perspective, using different research procedures to help make sense of this complexity.

We adopted a critical realism philosophical paradigm for this research. Critical realism sits within the postmodernism and poststructuralism philosophical paradigms. The paradigm asserts that knowing should be premised on an appreciation of the relationships between social structures, language, power, and subjectivity and should be focused on the taken-for-granted processes of truth and the emergence of dynamic patterns across space and time (Hartwig, 2015).

Critical realists embrace a stratified ontology—a view of how reality is constructed—which consists of a domain of the actual, the real and the empirical. Archer et al. (2013) argue that in an experiment, the scientist manipulates the order of events but not the causal laws that the ordered events help uncover. This argument implies that natural laws /causal mechanisms work independently of the patterns of events and that these laws emerge under certain conditions. Archer et al. further argue that it is because of actual events (the actual realm) and our experience of such events (the empirical realm) that social inquiries are conducted, and only because of natural mechanisms (the real) that we make sense of the outcomes of social inquiries.

In this thesis, the domain of the actual constitutes the current system of DM management in Ghana. The domain of the real consists of unquestioned, implicit, taken-for-granted causal mechanisms, such as how living in a rural community could influence acute DM that manifests in the actual realm. The empirical domain is how we experience reality and perceive phenomena, such as how people's experiences of high treatment costs affect treatment outcomes. These experiences and perceptions often differ from what occurs in reality (domain of the actual). Unravelling the domain of the real, which Bhaskar called generative mechanisms, will provide insights for designing interventions to change what happens and people's experience of them (Archer et al., 2013; Hartwig, 2015)

Critical realists believe in a fundamental difference between ontology (the nature of being) and epistemology (knowledge of being). Thus, ontology must not be reduced to epistemology (Hartwig, 2015). Knowing is often made possible through generative causality and explanatory dialectic. The critical realist is concerned with explaining the mechanisms generating the manifested phenomenon of interest. Premises built on generative mechanisms are based partially on empirical observations and the analysis of causality found beneath the empirical and actual realms (Blom and Morén, 2011).

Moreover, the concept of emergence is central to the critical realist worldview. Bhaskar, the founder of realism philosophy, explained in his theory of emergent power that society should be viewed as a product of emergent human behaviour rather than as a sum of individual properties (Hartwig, 2015). The process of knowing is a movement from incompleteness to a complete understanding, and it involves three steps:

1. Formation of a hypothesis (postulation) based on what is currently known (domain of the actual and empirical)
2. Explorations of causal mechanisms and emerging patterns (domain of the real)
3. Explanation, criticism, and corrections of initial hypotheses and theories to liberate people from the domain of the real.

5.2.2 Ontological Assumptions

Ghana is currently facing a double disease burden from both infectious and chronic diseases, but few resources and policies focus on chronic diseases. DM prevalence is rising, and it is associated with individual, community, and national factors (Pastakia et al., 2017). For instance, urbanisation and the associated consumption of high-calorie foods and less energy-demanding jobs–along with the community value of obesity as symbolising wealth and good living–encourage people to eat unhealthily, increasing their risk of DM (American Diabetes Association, 2024; Holdsworth et al., 2020). Increasing government spending on health indicates a prioritisation of health. However, it does not necessarily mean smart investments because not all health resource allocation decisions are based on evidence from health technology assessments. Developing interventions to improve the DM burden requires understanding the context, specifically how individual, community and national-level factors interact to generate the mechanisms that increase the disease burden.

Political, economic, cultural, and social factors are associated with DM prevalence and DM service delivery challenges in Ghana. As outlined in Chapters 1 and 2, people with DM suffer from medication non-adherence, health facilities have insufficiently trained DM providers, and government policy responses to DM are inadequate. In addition, the NHIS faces structural and financial challenges, and national coverage stagnates at around 40% of the total population (Ministry of Health, 2022b). These and many other structural and fiscal constraints explain the challenges with current DM services in Ghana (the domain of the actual).

The interactions between individual patients and the health system are evidenced in processes, including diagnosis, access to treatment and service payments. These interactions give rise to individuals' and health providers' experiences and perceptions of DM care (conceived as the domain of the empirical), which change with time and place. For instance, urban residents living with DM have increased access to DM treatment compared to those living in rural settings due to the inequitable distribution of DM services.

The current experience and challenges of DM services are a function of underlying causal relationships and generative mechanisms that are often taken for granted, called the domain of the real. The function of these hidden and taken-for-granted ideas and processes within social, economic, demographic, and cultural structures emerges/becomes established as 'demi-regularities'—dynamic patterns of DM outcomes (Hartwig, 2015). Therefore, understanding these mechanisms is the first step to developing interventions to break the chain, as displayed in Figure 5.1. I intend to uncover and leverage my

understanding of these taken-for-granted processes and relationships to develop strategies to improve current DM services in Ghana.

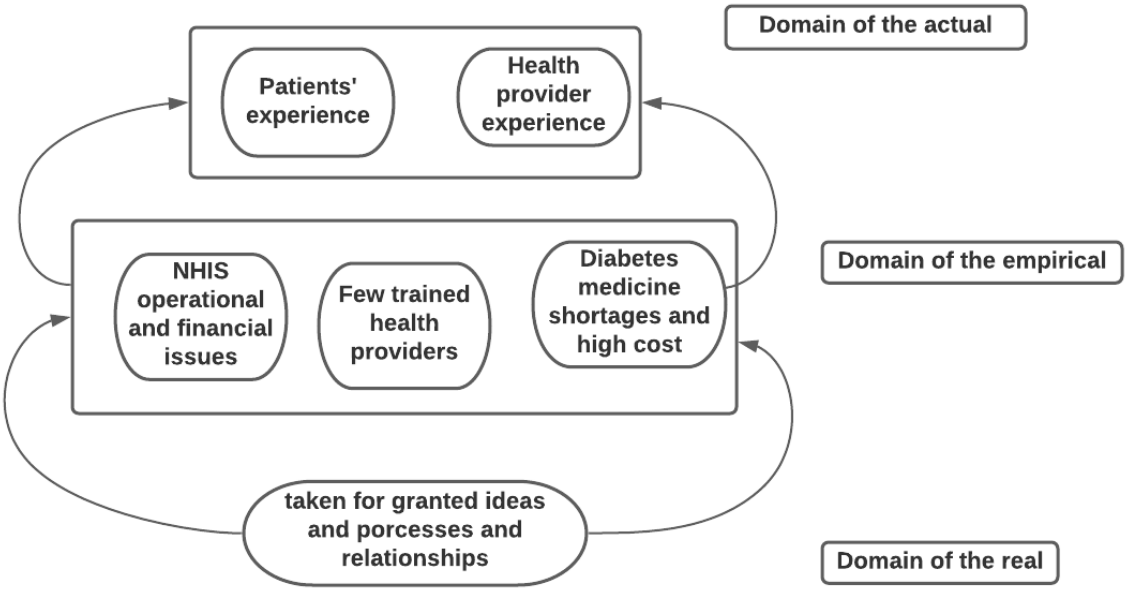


Figure 5.1 A critical realist perspective on diabetes service delivery challenges (Author's own research).

5.2.3 Axiology: Emancipation / Liberation

The value base of this research is emancipation, liberating individuals, health systems, and the government from the challenges of DM management by increasing their understanding of why these challenges result and developing strategies to overcome them. This thesis aims to draw public and policy attention to the presence and operation of causal structures that trigger challenges in the current system of DM service delivery. Ghana's DM service delivery and financing strategies need to be transformed by raising public awareness of what is generating the problem and making informed and strategic propositions on how to improve current DM service delivery in ways that will improve population-level treatment outcomes and eliminate the financial burden on patients, health systems and the government.

Ghana's health spending as a percentage of total government expenditure is small, and investments in NCD management, including DM, are limited. Consequently, several health demands compete for limited financial and material resources, and policymakers choose where to invest. This thesis provides additional value in developing and evaluating DM interventions based on their cost and benefits (economic and health) to inform resource allocation decisions. The goal is to guide policymakers in making better investments that will count toward achieving SDG 3.

5.2.4 Epistemological Assumptions

Epistemology outlines the process of acquiring knowledge and understanding, that is, the approach to inquiry (Saunders et al., 2019). From a critical realist approach, we focused on identifying and explaining how factors/processes, often taken for granted, generate the challenges with current DM care through retroduction—reasoning why and how things happen the way they do. According to Bhaskar in (Archer et al., 2013; p. xvii), *"theoretical explanation proceeds by description of significant features, retroduction to possible causes, elimination of alternatives, and identification of the generative mechanism or causal structure at work".* Thus, we can increase our understanding of a phenomenon with an initial account of the phenomenon, a tentative guess of a causal relationship and an experiment to help uncover the real cause.

In critical realism, knowing the world and generative mechanisms starts with appreciating the empirical and actual realm, i.e., an initial account of events and experiences (Blom and Morén, 2011). Similarly, our inquiry into DM management using generative mechanisms involves an exploratory study of the current structures—the Ghanaian health system, health financing, and pathway to DM service delivery—in which patients' subjective/adaptive decisions, behaviours, and experiences are manifested. This initial investigation further informs our analysis of what is generating the challenges with DM management and how to develop methodologies to address the problem.

From Archer et al.'s approach to inquiry, we identify five iterative steps to conduct research:

1. Describe key characteristics and structures of the DM service delivery system in Ghana.
2. Explore theoretical perspectives and explanations of the challenges within the service delivery system.
3. Identify mechanisms that explain the practical challenges.
4. Analyse mechanisms and outcomes
5. Based on insights from (2, 3, and 4), develop and analyse strategies to improve the current system.

5.2.5 Approach to inquiry

Based on the five steps outlined, I describe the processes followed in this research, from identifying the problem to communicating policy strategies likely to improve the current system of DM service delivery and population-level DM treatment outcomes.

Steps 1, 2 and 3: The literature review in Chapter 1 identifies service delivery challenges, including patient non-adherent behaviour, inadequate DM-trained providers, and national insurance-related challenges. Additionally, the nature of interactions between individual patients, health facilities, and national authorities/policies, evidenced in processes including treatment adherence, contributes to the challenges that influence individual- and population-level DM treatment outcomes, such as deaths and complications. How patients and service providers behave, financial and material resource limitations and national health insurance policies, among other factors, influence what services are delivered, how they are delivered, who has access to them, and their quality.

Furthermore, Ghana operates a three-tier hierarchical service provision structure: the capacity to deliver health services increases from primary to secondary and tertiary facilities. Tertiary facilities provide comprehensive clinical DM services but constitute less than one-third of total PH facilities, and they are in urban communities, making them difficult to access. Although primary facilities are numerous and dispersed, they provide limited DM services and are constrained in medical equipment and provider expertise. In addition, health facility-related factors, including providers' non-adherence to treatment guidelines, a few ambulance services, and limited physical space and infrastructure affect the quality of health services.

From the literature review, we understand that key actors in the DM service delivery system are patients with DM, health facilities and service providers, and national health authorities. Each actor's context influences their behaviour and interaction with other agents. For instance, patients live in a social, economic, and cultural context that influences their health behaviours. Health facilities operate within a fiscal and policy environment, such as government budget allocations and national treatment guidelines. Patients, health providers, and health facilities interact; such interactions influence DM treatment outcomes at the individual, health facility, and population levels. With this understanding, I use Chapter 2 to explore contextual and theoretical frameworks and perspectives that explain the challenges of the DM service delivery system.

Chapters 1 and 2 describe the pathway to clinical DM services and the factors influencing patients' treatment behaviours. We highlighted national and international treatment protocols that guide health providers' behaviour. The clinical DM service delivery system is a composite structure of interconnected health processes, including diagnosis and treatment monitoring, individuals, health providers and national health policies. This system of DM services influences, and is influenced by, a broader social, economic, and political environment within which it operates. Political environments include health policies and programmes as well as how these policies and programmes are funded, implemented, monitored, and evaluated.

Ghana has health policies that address NCD (discussed in Chapter 2), but no specific policy is directed solely at DM control. The NHIS indirectly addresses DM control by increasing access to care and medicines. However, policy implementation gaps, including financial constraints, result in poor implementation (Alhassan et al., 2016; Debpuur et al., 2015). As patients, health providers, and other implementors adapt to circumstances in the broader environment, expectations/ roles stated in national health policies may be missed, and a new order or treatment outcome emerges that is different from what was anticipated to be achieved with policies.

In addition to using a system-thinking approach to analyse DM patients, service providers, and policymakers' behaviour, we applied the health belief model (Strecher et al., 1997) and the theory of planned behaviour (Ajzen, 1991) to examine patients health-seeking behaviour and treatment adherence. Individual patients' behaviour is crucial in explaining the current challenges with the system of DM control. The decision to seek care and comply with treatment is influenced by an individual's perception of their health conditions: perceived severity, susceptibility, benefits, and barriers, as explained by the HBM. These perceptions are created from the knowledge and experiences of DM and the service delivery system. In Chapter 2, we argued that individuals' socioeconomic environment, including insurance status and lifestyle, influences SMBs and DM control.

Steps 4 and 5: In Chapter 4, we presented SM approaches that can be used to improve understanding of the Ghanaian DM service delivery system and evaluate strategies to improve health and economic outcomes. Specifically, the chapter examines DAM: Markov models, SD, DES, and ABM applied to study DM treatment challenges and interventions to guide policy decision-making. We discussed considerations, opportunities, and limitations related to applying DAM to DM intervention studies in LMICs. In chapters 6 and 7, we present insights into the DM service delivery and control system in Ghana and explain the appropriateness of ABM for representing the system, analysing mechanisms, and testing strategies to improve outcomes. In Chapter 7, we highlighted that compared with the other examined DAM, ABM is viable and appropriate for modelling how the behaviour and environment of patients, service providers and other health system factors combine to produce emerging behaviours and population-level DM treatment outcomes. ABM can represent behaviour and emergence and is flexible for modelling at a micro, mezzo or macro-level of abstraction.

5.3 Research methodology: A mixed-methods framework

This research addresses four questions about the system of DM service delivery in Ghana. The research questions can be classified under two broad purposes: 1) to describe and explain why and how the current system works (relating to research questions 1 and 2) and to evaluate strategies for improving

the system (relating to research questions 3, 4 and 5). Considering this research's descriptive and prescriptive purposes, we adopted mixed methods to address the research problem appropriately. In this research, we define mixed methods as combining qualitative and quantitative methods to investigate a research question, following Saunders et al. (2019). The overall methodological approach is summarised in Figure 5.2.

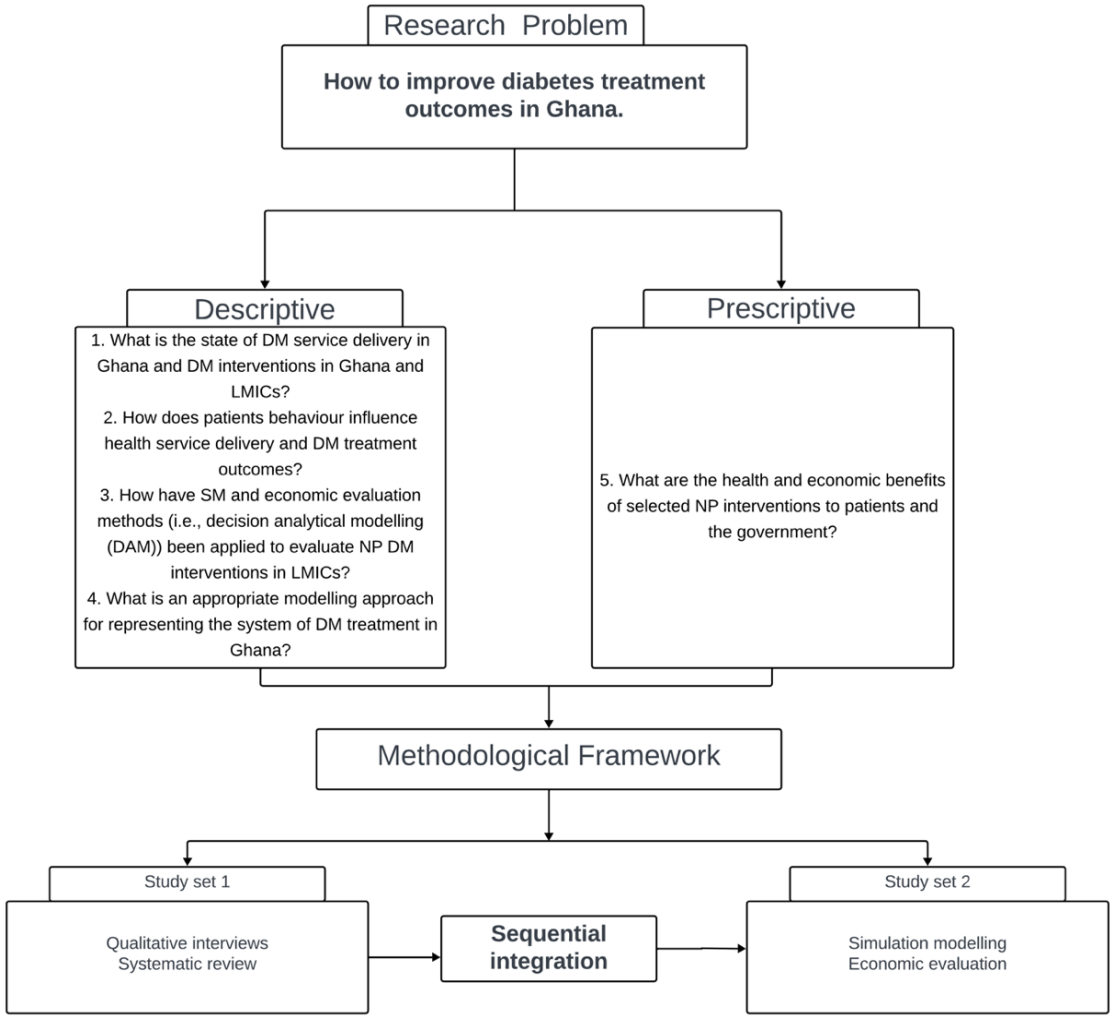


Figure 5.2 Methodological framework (Author's own research).

There are two major justifications for our adoption of a mixed-methods design. The first reason lies in the multifaceted nature of the research problem, which is congruent with the research's critical realist ontological underpinning. The overall research problem is how to improve the current DM service delivery system. Specifically, research questions 1 and 2 are descriptive as they seek to describe and explain the challenges within the system of DM service delivery in Ghana from the perspectives and experiences of patients and service providers. Research question 3 is also descriptive, exploring

appropriate SM approaches for representing the system and decision problem. However, research question 4 is prescriptive, evaluating interventions to determine their effectiveness in improving the burden. The questions can be addressed effectively with different methods. Mixed methods approaches are considered valuable in social intervention studies because such studies tend to have multiple components (Saunders et al., 2019). In the initial paragraphs of this section, we presented a stratified ontology. We argued that hidden causal mechanisms such as patients' and service providers' behaviours emerge as challenges to DM service delivery. Increasing understanding of what is known in the actual and empirical realm, which Research Questions 1 and 2 address, is an initial step towards uncovering hidden causal mechanisms.

Second, using a mixed methods approach can increase confidence in research findings. This research's descriptive components produced qualitative data that provided insights into the prescriptive component. Specifically, an account of how the current service delivery system functions was used to design ABM to represent the decision context and problem. In the conceptualisation and validation stages of model-building, we conducted qualitative and quantitative data collection and analysis to inform modelling decisions, enhance model fitness for purpose, and increase confidence in the model's outcome. This thesis utilises clinician interviews, SM, and CEA to examine interventions for improving health and economic outcomes for patients and the Ghana government. Policymakers should be confident in the study methodology and findings, especially outcomes from the SM, to achieve buy-in for the research findings and suggestions. Engaging policymakers in model conceptualisation and validation enhances the model's transparency and accountability and increases confidence in model outcomes. A mixed-method approach offers an opportunity to use qualitative data from policymakers and service providers alongside quantitative DM epidemiological data in this research.

In the subsequent section, we present the descriptive and prescriptive components of the research. We also outline approaches to mixing methods and describe how the qualitative and quantitative methods in the thesis are combined.

5.3.1 Descriptive study

Research questions 1 and 2 constitute the descriptive study we conducted to improve our understanding of the study context. The descriptive study included mapping relationships, outlining processes, and scoping contextual factors that influence the operation and challenges of the current service delivery system. Answering the questions generates evidence of the current state and helps identify PH interventions that could be adapted for controlling DM within the Ghanaian PH system. Research

Questions 3 and 4 are also descriptive, generating evidence to support an appropriate and viable approach to studying the system of interest.

A descriptive account of the current system of DM service delivery is an initial step in addressing the research problem. As Saunders and colleagues (2019) explained, descriptive research is "a means to an end"; it is often a precursor to explanatory studies, producing vivid accounts of a phenomenon that a researcher seeks to evaluate or explain. The objectives of the descriptive study are to identify inefficiencies in the current DM service delivery systems and to provide a justification for addressing these inefficiencies. Thus, this study acts as a forerunner to the evaluation study, which investigates how to improve the current system.

5.3.2 Prescriptive study

Research question 5 constitutes the prescriptive study, which evaluates interventions to identify how they improve the current system for individuals and the government. According to Saunders et al. (2019), prescriptive studies find out how rational people make better decisions by considering logical explanations of what ought to be and what actually is. Thus, in the prescriptive study, we used findings from the descriptive studies in addition to existing theories and empirical data in a structured approach, outlined in the next section.

5.3.3 Approaches to Mixing Methods

An important consideration for mixed methods research is how methods are combined to answer the study's questions. The manner and extent to which methods are combined have resulted in various types of mixed methods, some of which are discussed in Guetterman et al. (2015), Morgan (1998), Regnault et al. (2018) and Kaur et al. (2019). A primary motivation for combining methods is the principle of complementarity: to harness the strengths of different methods in the same study (Morgan, 1998). When mixing methods based on complementarity, researchers decide which method is principal or complementary and which is performed first. Morgan (1998) identifies four mixing designs depending on the role and sequencing of methods:

1. Qualitative preliminary: A small-scale qualitative study is conducted to support or guide the design of a quantitative study, which is given priority in the overall research project. The complementary qualitative study could be a focus group discussion to inform key topics/questions for inclusion in a survey.

2. Quantitative preliminary: This design is the opposite of qualitative preliminary. A qualitative study is considered principal, but a small-scale quantitative study is conducted to identify areas to investigate in depth. For instance, survey results may be used to design a topic guide for personal interviews.

3. Qualitative follow-up: For designs (3) and (4), the focus is on sequence or how methods are ordered. In qualitative follow-up, a principal quantitative study is first conducted, after which a relatively small-scale qualitative study is conducted to provide insights and context for interpreting the quantitative study findings.

4. Quantitative follow-up: This is the direct opposite of design (3). A small-scale quantitative study precedes a principally qualitative study to help evaluate or interpret the findings of the principal study. The quantitative study could also help test qualitative study findings in other samples.

We adopted a qualitative preliminary approach and a sequential integration approach in this thesis. The study began with an initial small-scale qualitative study to inform the design of a principally quantitative study. We conducted a descriptive study first, followed by a prescriptive study. Integration is an essential part of mixed methods research that details which phase(s) of the research process involves methods mixing or combining. In this study, integration occurred at the beginning/design stage when conceptualising the study and formulating research questions. Specifically, we collected and analysed qualitative and quantitative data in two consecutive stages during this research. The qualitative study is connected to the quantitative study in that the findings from the former informed and guided the latter's design. We used the methods and results chapters to discuss how insights from the qualitative study informed the quantitative study design.

5.3.4 Ethical consideration

The study required ethics approval to conduct interviews with service providers, hold discussions with NHIS officials, and collect cost data from clinicians. We applied for and received approval from both the University of Strathclyde Management Science Department and the Ghana Health Service Ethics Committee. The latter’s approval covered a four-year period (November 2020 to December 2024), allowing us to engage with NHIS officials and clinicians throughout the study. The former’s approval initially covered a four-month period (August 2020 to November 2020) but was later extended to match the duration of the latter’s approval.

5.4 Research Methods

In the remaining parts of this chapter, we describe the methods used in the descriptive and prescriptive studies to answer the research questions. For each method adopted, we discuss considerations for alternative methods, the motivation for choosing the method used, and the data collection and analysis process. First, we explain how we used semi-structured interviews to increase understanding of how DM services are organised and delivered in Ghana's PH facilities and identify the challenges within the service delivery pathway. Second, we describe the use of agent-based SM for abstracting key components of the pathway to DM service delivery: patient treatment compliance, clinical DM services delivery, and how these processes influence population-level DM treatment outcomes. Third, we describe how the simulation model and the cost-utility analysis were combined to generate potential costs and consequences of selected strategies to improve DM treatment outcomes.

5.4.1 Descriptive Study

5.4.1.1 Literature reviews

Literature reviews are an integral component of any research as they shape the research design, provide theoretical and empirical background, identify research gaps, and establish the significance of the study. A literature review is essential for 1) gaining a comprehensive understanding of the existing knowledge and theories related to the research topic, 2) identifying research gaps and contradictions or unanswered questions in the literature, and 3) refining their research questions and developing a sound research design. Literature reviews help researchers select appropriate methodologies, data collection techniques, and analytical approaches based on the strengths and limitations of previous studies.

We conducted multiple literature reviews to understand the existing literature and arguments surrounding 1) the pathway to clinical DM service delivery and the associated challenges faced by patients and service providers and 2) the application of SM techniques–system dynamics, discrete-event simulation, Markov models, microsimulation, and agent-based models–for DM intervention studies and to identify research gaps.

First, we conducted a narrative review of DM interventions in LMICs, treatment behaviour, and the delivery of DM services under Ghana's national health insurance and within the PH facilities, identifying the factors that influence treatment outcomes (Chapters 1 and 2), which, when addressed, could improve population-level DM treatment outcomes. This review identified the importance of patient behaviour and PH interventions in DM control, and the need to generate context-specific

evidence of interventions' effectiveness at improving DM treatment outcomes. The review also provided insight into the pathway to clinical DM services and the design of the qualitative study focused on eliciting service providers' perspectives regarding DM service delivery and patients' behaviour.

Second, we conducted a systematic review to explore the application of DAM for studying DM interventions and how to advance DAM methodologies in DM research in LMICs. The review focused on PH DM interventions, including fiscal policies and education programmes, due to their potential benefits for both individuals with DM and those without. The review of DAM studies provided further insight into how SM could be applied to DM interventions in this study, the challenges modellers encounter, and how to navigate the challenges throughout the model-building process.

We also reviewed the literature to obtain the values for parameters characterising the clinical delivery of DM services and patients' treatment behaviours. We determined the most likely value of each parameter for the base-case simulations and its distribution for sensitivity analyses.

5.4.1.2 Semi-structured interviews with diabetes service providers

We conducted qualitative interviews to increase understanding of the current DM service delivery system (related to Research Questions 1 and 2), especially because the COVID-19 pandemic may have caused significant changes to health service delivery. A qualitative interview elicits opinions from people with firsthand, in-depth knowledge and experience of the topic within specific context (Saunders et al., 2019). The method can generate insights for building a foundation for further quantitative research. A qualitative interview was helpful in this inquiry to examine how DM services are organised and delivered and how people involved in the delivery process behave within PH facilities.

Our inquiry explored the experiences of clinicians directly involved in delivering DM services, particularly with issues surrounding patients' adherence to DM services, organisation, and payments. The interviews helped map the service delivery barriers from the perspective of service providers, highlighted COVID-19-induced changes impacting service delivery pathways and patients' behaviour and helped identify interventions to examine for policy and practice in Ghana.

We used semi-structured interviews to collect data on DM service providers' experiences. There are many forms of interviews, such as structured, semi-structured and unstructured. However, the nature of the questions and the purpose of the research largely determine the researcher's choice of interview type and approach (Saunders et al., 2019). We chose semi-structured interviews because we could direct the conversation to issues of interest while permitting service providers to express other related opinions, which is challenging in unstructured interviews, where the conversation evolves without any set agenda

(Creswell and Poth, 2018). Moreover, semi-structured interviews incite a flexible two-way conversation. We could omit certain questions from an interview guide where appropriate and choose the terminologies to use in framing questions. Additionally, we could also order the questions to maintain the flow of the conversations and improve the interviewees' understanding of those questions. The two-way conversation in semi-structured interviewing helped us build rapport with DM service providers, increasing the chances of getting providers to provide data for our modelling studies.

5.4.2 Prescriptive Study

The overall objective of the prescriptive component of this thesis was to examine and propose strategies that improve health outcomes and economic efficiency for the PH system; this objective is linked with research question 5: "*What are the health and economic benefits of selected PH interventions to patients and the government?*" The prescriptive study drew upon findings from the descriptive studies, health behaviour theories, and published literature to build an ABM to improve understanding of the decision problem and investigate interventions for their health benefits. Evidence from the ABM intervention experiments was subsequently incorporated into a CEA to estimate the economic efficiency associated with interventions.

5.4.2.1 Justification for choice of Agent-based Simulation modelling

ABM is suitable for modelling cohort-level emergent behaviours from heterogeneous individuals and their autonomous decisions in a dynamic environment (Macal, 2016; Railsback and Grimm, 2019). We built an ABM to simulate the heterogeneity and stochasticity of T2DM patients' SMB and its interaction with clinical services and the socioeconomic environments, and the emerging population-level BGC outcomes. ABMs offer more flexibility in modelling dynamic interactions than Susceptible-Exposed-Infectious-Recovered and Markov models, among other epidemiological compartment models. The stochastic feature of ABM makes it suitable for modelling patients' adaptive behaviours and the randomness characterising clinical service delivery. Moreover, ABM generates a distribution of outcomes to account for the stochastic uncertainty of outcomes; this is impossible in deterministic compartment models due to their inability to produce anything beyond a single output for each set of parameters. Moreover, our conceptual model characteristics align with ABM design concepts described by Grimm et al. (2020), which we discussed in detail in Chapter 7.

Nonetheless, we explored the suitability of ABM by answering questions from Salamon (2011) about using ABM for modelling a system. Salamon argues that if several of the questions outlined below about the model problem are answered affirmatively, it can assist in determining whether ABM is

appropriate for the decision problem. We answered Salamon's questions, using the problem and system to be modelled, presented in chapters 1, 2, and 6, to establish the appropriateness of using ABM:

Are there entities that can make decisions? ***Yes***

The model represents individuals diagnosed with T2DM and receiving treatment at health facilities. The patients decide whether to live a healthy lifestyle. The research questions influenced the choice of entities and variables in the environment. As highlighted in Chapters 1, 2, and 3, patients interact with clinical services, and their socioeconomic environment, including lifestyle and public insurance coverage, influences DM treatment outcomes.

Are there many types of decision-making entities or many types of decisions? **There is one main entity (patients) that makes multiple decisions.**

The model represents patients and health facilities in the patients' environment. Patients make several decisions. First, the patient entity uses logical and simple (if-then) rules to make three main decisions: 1) to take medicine, 2) to live a healthy lifestyle, and 3) to attend review appointments. The decision process was developed based on discussions with clinicians, published literature, and health behaviour theories. Additionally, patients use deterministic decision rules. Specifically, when the conditional (if) part of the decision-making rule is satisfied, only one possible action/behaviour is assigned to the patient. For example, if a patient decides to attend a review appointment, it is definite that the patient receives care.

Does it look as if the system will have dynamic characteristics? **Yes**

The cohort-level blood glucose outcomes change over time because of individual patients' SMB and feedback loops in the model. Specifically, the cohort-level BGC, medicine adherence, and admissions keep changing as individual patients change their medicine intake and health-seeking behaviours. An example of a feedback loop in the system is how patients' behaviour interacts with health facilities' decisions. Patients' non-adherence to medicines and unhealthy lifestyles result in DM complications leading to admissions by health facilities. Admission, in turn, influences patients to adhere to treatment and then blood glucose levels are controlled. With controlled blood glucose, patients may miss review appointments and prescriptions, leading to medicine non-adherence and, consequently, poor blood glucose.

Do we feel a need to treat the overall behaviour of the whole system on a macro level? **Yes.**

We aimed to assess the overall system behaviour in responses to PH interventions to inform policy decision-making. The cohort-level behaviour aggregates the individual patients' SMB, health facility services, and the PH environment: medicine availability in communities and insurance coverage.

Is it difficult to describe the whole situation as a process (or activity) diagram or state transition diagram? **Yes.**

We represented aspects of the model using a flowchart and activity diagram. However, it was challenging to fully represent the feedback loop from each patient's interactions and behaviour as they made decisions at the individual level. Additionally, it was challenging to represent the treatment outcome that results from such individual-level interactions.

Is it difficult to 'count up' the entities into lump sums and then work solely with such amounts? **Yes**

Treating the patient agent as a lump sum and then working solely with the sum would mask individual-level behaviours stemming from patients' unique characteristics and environment. Patient-level behaviours, such as medicine intake, aggregate to produce cohort-level outcomes. Additionally, working with the average of patients' characteristics (usually the case in Markov Cohort models) would be misleading as individual patients' SMBs create feedback loops that could lead to dynamic interactions.

Are spatial factors of the environment important for the situation? **Yes**

Although the model does not incorporate a geographical layout, rural and urban areas are associated with access to medicine, which influences patients' SMBs. The model represented the medicine adherence behaviour of patients in rural and urban communities and explored the effect of medicine adherence behaviours on cohort-level treatment outcomes. Access to medicines is important for model outcomes.

5.4.2.2 Other simulation methodologies considered.

We considered whether SD, DES and microsimulation would be suitable for representing the decision problem. The study did not implement SD and DES because neither approach provides an opportunity to represent individual-level variations and decision-making processes. SD could have been helpful if the model or system focused solely on variations in macro-level factors and their influence on

population-level DM treatment outcomes, e.g., representing interactions between health facilities, government budget allocation for health, and national insurance policy. However, in addition to macro-level factors, we need to understand how individual-level heterogeneity and decision-making processes influence treatment outcomes at the cohort level. DES focuses on queueing systems and could be viable for representing DM service utilisation where the emphasis is on waiting time or delays in service delivery. Additionally, we considered a microsimulation approach for the opportunity to model details at an individual level and capture aggregate-level outcomes. However, microsimulation does not emphasise the agency of entities and the complex, dynamic, individual-level decision-making processes, which ABM does. Our model focuses on system-level behaviour that emerges from individual-level decision-making and autonomous behaviours. ABM captures these features.

We adopted Railsback and Grimm's (2019) key activities in ABM (shown in Figure 5.3), which helped us navigate the modelling process successfully. This process involved multiple iterations between the modelling stages. We also planned for and executed the model programming and its confidence-building simultaneously.

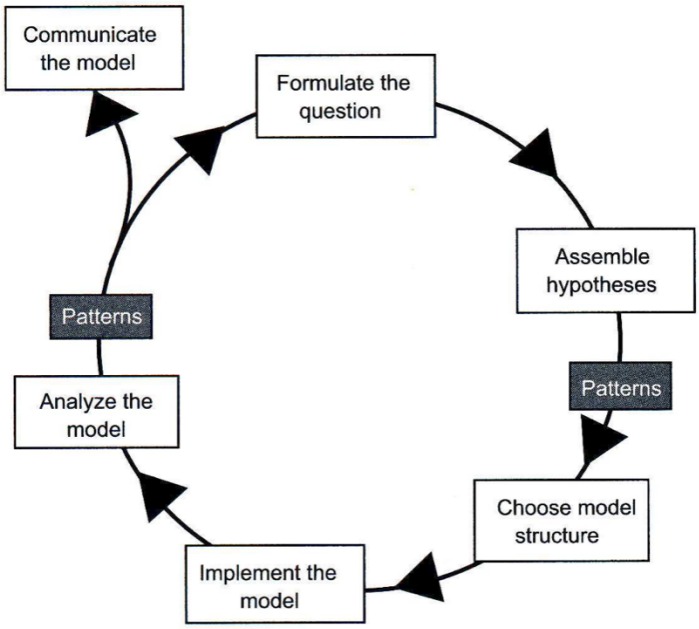


Figure 5.3 The modelling cycle (Adopted from Grimm and Railsback, 2005).

We collaborated with stakeholders, DM service providers and health insurance officers throughout the modelling process. Discussions with service providers and findings from the literature review were critical in the problem identification phase to gain insights, scope the problem, and determine the modelling objectives. Chapters 1, 2 and 6 describe the model problem/system. The model questions are

presented in our Research Question 2: "*How does patients' behaviour influence health service delivery and DM treatment outcomes?"* and part of Research Question 5: "*What are the health benefits of selected PH interventions to patients and the government?"* Our review of SMBs presented in Chapter 4, qualitative interviews in Chapter 6 and continuous informal interactions with clinicians helped identify what processes and structures are essential to the problem/system we address. These processes and structures include medicine adherence, health-seeking behaviours, clinical service delivery and lifestyle. We discuss hypotheses and patterns for the processes and structures in Chapter 7, Section 7.5. The model structure includes entities, scales, state variables, processes and parameters (Grimm and Railsback, 2019), which are presented in Chapter 7, Section 7.3. We discussed model implementation and verification in Chapter 7, Section 7.5. We described experiments and analyses to understand patient behaviour in Chapter 7. This thesis is a medium for communicating the model. Consultation with clinicians helped justify the modelling assumptions and simplifications emerging from the first three phases of the modelling process. Including clinicians' perspectives could increase the model's credibility and buy-in while building confidence in the model.

5.5 Chapter conclusion

This chapter has outlined the critical realist philosophical foundation and mixed-methods approach that guide this research. These choices are particularly suited to investigating the complex, multifaceted nature of DM management in Ghana, allowing us to explore the observable challenges and underlying mechanisms contributing to them. By combining qualitative and quantitative methods, we were able to comprehensively address our research's descriptive (Research Questions 1–4) and prescriptive (Research Question 5) components. We have highlighted the sequential integration approach for combining findings from the descriptive and prescriptive study to address the research aim. Having described the research approach, we present a qualitative interview with clinicians in the next chapter, describing the DM management system and exploring the challenges therein, to improve understanding and support conceptual modelling.

6 Clinical Diabetes Service Delivery in Ghana

6.1 Introduction

This chapter builds on the methodological framework outlined in the previous chapter by presenting the first phase of our original research: a qualitative study on DM service delivery in Ghana. This study operationalises the critical realist approach discussed earlier, seeking to uncover the complex realities of DM care from the perspectives of healthcare providers. In line with our mixed-methods design, the insights gained from this qualitative investigation provide context and data for the SM phase that followed.

As outlined in our methodology, we employ semi-structured interviews to address part of our first and second Research Questions: *"What is the state of diabetes service delivery and treatment in Ghana*?" and "*How do patients behaviour influence health service delivery and DM treatment outcomes?"* respectively. This approach allowed us to explore the 'actual' and 'empirical' domains of reality as experienced by healthcare providers while also beginning to uncover some underlying mechanisms in the 'real' domain that influence DM care in Ghana.

Parts of the chapter are amended or reproduced from a published paper:

Tagoe ET, Nonvignon J, van Der Meer R, Megiddo I, Godman B. Challenges to the delivery of clinical diabetes services in Ghana created by the COVID-19 pandemic. Journal of Health Services Research & Policy. 2023;28(1):58-65. https://doi.org/10.1177/13558196221111708

Specifically, Section 6.3 has been amended from the first two paragraphs of the introduction section in the published paper. The last five paragraphs of Section 6.4 and the entire Section 6.5 are from the discussion section in the published paper.

6.2 Study Design

6.2.1 Qualitative interviews

We conducted a qualitative study using semi-structured interviews, to improve understanding of the current DM service delivery system (related to research questions 1 and 2), considering that the COVID-19 pandemic may have caused significant changes to health service delivery and health system capacity.

Using semi-structured interviews and qualitative methods in health service research has several benefits. Creswell and Poth (2018) explained that qualitative research answers why and how decisions are made, or activities are undertaken, increasing understanding of the complexity of human behaviour, which is central to healthcare and treatment outcomes. Using a topic guide in semi-structured interviews helped optimise interview time by focusing the conversation on topics of interest. The results of qualitative health service research can feed into the development of interventions, health models, and theories (Saunders et al., 2019).

6.2.2 Other methods considered.

We considered conducting a survey: defining a set of questions with a predetermined set of answers to each question and asking service providers to check appropriate answers. Surveys would have been our choice if we had a theoretical understanding of how DM services are organised and delivered within the Ghana health system based on the literature review. However, developing a survey questionnaire with alternative responses/answers would have been challenging since we had little insight into the service delivery system. Using open-ended questions in a questionnaire may help increase understanding of DM service delivery but would likely elicit diverse responses because of service providers' different roles and experiences. We also considered focus group discussion and observational studies, but they were impractical because of COVID-19 protocols. Focus groups would have been an additional effective method to record service providers' and patients' perspectives and foster their collaboration in the model-building process. This approach was, however, impractical because it was difficult to assemble healthcare providers during the COVID-19 pandemic when they had a heavy workload and little spare time for a group discussion. Although observation may have revealed "backstage" elements of the diabetic treatment problem, many obstacles prevented the implementation of this technique, including government regulations on how much time one could be spent in hospitals during the pandemic for reasons other than care.

6.2.3 Developing the interview topic guide

The descriptive study aimed to describe the DM service delivery pathway and identify challenges and potential strategies to address them from the perspective of DM service providers. We developed a topic guide based on components of DM services identified through a literature review. These components of DM services included diagnosis, follow-up reviews, record keeping, patients' treatment adherence, medicines and supplies, referrals, staffing, and service payment. For each component, we asked interviewees about the processes involved, any challenges encountered, and potential strategies to overcome them. We acknowledge that some service providers indirectly involved in DM service

delivery may have little insight into our questions. For instance, a records keeper may have no experience with patient treatment adherence. Consequently, we tailored many of the questions to the expertise of the interviewees' roles.

Studies raise concerns about the reliability of qualitative studies due to the lack of standardisation in study approaches and reproducibility of study methods (Saunders et al., 2019). Even if a researcher religiously follows applied methodologies, individual factors–such as tone of voice and demeanour of the interviewer–could introduce bias and influence interviewees' responses, affecting study results. Nevertheless, the purpose of the study was to describe the pathway to delivering DM service and to explore contextual factors that contribute to challenges within the delivery pathway while identifying strategies to overcome them. Using a survey or other standardised methods would have interfered with the objective of gathering comprehensive, in-depth information. Instead, a qualitative research approach proved most suitable for eliciting the perspectives and experiences of individuals directly involved in DM service delivery.

Furthermore, using a topic guide does not control biases introduced by the tone of voice and demeanour. However, the topic guide helped structure the discussion to ensure consistency in the questions and limit any deviations from the topics. Generally, the interviewer (ETA) maintained an amiable posture, used polite words, and showed appreciation to interviewees for sharing their experiences and time.

6.2.4 Piloting the topic guide

To ensure the topic guide was comprehensive, void of ambiguity, easy for interviewees to understand, and reliable for collecting data, we piloted it with two DM service providers at a private health facility in Ghana. We do not include the findings of the pilot interviews in the study results. During the pilot, we noticed that interviewees did not understand the term "DM service delivery pathways" and required further clarification. Also, interviewees discussed changes introduced by COVID-19 control policies and their impact on DM service delivery, which were not included in the initial draft of the topic guide. Consequently, we substituted the term with "DM services" and included questions on changes and challenges presented by COVID-19 control policies. The topic guide (Appendix B) assumes interviewees had reviewed prior shared study information and were familiar with the study background. Below is the structure of the topic guide:

1. An ice-breaker question: Invite the interviewee to talk about their role and expertise in DM care as well as the DM services provided in their facility.

2. The second set of questions probes further to elicit details of activities performed, the impact of COVID-19 on activities, and challenges encountered in each component of DM services: diagnosis, medicines and supplies, referrals, staffing, treatment guidelines, record keeping, and service payment.
3. The final probes invite interviewees to mention any other issues that were not addressed and recommend strategies to improve DM service delivery.

6.2.5 Location and timing of interviews

We conducted all interviews in health facilities due to the convenience this method offered to service providers who were busy and unable to commute to other locations for the interview. We initially planned to conduct interviews over telephone and Zoom due to COVID-19 safety protocols; however, service providers delayed scheduling interviews, and expressed preference for face-to-face interviews citing their busy schedules and poor internet connectivity. Consequently, all interviews, except one, were conducted face-to-face with complete adherence to social distancing measures and other COVID-19 protocols and at mutually convenient times for interviewers and the researcher. We requested an over-the-phone interview from one participant because the participant worked in a health facility outside Accra, and travel restrictions due to COVID-19 prevented commuting for a face-to-face interview.

6.2.6 The Interviewing Processes

Pre-interview

Before conducting interviews, we shared the study information sheet (Appendix B) and consent forms with participants through email correspondence. We asked them to review the document and clarify any concerns via email or phone calls. The study information sheet contains details on the study context and purpose, what to expect in the interview, how data would be used, stored, and destroyed, and contact details for participants seeking additional study information. After addressing all questions and clarifications, we asked participants to voluntarily sign and return consent forms to indicate participation. We assured participants that declining to participate would not impact their work. We obtained verbal consent to record interviews for note-keeping purposes and assured participants that they could review and approve interview transcripts before data analysis. Two interviewees preferred note-taking over recording.

During Interview

The transactional power dynamics between an interviewer and interviewee during an interview can affect the validity of findings by reducing the ability of the interviewer to access the interviewees' experiences and interpretations. The interviewer has control over the questions asked and the interview scripts. However, the interviewees have power over what they say and how they say it and may devise ways to counter/avoid questions or curtail information provided to an interviewer (Creswell and Poth, 2018). Conducting interviews on hospital premises, we were concerned that interviewees might hold back specific information, especially when it pertained to management or colleagues who may be present at the facility during the interview. Therefore, we used a combination of open-ended questions and probes while asking interviewees to share past events to buttress their point of view and elicit additional insights. We believe these approaches helped us gain as much information as possible from DM service providers. For instance, asking service providers to recount an incident that illustrated what they wanted to communicate helped them share their judgements, beliefs and meanings about topics, helping us understand their perspective and not misinterpret what they said. Another approach we implemented to minimise service providers from feeling intimidated by the presence of colleagues or seniors was to conducting interviews in rest/changing rooms and conference halls, which were free of intrusion and distraction from other service providers. On average, interviews lasted 30–40 minutes and were audio-recorded using a smartphone.

Post-interview

After each interview, we consolidated notes and transcribed audio recordings verbatim, ensuring no details were lost. All interviews were conducted in English, so translation was unnecessary, avoiding potential information loss. By transcribing verbatim, we familiarised ourselves with the data before analysis.

We shared the interview scripts with interviewees and requested them to validate the transcript by correcting significant errors, clarifying ambiguous statements, and ensuring their perspectives were appropriately presented. Interviewees included details they had omitted during interviews and requested that some parts of the transcript, which they felt uncomfortable with, be deleted despite saying these things during the interview. We deleted the information as a sign of respect for their privacy and dignity, which aligns with ethical research practices. This validation process increased the transcripts' trustworthiness as they represented the interviewees' perspectives.

Researcher reflexivity

After conducting all interviews, we reflected on how the researcher's role throughout the research pathway could have influenced the study results. Researcher reflexivity is an active process that can sometimes be tough and probing. Still, it is necessary to maintain self-awareness to identify any factors that may alter data gathering or interpretation. The researcher had prior experience providing care in PH facilities in Ghana and was aware of the need to remain neutral during the interview, refraining from inserting personal views and reactions. However, it was challenging to remain objective, listening solely from a researcher's perspective without adopting an insider perspective. This experience could have influenced how questions were posed during interviews, how reactions to interviewee responses expressed, and data analysis.

6.2.7 Data analysis: thematic analysis using inductive and deductive coding.

We analysed the interview data in six iterative steps, using a combination of inductive and deductive coding in a thematic analysis as described by Fereday and Muir-Cochrane (2006). We described the activities involved in each step below:

Preparing data for analysis

At this stage, we uploaded all interview materials, interviewee-validated transcripts, signed consent forms, and notes to StrathCloud, a virtual storage system, to secure the data. We then uploaded transcripts to NVivo version 1.5, which the researcher (ETA) used for data analysis because she felt comfortable and possessed experience using the data analysis software.

Developing a code manual

We thoroughly read all transcripts. We then randomly selected three transcripts, one from a primary, secondary, and tertiary hospital, and applied a group of codes identified in a prior literature review on the same research topic. The prior codes included few DM-trained providers, high treatment costs, medicine shortages and low provider motivation. Specifically, we attached prior codes to phrases in the transcripts that matched the description of those code while maintaining an open mind to identify additional codes from the transcripts. We consolidated the prior codes with new ones identified in the three randomly selected transcripts: the high cost of laboratory/service, suboptimal patient information management systems, service organisation challenges, and health policy–related challenges.

Applying code manual and additional coding

We iteratively applied the codebook, the consolidated list of codes, to the remaining fifteen transcripts. To code text in each transcript, we highlighted and dragged the text to the appropriate code displayed on the left-hand side of the NVivo software interface.

Connecting codes and identifying themes

At this stage, we organised coded text based on corresponding codes and presented the data in a matrix, with interviewees listed as rows and codes as columns. The matrix allowed us to analyse data within codes and across interviewees and helped discover themes and patterns in the dataset. For example, we identified similarities in the experiences of service providers working within the same level of care.

Corroborating and legitimating coded themes

This stage focused on confirming findings that emerged during the data analysis process to avoid unintentional distortions, such as researcher bias or pre-set expectations. We examined steps 1–4 and ensured that the descriptions of the codes were consistent with associated phrases/text from transcripts.

Writing-up results

In this step, we engaged in an iterative process of reviewing the matrix and writing narratives to describe themes, supporting these narratives with direct extracts from transcripts.

6.2.8 Study setting

Before the COVID-19 pandemic, Ghana faced several challenges in DM service delivery, which the pandemic likely worsened. The country's health system would have adapted DM service delivery to accommodate the pandemic, and these adaptations may have impacted service delivery pathways, patients' SMBs, and BGC outcomes overall. We conducted this study to improve understanding and consolidate the literature on DM service delivery, especially its dynamics during the pandemic.

Ghana confirmed its first cases of COVID-19 in March 2020. From April, the government implemented a three-week lockdown in Accra (the country's capital and largest city), Kumasi (another large city), and its environs. Hospital outpatient services, including DM clinics and other NCD services, were temporarily suspended during the lockdown (Afriyie et al., 2020).

Ghana operates a government-introduced national health insurance scheme, the NHIS. Funded by various levies and other income sources, this scheme aims to ensure Ghanaian residents have access to affordable health care. Patients who receive health care from NHIS-accredited providers often have their services partially or fully funded by the insurer. All the facilities in our study, except for one of the primary facilities, were NHIS-accredited.

Health facilities and interviewees

We interviewed healthcare professionals and administrators in primary, secondary, and tertiary health facilities between November 2020 and February 2021, when most outpatient services, including DM clinics, had resumed operations. The interviews were semi-structured, using a topic guide developed based on a literature review conducted for this study and piloted with interviewees in private health facilities in Ghana.

We sent introductory letters to several public facilities, which were purposively sampled (Bell, 2005). These facilities were in the Greater Accra region, the only accessible area for interviews due to COVID–19–related travel restrictions. Two primary facilities and one secondary facility granted permission to interview service providers. Through a snowballing technique (Bell, 2005), we recruited and interviewed service providers in a tertiary facility. The two primary facilities served different municipal districts, delivering outpatient DM services twice weekly to diverse patient groups from rural and urban communities. The secondary facility provides care to a large population, acting as a referral point for primary facilities in the region. DM clinics for outpatients were held twice weekly. The tertiary facility is a referral facility providing comprehensive DM care, including daily outpatient DM clinics during weekdays.

In total, 18 interviews were conducted, eight at primary facilities, four at secondary facilities and six at tertiary facilities. Table 1 shows the characteristics of the study participants. After this, no further interviews were conducted due to data saturation–responses to the same questions began repeating. The interviewees had various administrative and clinical roles. These included physicians, nurses, a physician assistant, a laboratory technician and records officers from the Ghana Health Service. The rationale for including staff across these various roles was to represent the perspectives of clinicians and others providing different DM services in order to present a comprehensive picture of activities carried out along the service delivery pathway during the pandemic.

Table 6.1 Characteristics of interview participants (Adopted from Tagoe et al., 2023).

Participant number	**Role/Expertise**	**Facility type**
P1	Chief Nursing Officer	Secondary
P2	Pharmacist	Tertiary
P3	Physician	Tertiary
P4	Nurse	Tertiary
P5	Chief nursing officer	Tertiary
P6	Nurse	Secondary
P7	Laboratory technician	Tertiary
P8	Physician	Secondary
P9	Records officer	Primary
P10	Pharmacist	Tertiary
P11	Records officer	Primary
P12	Physician Assistant	Primary
P13	Nurse	Primary
P14	Dietician	Secondary
P15	Records officer	Primary
P16	Hospital Administrator	Primary
P17	Nurse	Primary
P18	Nurse	Primary

6.2.9 Ethics

We obtained ethics approval for the study from the ethics committee of the University of Strathclyde and the Ghana Health Service Ethics Review Committee (Protocol No. GHS-ERC 011/09/20).

6.3 Diabetes service delivery in public health facilities in Ghana: clinicians' perspectives

This section presents the interview results on the structure of DM service delivery and existing challenges to clinical services before the COVID-19 pandemic. The results are presented under four themes related to clinical DM service organisation: appointment scheduling, counselling and adherence, admission and complications management, and resources, equipment, and technology.

Appointment scheduling

Outpatient review appointments are paper-based and scheduled based on the availability of appointments and patients' conditions. According to clinicians, because appointment scheduling is paper-based and there is no software to track scheduling, overscheduling and oversight of missed appointments often occur. Missed appointments are rarely rescheduled because clinicians usually fail to follow up on them. The clinicians elaborated that when patients do not show up for appointments, the clinical team does not typically follow up on patients to investigate missed appointments and reschedule them due to the clinician's considerable workload and limited resources, including telephone and airtime. Consequently, patients are left unattended until they return to seek care in health facilities. Few patients call available hospital contacts to reschedule appointments. A nurse said:

"We give some contact numbers to patients to call in case of anything. We have appointment cards with contact numbers on them. So, we tell them that if for one reason or the other, they would not be able to keep their appointment, just call for rebooking. Sometimes, they don't call, and honestly, we do not follow up. I know it is quite fulfilling if you even call to remind them…but we are unable to do that. The work is overwhelming, actually." (P1 Nurse).

Clinicians explained that outpatients with controlled DM usually have review appointments scheduled 3–4 months apart. Such patients are assumed to adhere to treatment and require reiteration of sick day rules, prescriptions, and discussion on treatment concerns. Clinicians in tertiary facilities explained that they book between 250 and 350 appointments per week, while those in secondary and primary facilities mentioned scheduling between 60 and 80 appointments per week. Where there are no available appointments within the usual interval of 3–4 months, appointments are delayed for patients with controlled DM, and patients are informed to seek care at any time if they are unwell.

The clinicians explained that the interval between review appointments for patients with moderate DM control (but not poorly controlled enough to trigger an emergency) is shorter (1–3 months) than that for patients with controlled DM. According to clinicians, the short interval is intended to increase the frequency of monitoring, improve the quality of care and increase the chance of early detection and intervention in case of complications. Like controlled DM cases, review appointments for patients with moderately controlled DM can be delayed, and patients are told to seek care when unwell. Clinicians at all levels of care emphasised the urgency of care in patients with poor BGC: fasting blood glucose >= 13.0mmol/l. Patients reporting high blood glucose levels are admitted, or their blood glucose is brought to normal levels and rescheduled for a review appointment between 1 and 4 weeks. According to clinicians, because inpatient monitoring and discharges are done before outpatient clinics, it is rare for discharged inpatients to encounter unavailable review appointment slots. Clinicians explained:

"*We run our diabetic clinics on Tuesdays. So, when a patient comes on Tuesday, we make sure we check their blood sugar levels before they see the doctors. So, depending on the level of blood sugar, if it is within normal range, you go ahead and see the doctors, but if it is lower than about 2.6mmol/l, we just send them directly to the emergency to be seen. If the patient needs to be admitted, they are usually admitted at either the emergency or the medical ward."* (P1 Nurse).

"… if it is a first-time visit, we check the sugar it is high, we resuscitate. So, we either admit you or we detain you for about 24 hours and monitor the sugars." (P12 Physician Assistant).

Counselling and adherence

Few health facilities have trained dietitians and counsellors to guide patients on healthy lifestyles, food choices, and the importance of DM control. According to clinicians, DM patients must be guided on dietary choices and medicine administration. However, not all patients receive such services due to the few trained dietitians, physiotherapists, and counsellors who are primarily based in tertiary facilities. Patients are referred to seek dietetic services in private hospitals; however, most such patients do not return to the initial health facility to continue care and are lost to follow-up. An assistant physician in a primary facility described the situation:

"We manage patients very well except for the fact that we do not have a dietitian here. Yes, so for patients with poorly controlled sugars, we have to refer them to the nearest hospital, mostly it's Legon Hospital, for dietary advice." (P12 Physician Assistant).

Clinicians in facilities with dietetic services explained that a majority of patients are reluctant to modify lifestyle behaviours developed over their lifetime regardless of their DM condition. They noted that patients often cite cost as a barrier to healthy eating, claiming they cannot afford nutritious options like fruits and vegetables. However, clinicians argued that this reasoning is flawed, as affordable and healthy alternatives are available. The challenge lies in patients' preferences: they are accustomed to the taste of unhealthy foods and continue eating with their households and friends. Moreover, many food staples in Ghana are full of carbohydrates (e.g., "banku" and "fufu") and saturated fats, which contribute to elevated blood glucose and low-density lipoprotein—'bad' cholesterol—in the body. Patients have developed unhealthy lifestyles over several years in their households and among their friends and find it hard to change substantially. According to clinicians, patients follow dietary advice upon admission, after experiencing a diabetic emergency, or post-discharge. However, they revert to unhealthy behaviours when they feel well. Clinicians explained that patients' unhealthy dietary behaviours often mirror those of their household and close contacts, since patients are mostly older people who primarily rely on meals prepared by their children or partners. A dietitian and a nurse explained:

"*Sometimes you see dietary habits are formed way back from childhood or infancy all the way up. Imagine this is you: you have been eating two times a day, and that is what you have done all your life, and then this dietitian comes to tell you that what you are doing is really having that great impact on your sugars. This is how I have been eating … it is difficult to change dietary patterns. It is not like medication that you take, and you are just done. Unfortunately, the way we eat as Ghanaians, our local dishes are full of carbohydrates."* (P14 Dietician).

"*I think most of them are not able to comply with the rules and regulations regarding DM, especially the diet and having to take medicines daily. They are not used to that, so sometimes they tell you I went to the dietitian and was asked to eat a lot of vegetables. I do not like veggies. So, they eat anything, and then they come in with very high blood sugar. So, their problem is with their diet. They are not able to comply. I will say about four in every ten diabetics visiting this hospital have a problem with diet, they do not comply with the dietitians' recommendations*." (P1 Nurse).

Clinicians in all levels of care explained that patients are non-adherent to medication mostly because of persistent medicine shortages, unaffordable medicines, and poor understanding of DM medication. Insulin and metformin, essential medicines in DM care, are covered under the NHIS, making them affordable for patients. However, the medicines are frequently out of stock in pharmacies, contributing to non-adherence, according to clinicians. Also, most DM complication medicines are expensive and not covered by NHIS; patients cannot afford them and do not take them as prescribed. A physician complained:

"*Well, as I said, 90% of our patients use the national health insurance for the payment of the service [consultation]. But, for the original drugs, the labs and others, patients have to pay out-of-pocket. If the patient says he cannot do the lab, you cannot force him. So, we just encourage him until they eventually do the labs. There is nothing really, we can do."* (P3 Physician).

Admission, referral, and complications management

Admissions are generally based on patients' DM and comorbid conditions, but not all health facilities are resourced to admit patients for comorbidity and chronic DM complications. However, all facilities have the capacity to bring uncontrolled blood glucose levels to normal and then refer patients to high-level facilities for continuity of care. According to clinicians, when patients seek care through review appointments or emergencies, their eligibility for admission is guided by standard treatment protocols from Ghana and sometimes the American Diabetes Association. All DM emergencies are admitted or referred for admission. Patients may require admission due to hypertension and cardiovascular disease, which in turn affect their blood glucose levels.

Clinicians explained that the average length of stay in admission is two weeks. During admissions, clinicians ensure that DM and comorbidities are controlled, and patients eat healthily and adhere to medication. Clinicians schedule patients for a review appointment upon discharge within 1–4 weeks. Clinicians in primary and some secondary facilities mentioned not admitting patients due to a limited number of beds, lack of medical equipment and few trained staff to provide inpatient services. The clinicians explained that they write a referral note for patients to seek care in resourced facilities but rarely check with the "referred-to" facility if there is capacity to admit, contributing to poor coordination and continuity of care. Tertiary facilities rarely refer patients to secondary or primary facilities. A Physician said:

"*They [patients] are mostly referred because the doctors think they would not be able to manage such cases because most of the peripheral hospitals do not have specialists. There are no specialists at those places. Mostly, the people that are referred are those with very high sugars and those who are likely to have ketoacidosis and other complications ... we only refer to other departments within the hospital." Over here, the treatment guidelines I am aware of are the American Diabetes Association guidelines for the management of DM."* (P3 Physician).

Clinicians mentioned that there are few specialists required to manage DM complications. According to clinicians, few public tertiary-level facilities have adequate numbers of podiatrists, endocrinologists and diabetologists, and many patients are in demand of specialised care. Consequently, a long waiting list discourages patients from seeking care. A pharmacist said:

"*Like right now you just asked about an endocrinologist, and I was trying to rub my neck to see if there is one because I haven't heard of one coming. Even the physician specialist that we have, we hauled from Korle Bu. So, he comes on Fridays and leaves on Saturdays. Then, the cardiologist, too, I think he also comes once or twice a week.*" (P10 Pharmacist).

Equipment and technology

Inadequate medical equipment and technology influenced health facilities' capacity to provide optimal DM care. According to clinicians, although basic laboratory services are covered under the NHIS, there is a lack of laboratory equipment/technology in primary and secondary facilities, making it challenging to conduct investigations on DM patients. Patients are referred to private laboratories to pay out of pocket for services. If they cannot afford the services, care is delayed until necessary laboratory tests are conducted. A physician said:

"… we do have problems with logistics, shortage of reagents, and materials. Sometimes, we end up shutting down the whole place for a week or two when we are in short supply of medical supplies or reagents. We need more staff to come in and assist. For example, when you came this afternoon, you saw the place was overcrowded. We are only two permanent staff; the others are service personnel who are assisting. So, we need more people to support us." (P7 Laboratory Technician).

Clinicians also mentioned that the lack of planned maintenance has resulted in the breakdown and abandonment of medical equipment that could have served patients. They explained that many medical equipment is purchased from overseas companies, and no trained local engineers maintain the equipment. It takes a long time for hospital management to arrange maintenance with engineers from outside the country. Consequently, many pieces of equipment that are out of order are abandoned.

6.4 Challenges to the delivery of clinical diabetes services associated with the COVID-19 pandemic[1]

This section presents the perspectives of DM service providers regarding COVID-19 and DM service delivery under six themes: high medicine and service costs and medicine shortages, poor patient information management, few trained providers, low provider motivation, service organisation challenges and national health policy-related concerns.

High medicine and service costs and medicine shortages

Service providers at all levels of care said the challenge of limited access to medicine and laboratory services in their work had worsened because of COVID-19. They explained that the pandemic has disrupted the supply chain, causing rationing of medicines and reagents in the manufacturing countries and frequent stockouts in their facilities. The NHIS continued to pay for insulin, metformin and glibenclamide. However, other medicines, such as those for treating diabetic retinopathy, were not covered, and consequently cost the patient comparatively more. The high treatment cost is causing concern because many patients are self-employed traders or dependents of traders who could not engage in trading due to the lockdown. Consequently, these medicines must be paid for out of dwindling savings or simply not purchased. One nurse explained:

[1] Published as Tagoe ET, Nonvignon J, van Der Meer R, Megiddo I, Godman B. Challenges to the delivery of clinical diabetes services in Ghana created by the COVID-19 pandemic. Journal of Health Services Research & Policy. 2023;28(1):58-65

"*All our eye drugs, NHIS do not provide for clients, so patients pay for all our eye care services except the consultation fee, which NHIS pays. For the drugs, because most of them are imported, they are expensive…about 65% of clients are not able to afford drugs*" (P4 Nurse).

A physician said:

"*Sometimes, you see a patient, and he would benefit from one or two things…but because of the cost, you have to give them the cheaper option, which may not be the ideal thing that will help"* (P3 Physician).

As part of its efforts to control the spread of COVID-19, the Ghanaian government closed its national borders. As most reagents used in laboratory testing are imported, interviewees at secondary and tertiary facilities said the border closure limited access to most of the reagents used in laboratory tests for people with DM. Providers referred patients to private laboratories when there were no reagents. Patients had to pay out of pocket because most private laboratories were not NHIS-accredited, increasing their financial burden.

Interviewees said the pressure on health facilities due to the surge in COVID-19 patients had led them to ration care to existing patients, such as those with DM. The ration contributed to review schedules for prescription drugs lengthening from one month to about three months. Such prescriptions increased the cost to patients because the NHIS only covered about a month's prescription. Patients must pay out of pocket for the remaining medicines or return to health facilities for a dated and signed copy of the same/initial prescription to obtain medicines under NHIS. Some participants said their health facility offered its social welfare system to help patients cope with increased costs. Local and international donors usually fund the hospitals' social welfare systems. One pharmacist explained:

"*The attending physician has to declare the patient unable to pay and refer him/her to social welfare*" (P2 Pharmacist).

Poor patient information management

Clinicians reported that providers temporarily stopped measuring patients' weight and blood glucose to avoid close contact with patients who could be infected with COVID-19. In other cases, patients were made to stand on weight scales while wearing footwear to prevent direct bodily contact with measuring scales. Interviewees acknowledged this could lead to inaccurate weight measurements but said the situation was necessary.

Clinicians said missing paper folders and identification cards, incomplete entries, and illegible writing had worsened since outpatient services had resumed. The situation resulted from the haste in which health workers had to create free space to serve the increasing number of cases attending after the lockdown. On the other hand, patients asked known contacts working in hospitals to keep their medical folders in personal lockers so that they could quickly access them and be seen earlier on their next visit. However, these folders are easily misplaced. According to clinicians, providers could forget critical medical information about patients' conditions because the information had been written in misplaced folders. When patients' folders were unavailable, physicians had to rely on prescription records or patients' descriptions of their medicines, which ca be misleading. A physician assistant said:

"[Patients] *mostly come with the medications they take - the boxes - so you are able to at least get the patient and the past medical history and the drug history*." (P12 Physician Assistant).

Few trained service providers

During the lockdown, DM clinics and outpatient department services were temporarily halted to allow DM-trained doctors and nurses to attend to the high numbers of COVID-19-infected patients. Clinicians said they found the situation frustrating because they could not properly manage and treat their DM patients during lockdown. One physician complained:

"*We have to start all over again with the patients because most of them return after the lockdown with uncontrolled sugars…probably because they were eating a poor diet, or they were stressed, and not exercising*" (P8 Physician).

Clinicians said that because there were few trained DM service providers and resources in primary health facilities, they frequently referred patients to secondary and tertiary facilities. However, patients hesitated to go to higher facilities for fear of contracting COVID-19 and so they either received no treatment or sought treatment elsewhere. A physician shared their experience of a 16-year-old patient with high blood sugar:

"*She had been to a private clinic…they gave her metformin. Maybe the person [at the private clinic] does not know that high sugar in the child is not T2DM; it is likely type 1, and that person will need insulin. So, the patient's time and money were wasted on metformin. The day she came here, she was in DKA [diabetic ketoacidosis], so she had to be admitted*" (P3 Physician).

Low provider motivation

Clinicians in secondary and tertiary facilities said other providers and hospital management had not been receptive to new ideas to improve service delivery during the COVID-19 pandemic. Interviewees said strategies had been devised to reschedule appointments to prevent facilities from becoming overcrowded with COVID-19 patients and thus allow clinicians to treat DM patients and others. But management responded with indifference. Participants found this demoralising, as a nurse explained: "*They* [hospital management] *simply do not want to change because they have been here for a long time, and that is exactly what they have been doing all the time*." (P6 Nurse).

Service organisation challenges.

Clinicians said that COVID-19 had led to a reorganisation of DM services. The usual monthly reviews of patients have been extended to three months to limit patients' risk of contracting COVID-19 due to frequent hospital visits. However, this could have adverse effects on patient care. A prolonged time between reviews limited opportunities for providers to reemphasise healthy behaviours and intervene early in patients' conditions to prevent DM complications. As one physician said:

"*If I see a patient whose sugars are not controlled, ideally, the next review should be closer. But now this is very difficult. COVID allows us to see a certain number of patients a day, so we cannot see so many patients. So, you realise that the clinic's dates are longer intervals than usual. So, control is very difficult.*" (P8 Physician).

Clinicians said they had no way of checking up on patients between appointments. During those intervening periods, some patients listened to ill-informed advice on managing their high blood sugars, engaged in unhealthy behaviours, and ended up in hospital with severe illness. A physician said:

"*I wish we had a telephone service, where if a patient is at home and review is in the next three months…and if he has a challenge, he can be able to call for guidance before review time is due. It is something that, if we had, it would help because, for all you know, they may be at home receiving misguidance from friends. Sometimes, if the patient is in contact with the health care worker who can give the correct advice, it will help our management.*" (P3 Physician).

Another problem was overcrowding and long waits at clinics. According to clinicians, patients crowd outpatient departments early in the morning, hoping to receive care early so they can go to their workplaces. However, this is not always possible because doctors attend to inpatients before seeing outpatients. Clinicians raised concerns about COVID-19 spreading during DM clinics due to

overcrowding and some patients' disregarding safety protocols (e.g., wearing a face mask). To help address this issue, providers reduced the number of patients scheduled per clinic day. A records officer said:

"*We need to expand in terms of physical space. Our consulting rooms are not many, and the wards are getting full. We are trying to obtain funds to erect more buildings, but that has not been easy. The DM clinic has only two consulting rooms, and since we resumed from the lockdown, on Tuesdays and Fridays, the place is always full, with long queues, and some patients don't even wear nose masks*." (P15 Record Officer).

National health policy–related concerns

Clinicians stated that the NHIS opposes facilities selling covered medicines to insured patients to standardise medicine prices. Even when medicines are out of stock in the central medicine store, health facilities cannot buy medicines on the open market without the central medical stores' permission. Clinicians explained that after purchasing from the open market, hospitals should not sell medicines to patients at 15–20% more than the NHIS prices. Participants said these restrictions contributed to a shortage of DM medicines during the COVID-19 pandemic because they could not readily buy limited available medicines on the market without the central store's permission. According to interviewees, obtaining permission can be a slow and complex process. During the wait, treatment is delayed, and patients could suffer complications or death due to unavailable medicines, especially with insulin shortages. As one nurse said:

"*If there is any delay in procurement from the central point, you do not have the liberty to go to the market to procure [medicine]. So, then we run out of a lot of vital or essential medicines, like paracetamol, metformin, glibenclamide.*" (P4 Nurse).

Additionally, the NHIS does not allow for the sharing of medicine costs with insured patients, and doing so can attract disciplinary action from the National Insurance Authority. An administrator explained how concerns about patient cost-sharing led to his facility being declined NHIS accreditation:

"*NHIA had to pay us more, but they were not willing to, and they did not want us to charge patients for the difference in payment. So, we quit*." (P15 Record Officer).

Respondents explained that if patients are made to pay the price difference after deducting the NHIS reimbursement price, there would be less incidence of treatment delays due to unavailable medicines as facilities will source from the open market with fewer price restrictions.

6.5 Discussion of results[2]

This study explored DM service delivery and treatment in Ghana, changes induced by the COVID-19 pandemic, challenges, and recommendations from service providers' perspectives. We interviewed 18 DM service providers from primary, secondary, and tertiary facilities and analysed interview data using a hybrid approach of deductive and inductive coding.

The study found that suboptimal appointment scheduling structures challenged effective DM service delivery. Researchers have reported that poor systems for patient appointment scheduling and follow-up, especially in PH facilities in LMICs, contribute to overcrowded clinics, long waiting times, and loss of follow-up (Mensah et al., 2014). Patients who lose productive time to long waiting times may reduce their demand for clinical healthcare or seek alternative healthcare options, increasing their risk of being lost to follow-up (Grossman, 2017). Another factor contributing to suboptimal appointment scheduling is the gap between estimated workload, available technology, and the health workforce.

We found that few trained clinicians hinder the delivery of optimal DM services. In Ghana, the increase in healthcare demand is incommensurate with the number of health professionals and medical equipment, resulting in suboptimal care (Asamani et al., 2021). Policymakers need to engage in evidence-based planning for the staffing needs of the healthcare system and consequently adjust health professional education and employment. Researchers have suggested using queuing models instead of manual paper-based scheduling to optimise appointment scheduling (Safdar et al., 2020; Yaduvanshi et al., 2019). Queuing models are mathematical tools used to analyse and improve the flow of entities through a system where they wait in line, such as patients in a healthcare facility. Queuing models can help healthcare administrators and practitioners understand and enhance patient pathways, including waiting times, clinicians and medical resource use, and overall system efficiency, by generating evidence of the resource capacity required.

Clinicians noted that counselling sessions at health facilities alone are insufficient to cause a significant change in patients' unhealthy behaviours as these behaviours have been developed over a lifetime. While acknowledging the influence of various factors on food choices, advancements in behavioural science have enhanced our understanding of strategies for designing diet modification interventions among adults. These strategies include giving information on the health consequences of diet, action

[2] Amended for the published paper: Tagoe ET, Nonvignon J, van Der Meer R, Megiddo I, Godman B. Challenges to the delivery of clinical diabetes services in Ghana created by the COVID-19 pandemic. Journal of Health Services Research & Policy. 2023;28(1):58-65

planning and tailored feedback based on participants' dietary self-monitoring (McGowan, 2021). In Nigeria, Mali, Rwanda, and other LMICs, structured DM self-management education programs have been associated with improved diet and DM biomarkers (Lamptey et al., 2022). The education program in these countries consists of sessions on exercise, nutrition, medication administration and adherence, glucose monitoring, routine medical reviews, foot care, cardiovascular risk management and complications management. Lamptey et al., 2022 tested the effectiveness of a structured DM education program for BGC among T2DM patients in Ghana through a randomised control trial. The trial indicated a reduction in HbA1c, but the reduction in the treatment group was not significantly different from the control group. The duration of the intervention could explain its ineffectiveness in Ghana compared with its effectiveness in Nigeria, Mali, and Rwanda. In Ghana, the intervention included one six-hour session in a day. In Mali, two-hour sessions were held quarterly for one year; in Nigeria, two-hour sessions are biweekly for six months; and in Rwanda, 45-60-minute sessions were held monthly (intervention timeframe not specified). More studies in Ghana could provide evidence of the effectiveness of structured DM self-management education programs for BGC in DM.

Clinicians discussed how poor maintenance culture and insufficient medical equipment contribute to suboptimal DM service delivery. Evidence from the Ghana Medical Equipment Guideline indicates that a significant number of medical devices in the country have broken down, and there are no regular maintenance services due to a lack trained maintenance officers in health facilities (Ghana Health Service, 2018). Factors such as inadequate numbers of trained engineers and technicians, data deficiencies, and the lack of predictive and preventive maintenance models contribute to equipment breakdown (Kutor et al., 2017). Ghana has deliberated on ways to resolve the challenge, including developing the Medical Equipment Guidelines, but policy implementation remains stalled mainly due of inadequate funds (Ghana Health Service, 2018; Kutor et al., 2017). The country could leverage existing structures and partnerships, such as collaborations with non-government organisations and the private sector, to train and build capacity for maintenance engineers.

The COVID-19 pandemic and related control measures have further worsened the challenges with DM management in Ghana. Clinicians stated that the high cost of non-NHIS-funded medicines impeded effective DM treatment because patients could not afford these medicines. Ghana has identified the high cost of medicines as a general problem. The country has instituted the National Medicine Policy to streamline drug manufacturing, procurement and pricing in the pharmaceutical sector (Ministry of Health, 2017b). However, the challenge with unstandardised medicine prices remains in Ghana and other LMICs, with DM medicines ranging from US$15 to over US$500 per year (Butt et al., 2024; Moucheraud et al., 2019). The price of DM medicines has also increased in high-income countries. For instance, in England, there has been a 17% increase in the total cost of DM medicines over the past five years (NHS Business Services Arthority, 2024). Steps to standardised medicine prices should include

negotiations between key stakeholders (e.g., government, pharmaceutical companies and consumers) to determine price floors/ceilings to ensure fair prices for manufacturers and patients (Moon et al., 2020).

Clinicians noted that the COVID-19-related lockdown and the closure of DM clinics during the pandemic contributed to the reduced availability of DM services. While similar findings are reported in many countries (Hartmann-Boyce et al., 2020), some nations developed innovative responses to the problem. However, not all responses may have effectively and completely addressed the problem. The United Kingdom, for instance, developed strategies to deliver DM care during the pandemic, including posting urinalysis dipsticks to T1DM patients, who self-tested and then uploaded the results to a mobile phone application, which transferred the information to healthcare providers (Ranscombe, 2020). Further, online DM support groups for people with DM were formed in Scotland to support health promotion and education delivered remotely (Ranscombe, 2020). In Italy, health providers used Facebook, video teleconsultation, and websites to deliver DM services (Hartmann-Boyce *et al.*, 2020). In India, teleconsultations using trained pharmacologists have proven effective in delivering DM care (Joshi et al., 2020). Drones were even used in some parts of Africa to deliver medicines during the pandemic (Ranscombe, 2020).

COVID-19 has reaffirmed the need for more trained health professionals worldwide, including in LMICs, to avoid the anticipated shortage of 15 million healthcare workers in the global health labour market by 2030 (Liu et al., 2017). Interviewees described how the surge in COVID-19 patients exacerbated workforce shortages, with already limited trained DM services providers diverted to treat COVID-19 patients. In addition to training more health professionals, existing staff can be redeployed. In India, for instance, using trained pharmacists to replace doctors in providing DM follow-up consultations during the COVID-19 epidemic proved viable and effective (Joshi *et al.*, 2020). Likewise, other non-physician healthcare providers, such as physician assistants and nurses, can pick up some doctors' roles in delivering NCD services if they are provided with adequate training and continuous learning. For example, physician assistants and nurses have been reported to substitute or supplement physicians' roles in delivering DM care to adults in the US (Everett et al., 2014).

Additionally, clinicians mentioned that inadequate material and human resources in primary care and the lack of recognition and appreciation of providers in secondary and tertiary facilities reduced their motivation to perform optimally. Working conditions, financial and social incentives, and career development are commonly reported to influence health providers' motivation (Godman et al., 2020). Interventions focused on continuous education and mentorship can improve provider knowledge and skills in the short term. However, the level of performance improvement may differ depending on the nature of the task and the health worker's cadre (Godman et al., 2020).

Finally, clinicians noted that the persistent medicine shortage and health facilities' limitations in procuring and pricing medicines delayed patients' access to DM medicines. In Ghana, only a few health facilities (mostly those in urban areas) have a stock of essential medicines for people with DM (Godman et al., 2021; Moucheraud et al., 2019). Three multinational companies dominate insulin production globally–Novo Nordisk, Eli Lilly, and Sanofi. These companies control 96% of the global insulin supply, and the failure of governments to outsource supplies from different manufacturers means medicines may experience stockouts if these companies do not meet demand (Beran et al., 2019). The WHO prequalification programme, whereby the WHO prequalifies the quality of biosimilar insulins (Blaschke et al., 2020), could help increase access to insulins and other key medicines by fostering competition, making low-priced DM medicines and equipment more accessible while ensuring they meet agreed quality, safety, and efficacy standards. The WHO programme prequalifies pharmaceuticals and diagnostics that satisfy international standards through multiple assessment methods, discovering and correcting quality concerns while strengthening quality assurance. In addition, the programme encourages global competition for high-quality medications and diagnostics. Ghana and other LMICs could work with drug manufacturers to build on interventions such as the Base of the Pyramid Initiatives in Nigeria, Tanzania, and Kenya (Shannon et al., 2019) to increase access to DM medicine. A study on insulin uses in multiple countries, including Ghana, has recommended that Ghana's MoH should seek to reimburse low-cost biosimilar insulins listed on its essential medicine list to ensure consistency in treatment, procurement, and reimbursement and should focus on medicines prequalified by the WHO to achieve the best value for money (Godman *et al.*, 2021).

6.6 Limitations of the qualitative interview[3]

The study has three main limitations. First, in response to waves of the COVID-19 pandemic, health facilities continued to change how health services are organised and delivered. As such, the findings of this study may not reflect present circumstances. Second, the interviews were conducted in open workspaces within health facilities, which might have reduced interviewees' level of candour. Third, we could not interview DM service providers outside the Greater Accra region (except for one interviewee using a Zoom call) or those in facilities that were closed to outpatient DM care at the time of the interviews. Furthermore, we did not gather the views of people with DM. As such, this study only captured a limited number of perspectives.

[3] Published as Tagoe ET, Nonvignon J, van Der Meer R, Megiddo I, Godman B. Challenges to the delivery of clinical diabetes services in Ghana created by the COVID-19 pandemic. Journal of Health Services Research & Policy. 2023;28(1):58-65

6.7 Insights from the interviews related to Interventions considered for simulation

This section builds on the discussion about interventions to be considered in the simulations study, presented in Chapter 3, drawing on insights from the interview and informal discussions with government officials in NHIS.

Intervention 1: Increasing access to DM medicines

Clinicians explained how the persistent shortage of DM medicines contributes to medicine non-adherence, leading to poor DM treatment outcomes. According to a national pharmaceutical study, improving transport systems and introducing effective planning, forecasting, and budgeting structures could address the inefficiencies in the local medicine supply chain and improve medicine availability.

Intervention 2: Increasing NHIS coverage

Insights from the interviews confirmed the challenge patients have with accessing medicines. Clinicians explained that medicine non-adherence results from the high medicine cost for uninsured patients and instances where medicines are not covered by NHIS.

Increasing the proportion of patients covered by NHIS increases the pool of DM patients who can access medicine. Patients who previously could not afford medicines may now have access through the insurance scheme. Given that medicine cost to patients is one of the reasons expounded for non-adherence, increasing insurance coverage could potentially enhance medicine adherence.

The researcher (ETA) had an informal discussion with an NHIS official on the feasibility of increasing insurance coverage. Insights from the conversation indicate that funding for claims payment and operations poses a significant challenge to expanding coverage. The NHIS reports to the MoH, headed by a political appointee from the government. Thus, the government's will and investment are essential to support and sustain increasing coverage. However, the increase should be incremental to avoid unexpected substantial changes in NHIS budgetary conditions that disrupt its financial planning. Given that the MoH's programme of work is often planned over five years, we considered an intervention that spans over five years. Specifically, we discussed that a 10% increase in the proportion of insured DM patients annually for five consecutive years could be feasible for the NHIS. The NHIS is interested in

understanding how much the intervention changes service and medicine costs for the scheme and improves DM outcomes for patients and the population.

The effectiveness of the national medicine supply chain partly depends on the global pharmaceutical market, as Ghana imports most medicines and supplies. Achieving 100% availability of DM medicines may be unrealistic for the Ghanaian government, as global supply chain factors are beyond its control. Therefore, in our simulation studies, we examined the impact of a 10% increase in the frequency with which patients could obtain DM medicines. We assumed that the strategies proposed in the national pharmaceutical study could support the 10% increase and thus investigated its effect on DM treatment outcomes.

Interventions 3: 20% SSB tax

Clinicians explained that most patients are hesitant to modify dietary behaviours developed over their lifetime despite DM. They noted that patients are accustomed to unhealthy food preferences and struggle to make significant changes to their dietary behaviours.

The insight from clinicians supports the view that most patients, by themselves, cannot maintain healthy dietary behaviours. Ghana's 20% SSB tax policy, if enforced effectively, can influence patients to reduce consumption of SSB by increasing their prices, making them less affordable to patients (Basu et al., 2014; Jevdjevic et al., 2019; Manyema et al., 2014). At the time of this study, data on changes in dietary consumption following the tax implementation were not yet available. As a result, we estimated the effect of Ghana's SSB tax using findings from India and South Africa (Basu et al., 2014; Manyema et al., 2014).

Intervention 4: Increase NHIS coverage and a 20% SSB tax.

As discussed in Chapter 2, the NHIS requires more funding to sustain its operations. This intervention is motivated by the idea that the government could allocate revenue from the SSB tax to expand NHIS coverage. SSB taxes provide a source of revenue for governments, which could support NHIS and other health initiatives (Singh et al., 2023).

6.8 Chapter Summary

This chapter has partly addressed Research Question 1: *'What is the state of DM service delivery in Ghana …*?" and Research Question 2: *"How do patients' behaviour influence health service delivery*

and DM treatment outcomes?" We have presented the perspectives of clinical service providers on the pathways to DM services within the PH sector. The interviews revealed significant service delivery system gaps that affect patient SMB and DM treatment outcomes. The gaps described include suboptimal appointment scheduling, few trained clinicians, few medical equipment, and poor maintenance culture. The qualitative interviews revealed patients' difficulty maintaining healthy lifestyles, highlighting how unhealthy diet behaviours relate to attitudes, culture and the food environment. We described clinicians' perspectives on the influence of the COVID-19 pandemic on DM service delivery and recommendations for improving DM control. The insights on DM service delivery and patients' behaviour from the qualitative interviews informed and refined potential interventions to be explored in simulations. The interviewing process presented in this chapter helped us build rapport with clinicians, which will be leveraged for further engagement in the model-building phase to build confidence in our ABM model. In the next chapter, we describe the model-building processes, experiments, and analysis conducted to answer part of Research Question 5: "*What are the health and economic benefits of selected PH interventions for patients and the government?"*

7 Case study: ABM for modelling type 2 diabetes treatment behaviour and outcomes in Ghana

7.1 Introduction

Building on the methodological framework outlined in the previous chapter, and the insights from interviews with clinicians and literature reviews, this chapter presents the second phase of our original research: an agent-based modelling study on DM service delivery and patients SMB in Ghana. This study operationalises the critical realist approach discussed in Chapter 5, seeking mechanisms and interactions that give rise to DM treatment outcomes by combining insights from the sources earlier mentioned. The simulation study addresses Research Question 5: *What are the health benefits and economic efficiency of selected PH interventions to patients and the government*? In line with our mixed-methods design, evidence generated in the simulation experiments was used as input data in the CEA study.

In the subsequent sections, we describe the context for the modelling study (7.2) and the choice of modelling approach (7.3), followed by a description of the model (7.4 – 7.6), simulation experiments and results (7.7 – 7.8), discussions of model results and limitation (7.9 – 7.10) and chapter conclusion (7.11).

7.2 Research Context

This study aims to investigate patients' SMB and DM treatment outcomes within Ghana's PH system. As discussed in Chapters 3 and 6, we identified three key interventions for modelling based on literature review and expert interviews: increasing NHIS coverage, increasing medicine availability in communities and a 20% SSB tax. These interventions operate at different levels (individual, community, and national) and involve complex behaviours and influences of patients, healthcare providers, and policy environments. For instance, patients' poor medicine adherence behaviours and unhealthy lifestyles lead to poor blood glucose and acute DM complications, influencing their demand for health services. However, patients cannot access clinical services and medicines without insurance coverage or sufficient funds. Traditional models, such as SD, struggle to capture these multi-level interactions and individual-level decision-making processes. Furthermore, the heterogeneity of patients' characteristics and behaviours, as discussed in Chapters 4 and 6, suggests the need for a

modelling approach that can represent individual-level heterogeneity, behaviours, and decision-making processes.

Consequently, we turn to ABM as a potentially suitable approach. We discussed the appropriateness of ABM for investigating the decision problem in Chapter 5, Section 5.4.2. The following sections focus on the model conceptualisation and building, experiments, analysis, and results.

7.3 Agent-Based Model: Overview and Design Concepts

This section presents key details on the model overview and design concepts per the Overview, Design Concepts, and Details (ODD) Protocol (Grimm et al., 2020). The full ODD protocol is in Appendix C.

7.3.1 Purpose and Patterns

The purpose of the model is to describe the behaviour of T2DM patients undergoing clinical treatment and test the effectiveness of selected PH interventions on population-level treatment behaviour and treatment outcomes. Treatment outcomes include the proportion of patients with good, moderate, and poor BGC. BGC is modelled as a weekly estimate (using lifestyle and medicine adherence behaviour) and a 13-week estimate (using the most BGC states over the period). We evaluated our model by its ability to reproduce behaviour patterns and outcomes reflecting clinicians' opinions and what has been reported in the literature, a process termed confidence building (details in Section 7.7).

7.3.2 Entities, States Variables and Scales

This model has one agent: T2DM patients currently receiving treatment in a PH facility (represented by 'turtles'—mobile individual agents in NetLogo programming that can take on multiple characteristics and perform several procedures). The patient agent has a unique set of state variables detailed in Table 7.1. Patients are described by sociodemographic variables and biomarkers describing BGC. Hospitals are not agents; they are represented in the agent's environment.

The model does not represent geographic location and distance. However, patients in the model could live in an urban or rural area; this residence state variable only captures the difference in health infrastructure, specifically access to medicines, but not the geographical landscape. The patients do not enter the model through birth but exit through death. Consequently, the number of patients shrinks over time until all the patients die. The model runs at a weekly time step as a week is adequate to observe changes in BGC and medicine adherence.

Table 7.1 The state variables of patient agents and the global environment (Author's own research).

Variable name	Variable type, units, and range	Meaning and rational
Patient-agent-specific state variables		
Demographic variables		
age	Integer, dynamic; years 27 -84	It affects the incidence of death and influences treatment for BGC.
sex	Integer, static, no unit 1 = female 0 = male	Patients' sex is used to set other variables, e.g., crude mortality and reporting result purposes.
residence	Integer, static; no unit 0 = rural 1 = urban	The residential location of patients not geographically modelled. Affects patients' dietary behaviour and medicine availability.
comorbidity	Integer, dynamic, no unit 0 = no comorbidity 1 = comorbidity	Prevalence of comorbidity, using hypertension as a proxy. It is used in a sub-model that estimates BGC.
Sociodemographic variables		
wealth	Integer, static, no unit, 0 = poorest 1 = second 2 = middle 3 = fourth 4 = richest	Wealth affects uninsured patient's ability to afford medicines, which affects medicine adherence behaviour.
life-expectancy	Integer, dynamic, weeks	The number of weeks a patient is expected to live. Determines when a patient dies/ exists the model
insurance	Integer, static; no unit, 1 = insured, 0 = uninsured	Indicates if a person is insured under the national health insurance scheme; affects medicine affordability and adherence behaviour.
lifestyle	Integer, dynamic; no unit, 1 = healthy 0 = unhealthy	Diet and exercise behaviour of patients. Affects patients' BGC.
Diabetes-related variables		
HbA1c	Integer, dynamic; no unit, 1 = good control 2 = moderate control 3 = poor control	13 weeks frequent occurring fbg, a fair representation of BGC considering the spikes in weekly estimates; reported for BGC
clinical-state	Integer, dynamic; no unit 0 = outpatient 1 = discharged patient 2 = inpatient	Indicates patients' clinical state, affects the kind of services they receive in the attending health facility, and affects patients' medicine intake behaviour.
discharge-time	Integer, dynamic; weeks, 1 – 3	The number of weeks a patient stays on admission affects BGC, lifestyle, and medicine adherence behaviour.
recovery-period	Integer, dynamic; weeks, 1 – 4	The number of weeks a patient engages in a healthy lifestyle for the fear of readmission following discharge
med-in-com	Integer, dynamic; no unit, 1 = medicine available, 0 = medicine unavailable	Indicate if a patient could find medicines available in their residence. Affect medicine adherence behaviour.
duration	Integer, dynamic; years; 1 – 10	The number of years a patient has lived with T2DM
appointment	Integer, dynamic; week; 1 – 2080 weeks, the length of a simulation	The week a patient is scheduled for a clinical review appointment could influence diet and medicine adherence behaviour.
my-fbg	List of integers, dynamic, no unit. In the list,	A list of patients' weekly BGC that is used to estimate 3-month average BGC

	1 = good control 2 = moderate control 3 = poor control	
my-med	List of integers, dynamic, no unit. In the list, 1 = took medicines as prescribed, 0 = did not take medicines	A list of patients' weekly medicine intake behaviours, which affects BGC, is used to estimate the 3-months
prescription	Integer, dynamic; weeks; ranges -1, 0, >1	The number of weeks of medicine prescribed for a patient. -1 means a patient couldn't afford medicines, 0 means the prescribed medicines have been bought, or there is no outstanding prescription, >1 means the number of weeks medicines yet to be bought. This variable affects medicine adherence behaviour.
Global variable		
noMed	the number of times patients could not access medicines due to unavailability.	For model internal validation
insuredAdmi	Count of admissions in insured patients	For gathering data for CEA
uninsuredAdmi	Count of admissions in uninsured patients	For gathering data for CEA
insuredAttendance	Count of OPD visits in insured patients	For gathering data for CEA
uninsuredAttendance	Count of outpatient appointments attended by uninsured patients	For gathering data for CEA
PDiet	The prevalence of obesity and overweight in the patient cohort.	Used to set patients' lifestyle (i.e., diet and exercise), which affects BGC.
ruralProDiet	The proportion of the national prevalence of obesity and overweight in rural communities.	Combined with PDiet to set the lifestyle of rural-resident patients, which affects BGC.
urbanProDiet	The proportion of the national prevalence of obesity and overweight in urban communities.	Combined with PDiet to set the lifestyle (of urban-resident patients, which affects BGC.
MedUrban	The percentage of times DM medicines are available to buy in urban communities.	Influence medicine adherence behaviour of outpatients and discharged patients, which affects BGC.
MedRural	The percentage of times DM medicines are available to buy in rural communities.	Influence medicine adherence behaviour of outpatients and discharged patients in rural areas, which affects BGC.
InsuranceCoverage	The proportion of patients who are actively insured under the NHIS	Influence medicine affordability and, thus, medicine adherence
HypertensionPrev	The proportion of patients who have comorbidities, using hypertension as a proxy.	Influence clinical service provision and thus BGC.

Note: State variables are not derived from patients' procedures or decisions. They are basic characteristics that patients are initialised with, which they use in model procedures and decision-

making. Global variables are characteristics owned by the entire model and accessible to all agents in a model. NHIS = National Health Insurance Scheme. BGC= blood glucose control.

7.3.3 Design Concepts

Basic principles

System-level concept:

This model addresses a key PH management question: How do various PH interventions affect treatment outcomes for T2DM in a low-resource setting? Specifically, it explores how factors such as medicine availability, insurance coverage, and SSB taxes influence BGC, diet, and medicine adherence at a population level in Ghana.

Theoretical foundation:

At the agent level, the model is grounded in the Health Belief Model (HBM), a well-established psychological theory explaining health-related behaviours (Strecher & Rosenstock, 1997) and the Theory of Planned Behaviour (TPB). The HBM's constructs–perceived severity, perceived susceptibility, perceived barriers, perceived benefits, cues to action and self-efficacy– and the TPB constructs–subjective norms, attitudes, and perceived behavioural control–are used to inform patient decision-making processes regarding treatment adherence and health-seeking behaviours.

Table 7.2 summarises how we use the theories to represent patients' behaviour. Perceived barriers in HBM and perceived behavioural control in TPB are similar; they refer to the individuals' assessment of obstacles, including cost and availability of resources. Implementing the constructs, we set patients to not take medicines when they are unavailable in communities, they cannot afford medicines or do not have a prescription. Cues to action are external or internal stimuli that trigger a decision to engage in recommended health behaviours. Using the concept of perceived severity and cues to action in HBM, patients with poor BGC, who have unhealthy lifestyles and do not take medicines seek care regardless of not having an appointment. Poor SMB behaviours in such patients result in acute complications, which trigger the decision to seek care. Patients with good to moderate BGC may miss review appointments as they do not feel unwell and, therefore, have a low perception of severity, susceptibility, and triggers. Perceived susceptibility is the perception of the likelihood of experiencing a health threat. Perceived severity describes the perception of how serious a disease or health condition is and the medical, clinical, and social consequences of leaving it untreated. Perceived susceptibility and perceived severity influence an individual's evaluation of behaviour. Discharged patients have a high

perception of susceptibility and severity of DM after experiencing acute DM complications that led to their admission. Therefore, such patients live healthy lifestyles and take medicines if they can afford them, and the medicines are available. Inpatients live healthily and take medicines. Perceived benefits describe the belief in the effectiveness of a recommended behaviour in reducing the severity of the health condition. Patients perceive the effectiveness of clinical services in resolving acute complications and, therefore, seek care in such a condition. Subjective norms in TPB describe perceived social pressures to conform to a behaviour. Patients follow the diet and exercise trends in their communities.

Table 7.2 Health behaviour theories applied to model patient self-management behaviour (Author's own research).

Behaviour	Tenets of HBM	Tenets of TPB	Application in the ABM model
Lifestyle (diet and exercise)	N/A	subjective norms	Outpatients follow the lifestyles of people in their community. Inpatients follow the guidelines of clinicians, including living a healthy lifestyle and adhering to medication.
Medicine intake (patient has a prescription)	Perceived barriers	Actual behavioural control	Cost and availability hinder medicine intake. Uninsured patients cannot afford medicines if they are too poor to afford them. Patients cannot access medicine if they are stockout. Therefore, patients do not take medicines.
Medicine intake (patients have no prescription)	Perceived barriers	Actual behavioural control	DM medicines need a prescription to buy. The patient missed an appointment and had no prescription to buy medicines.
Review appointment attendance	Perceived severity and cue to action	Attitude	Attitude The patient is feeling well and has no signs of illness; therefore, he/she may miss an appointment.
Seeking care in acute complication state	Perceived severity and susceptibility of DM Perceived benefit of clinical services	Attitude	Attitude The patient's glucose level is poor, and he feels unwell. The patient believes health facilities can manage the condition and, therefore, seeks care.
Inpatients' behaviour	Perceived severity and susceptibility	Subjective norms	Patients experience the severity of DM and are vulnerable to it, so they adhere to recommended treatment and follow clinicians' instructions.
Discharge patients' behaviour	Perceived severity and susceptibility, perceived benefit	Attitude	Patients experience the severity of DM and their vulnerability to it and appreciate the benefit of adherence; therefore, adhere to recommended treatment.

Note: HBM = Health Belief Model, TPB = Theory of Planned Behaviour, N/A means there is no construct from the Health Belief Model that we combined with the Theory of Planned Behaviour to conceptualise a behaviour.

Novel approach:

This model uniquely combines patient behaviour, clinical service delivery, health system factors, and policy interventions. It aims to provide insights into how system-level changes due to PH interventions can influence individual patients' behaviours and, consequently, population-level health outcomes.

Integration of clinical and behavioural aspects:

The model integrates clinical aspects of DM management (e.g., BGC) with behavioural factors (e.g., lifestyle and medicine adherence). This integration allows for a more comprehensive understanding of the complex dynamics involved in T2DM management in real-world settings. The model simulates the effects of selected PH interventions and serves as a framework for evaluating potential policy decisions. This approach allows for exploring intervention impacts without costly and time-consuming real-life trials.

Emergence

Patient-level and cohort-level treatment outcomes, including the proportion of patients with poor, good, and moderate BGC, medicine adherence, admissions and outpatient service utilisation, are the main model outcomes that emerge from patients' decisions on medicine adherence, health-seeking, lifestyle, and how they interact with clinical services, medicine availability and affordability in communities, and community-level lifestyle trends. Deaths from all causes, including DM, are imposed.

Adaptation

The decision to attend outpatient appointments or seek care is an adaptive behaviour of patients. Patients decide to attend or not attend based on their state variables: appointment date (appointment), comorbidity (comorbidity), BGC (fbg), medicine adherence (med), and lifestyle (lifestyle). The AttendanceProp variable affects the decision. Outpatients who have appointments in the present week and poor BGC (fbg = 3) decide to attend appointments. Comorbid outpatients who experience poor BGC, engage in unhealthy lifestyles, and do not take medicines in a given week are set to have poor BGC and, therefore, attend outpatient services even without an appointment. Outpatients who have an appointment in the present week but have moderate to good BGC (fbg = 2 or fbg = 1) decide to attend or miss an appointment using the AttendanceProp parameter. Specifically, the patient selects a random number between 0-1 and attends if the selected number is less than AttendanceProp. Otherwise, the patient does not attend.

The decision of when to schedule an outpatient appointment is an adaptive behaviour of patients that changes their appointment state variable. Patients who attended appointments and were not admitted set their next appointment based on their BGC, insurance status and the availability of appointments. Those with good BGC set the next appointment to any week between 9–14 weeks, and moderate control set to any week between 7–9 weeks. Insured patients ensure they have no more than six appointments in a year. Patients who missed an appointment set the next appointment using stochasticity.

The patient's blood glucose, medicine adherence, lifestyle, and comorbidity affect whether the patient is admitted or scheduled for an appointment. The decision changes the patient's clinical-state variable. Patients with poor control (fbg = 3), medicine nonadherence (med = 0), unhealthy lifestyle (lifestyle = 0) and comorbidity (comorbidity = 1) get admitted. Patients in other states, including the mentioned states, but with no comorbidity, get their BGC checked and scheduled for an appointment.

Another adaptive behaviour of patients is the decision to check or not check if the medicine is available in their community. The decision is affected by patient-level variables, such as prescription and medicine availability in their community, MedUrban and MedRural. The decision changes the patient's med-in-com variable. Patients check for medicines if they have outstanding prescriptions (prescription > 0). Otherwise, patients do nothing.

Medicine intake is an adaptive behaviour of patients. Patients decide to take medicines as prescribed or otherwise based on access to and affordability of medicines. Patient-level variables that affect medicine access are prescription and med-in-com, while wealth and insurance affect affordability. Medicine availability in the community (MedUrban and MedRural) affects the decision. Inpatients take medicines as prescribed.

Lifestyle, the decision to exercise and eat healthily or otherwise, is an adaptive behaviour affected by lifestyle trends in patients' community, represented by Pdiet, ruralProDiet and urbanProDiet. Patients select a random number and compare it to the lifestyle trend in their community (Pdiet * ruralProDiet in rural residents; Pdiet * urbanProDiet in urban residents). If the selected number is less than the comparator, the patients set an unhealthy lifestyle. Otherwise, the patients set a healthy lifestyle.

The decision to be covered by insurance and to develop comorbidity is affected by trends in patients' environments, represented by InsuranceCoverage and HypertensionPrev, respectively. Patients use the same behaviour rules when deciding on lifestyle to decide on insurance and comorbidity. The decision updates patients' insurance and comorbidity state variables.

Patients remain or exit/die from the model based on their age, sex, life expectancy, and environmental variables: female and male crude mortality. First, patients who have lived to the expected age (age =

life expectancy) exit the model. Second, patients use stochasticity, sex, and age, as well as female-crude mortality or male crude mortality, to decide if they exit the model for other reasons.

The decision to remain in admission, discharge or recover is an adaptive behaviour of patients and is affected by recovery-period and discharge-time. If discharge-time is the same as the present week, inpatients are set to discharged patients (change clinical-state from 2 to 1). Otherwise, inpatients remain in admission. Discharged patients are set to outpatients (change clinical-state from 1 to 0) if the recovery period is the same as the present week. Otherwise, discharged patients remain in a recovery state.

Aside from the decision to admit, patients simply follow the rules in all the adaptive behaviours described; they do not seek to directly increase some form of utility.

Objectives

Outpatients experiencing poor BGC but having no hospital appointments decide explicitly to pursue an objective of improving their BGC state by attending a health facility. Such patients are set to change from poor to good BGC (from fbg = 3 to fbg = 1).

Prediction

Outpatients with acute DM complications seek care and get admitted to hospital based on an implicit prediction that they will get better on admission. Patients implicitly predict that taking medicines will improve their DM condition. According to clinicians in the study setting, these predictions are mostly correct.

Sensing

We model DM patients receiving treatment in health facilities; all patients know they have DM, the prescribed medicines, and the recommended lifestyle. Patients know the following characteristics about themselves: review appointment, BGC state, when they recover from acute complications, when they are discharged, their clinical state, age, sex, insurance status, comorbidity status and life expectancy.

Interaction

Patients interact with health facilities present in their environment. They interact directly with the health facility to seek care for uncontrolled blood glucose; patients change their blood glucose to a controlled state to indicate that they received treatment for their uncontrolled blood glucose state.

Stochasticity:

The model initialises age, sex, diet, and residence stochastically; these characteristics are used to reproduce variability in the modelled population as observed in the data. Patients' lifestyles, wealth and insurance are randomly assigned to reproduce observed patterns in empirical data. Wealth and insurance affect patients' access to medicines, influencing medicine adherence and BGC outcomes. Patients' first review appointment is assigned randomly. The duration of DM in patients is set using stochasticity. Details of how randomness is used in these procedures are in the submodel section of the ODD protocol in Appendix C.

Collectives:

There are no collectives in the model.

Learning

There is no learning in the model.

Observation:

We collected data on treatment outcomes (the count of patients with poor, moderate and good BGC, medicine adherence and admissions) from the model for analysis. The data are collected directly in R, and a copy is saved in a CSV file for analysis outside R. We displayed weekly and three-month outcomes using graphs in the model interface. We also used graphs to visualise trends in insurance coverage and the distribution of inpatients, outpatients, comorbidity, and admissions in the patient cohort.

7.4 Data Collection and Parameterisation

We used data from literature, expert knowledge, and calibration techniques to define and quantify the model parameters. We had periodic discussions with clinicians to scope the problem and build and validate the model structure and assumptions. Using a semi-structured interview, we asked clinicians about the model assumptions relating to lifestyle and medicine adherence, when, what and how clinical services are provided, and the relationship between medicine adherence, lifestyle, and BGC. We ran model iterations and asked clinicians to comment on the model's outcomes. Section 7.6 summarises findings from our engagement with clinicians. We reviewed the literature to obtain the values for

parameters characterising the patient sociodemographic features and DM treatment-associated factors, presented in Table 7.3. We found from health facility records that the age of DM patients followed a normal distribution (highlighted in Table 7.3). Where we did not find data on the Ghanaian population, we used available data from other countries with similar socioeconomic and cultural features.

Table 7.3 Model parameters (Author's own research).

Parameter name	Meaning and rationale	Default value	Sensitivity analysis	Source
age	Age of patients. used at initialisation to populate patients' age	Mean = 59 Standard deviation = 12 Min = 27 Max = 88		Osei-Yeboah et al. (2018)
PDiet	The prevalence of obesity and overweight (used as a proxy for diet and exercise behaviour). Used to increase the prevalence of poor diet and exercise behaviours among patients).	Estimated from an S-shaped distribution (details in **update-obesity** sub model section Appendix C)		Amugsi et al. 2017
ruralProDiet	The proportion of the national prevalence of obesity and overweight in rural communities.	0.4		Yussif et al. (2024)
urbanProDiet	The proportion of the national prevalence of obesity and overweight in urban communities.	0.6		Yussif et al. (2024).
InsuranceFemale	The proportion of female patients who are NHIS-insured by wealth quintile. Used to adjust insurance coverage in females by wealth. Used in **set-insurance** sub model.	Poorest = 45.4% Second = 49.3% Middle = 53.0% Fourth = 55.8% Richest = 70.1%		Ghana Multiple Indicator Cluster Survey 2017/2018 (Ghana Statistical Services, 2018)
InsuranceMale	The proportion of male patients who are NHIS-insured by wealth quintile. Used to adjust insurance coverage in males by wealth. Used in **set-insurance** sub model.	Poorest = 32.2% Second = 28.1 Middle = 36.2% Fourth = 40.0% Richest = 59.8%		Ghana Multiple Indicator Cluster Survey 2017/2018 (Ghana Statistical Services, 2018)
UrbanProp	The proportion of the population living in urban areas. Used at initialisation to populate patients' residence	0.52	0.50 – 0.58	Ghana Multiple Indicator Cluster Survey 2017/2018 (Ghana Statistical Services, 2018)
MedUrban	The percentage of times DM medicines are available to patients in	0.8	triangular distribution	Assumed based on (Masters et al., 2014)

	urban communities. Used in setting **med-in-com,** which indicates if the patient found medicines. Details in **check-meds** sub model in Appendix C.		(min= 0.6 mode= 0.8 max= 1)	
MedRural	The percentage of times DM medicines are available to patients in rural communities. Used in setting **med-in-com,** which indicates if the patient found medicines. Details in **check-meds** sub model.	0.7	triangular distribution (min= 0.4 mode= 0.7 max= 1)	Assumed based on (Masters et al., 2014)
rural-wealth	The proportion of rural-resident patients falling in wealth quantile. Used at initialisation to populate patients' wealth in **the set-wealth** sub model.	Patients in rural areas: 0 = poorest 33.5% 1 = second 27.3% 2 = middle 19.7% 3 = fourth 12.2% 4 = richest 7.2%		Ghana Multiple Indicator Cluster Survey 2017/2018 (Ghana Statistical Services, 2018)
urban-wealth	The proportion of urban-resident patients falling in wealth quantile. It is used at initialisation to populate patients' wealth in **the set-wealth** sub model.	Patients in urban areas: 0 = poorest 4.2% 1 = second 11.4% 2 = middle 20.4% 3 = fourth 29.1 % 4 = richest 34.9%		Ghana Multiple Indicator Cluster Survey 2017/2018 (Ghana Statistical Services, 2018)
female-crude-mortality	The probability of female patients dying from all causes by age. Used in the **estimate-crude-mortality** sub model.	Drawn for each female patient from an empirical distribution: 80+ years old: 6.8% 75 – 79 years: 4.0% 70 – 74 years: 4.0% 65 – 69 years: 2.5% 60 – 64 years: 1.9% 55 – 59 years: 1.4% 50 – 54 years: 1.1% 45 – 49 years: 0.8% 40 – 44 years: 0.8% 35 – 39 years: 0.5% 30 – 34 years: 0.4% 25 – 29 years: 0.3% 20 – 24 years: 0.2%		Ghana Demographic and Health Survey (Ghana Statistical Service et al., 2015)
male-crude-mortality	The probability of male patients dying from all causes by age. Used in the **estimate-crude-mortality** sub model.	Drawn for each male patient from an empirical distribution: 80+ years old: 4.4% 75 – 79 years: 2.2% 55 – 59 years: 0.8% 50 – 54 years: 1.0% 45 – 49 years: 0.8% 40 – 44 years: 0.8%		Ghana Demographic and Health Survey (Ghana Statistical Service et al., 2015)

		70 – 74 years: 1.7% 65 – 69 years: 1.5% 60 – 64 years: 1.1%	35 – 39 years: 0.6% 30 – 34 years: 0.5% 25 – 29 years: 0.3% 20 – 24 years: 0.3%		
AttendanceProp	The proportion of patients who attend outpatient appointments at scheduled times. Used in the **attend-review** sub model.	0.6923		uniform distribution min= 0.38 max= 1.00	Amaltinga (2017)
life-expectancy-male-urban	The average number of additional years a male patient in an urban area is expected to live. Used to initialise how long male patients in urban areas stay in the model. Also used in the **update-age** sub model.	Drawn for each patient from an empirical distribution: 80+ years old: 5.9 75 – 79 years: 7.9 70 – 74 years: 10.4 65 – 69 years: 13.3 60 – 64 years: 16.1	55 – 59 years: 20.2 50 – 54 years: 23.9 45 – 49 years: 27.8 40 – 44 years: 31.9 35 – 39 years: 36.0 30 – 34 years: 40.1 25 – 29 years: 44.1 20 – 24 years: 48.1		Ghana Demographic and Health Survey (Ghana Statistical Service et al., 2015)
life-expectancy-male-rural	The average number of years a male patient in a rural area is expected to live is used to initialise how long they live in the model. It is also used in the **update-age** sub model.	Drawn for each patient from an empirical distribution: 80+ years old: 6.0 75 – 79 years: 8.0 70 – 74 years: 10.5 65 – 69 years: 13.4 60 – 64 years: 16.7	55 – 59 years: 20.4 50 – 54 years: 24.1 45 – 49 years: 28.1 40 – 44 years: 32.1 35 – 39 years: 36.2 30 – 34 years: 40.5 25 – 29 years: 44.5 20 – 24 years: 48.5		Ghana Demographic and Health Survey (Ghana Statistical Service et al., 2015)
life-expectancy-female-urban	The average number of years a female patient in an urban area is expected to live is used to initialise how long they live in the model. It is also used in the **update-age** sub model.	Drawn for each patient from an empirical distribution: 80+ years old: 6.5 75 – 79 years: 8.7 70 – 74 years: 11.4 65 – 69 years: 14.7 60 – 64 years: 18.3	55 – 59 years: 22.2 50 – 54 years: 26.2 45 – 49 years: 30.4 40 – 44 years: 34.6 35 – 39 years: 38.9 30 – 34 years: 43.3 25 – 29 years: 47.6 20 – 24 years: 52.0		Ghana Demographic and Health Survey (Ghana Statistical Service et al., 2015)
life-expectancy-female-rural	The average number of years a female patient in a rural area is expected to live is used to initialise how long	Drawn for each patient from an empirical distribution:	55 – 59 years: 21.9 50 – 54 years: 25.9		Ghana Demographic and Health Survey (Ghana Statistical Service et al., 2015)

	female patients in rural areas stay in the model. It is also used in the **update-age** submodel.	80+ years old: 6.4 75 – 79 years: 8.6 70 – 74 years: 11.3 65 – 69 years: 14.5 60 – 64 years: 18.1 45 – 49 years: 30.1 40 – 44 years: 34.2 35 – 39 years: 38.5 30 – 34 years: 42.8 25 – 29 years: 47.1 20 – 24 years: 51.4		
FemaleProp	The proportion of patients who are female. Used at initialisation to populate patients' sex variables.	0.60		Sarfo-Kantanka et al. (2016)
DiabetesPrev	The prevalence of DM in the adult population in Ghana. At initialisation, it is multiplied by adult-pop to estimate the number of patients to model.	0.06	uniform distribution min= 0.046 max= 0.074	Asamoah-Boaheng et al. (2019)
AdultProp	The total number of adults (20+ years old) living in Ghana; used at initialisation to estimate the number of patients to model	19 million (0.617 * 30.8 million)		Estimated from the Ghana Demographic and Health Survey (Ghana Statistical Service, 2022b)
ReviewInterval	The average number of weeks between outpatient appointments is used in the **schedule-appointment** procedure within the **treat** submodel to populate patient appointment weeks.	13	uniform distribution min= 8 max= 18	Estimated from clinicians' opinion
recoveryPeriod	The number of weeks the patient adheres to treatment following discharge for an acute DM complication that led to admission. Set the weeks between discharge and the next appointment. This is used in the **discharge** and **check-clinical** procedures.	The weeks between when a patient is discharged and the patient's next appointment		Assumed based on clinicians' opinion.
HypertensionPrev	The annual prevalence of hypertension and overweight (used as a proxy for comorbidity). Used to increase the prevalence of comorbidity among patients).	Estimated from an S-shaped distribution with equation and parameters. (details in submodel section)		Opoku et al. (2020) Adeloye and Basquill (2014)

DiabetesDuration	The proportion of patients who have had DM for a given number of years. used at initialisation to populate patients' *duration* state variable in the **set-duration** sub model.	1 – 5 years = 46.7% 6 – 10 years = 29.3% >10 years = 24.0 %		Osei-Yeboah et al. (2018)
LenStay	The number of weeks a patient stays in admission. used in the **admit** sub model.	2	uniform distribution min = 1, max = 3	Sarfo-Kantanka et al. (2016)
InsuranceCoverage	The proportion of the cohort actively insured under the NHIS. Used at initialisation in the **set-insurance** procedure and the **update-insurance** submodel.	Estimated from an S-shaped distribution with equation and parameters (details in submodel section)		Ministry of Health, 2023
MaxInsuredAppointment	The maximum number of outpatient appointments that the NHIS covers for insured patients.	6		Assumed based on NHIS operational tariff (National Health Insurance Authority, 2022)
ScaleDown	Used to estimate patient cohort size at initialisation.	0.5%	0.1 and 1%	Modeller's assumption.

Note: Details of submodels are in the ODD protocol in Appendix C.

Model calibration

We calibrated insurance coverage, lifestyle, and the prevalence of comorbidity in the model, ensuring that they matched observed real-world patterns identified in the literature. We used obesity and overweight prevalence as a proxy for patients' lifestyle. Evidence from the GBD suggests that the shape of the proportion of obesity and overweight in the Ghanaian population over time follows a sigmoidal distribution (Institute for Health Metrics and Evaluation, 2019). The distribution is characterised by an initial slow increase, followed by a rapid increase and a tapering-off as it reaches an upper limit. We defined the S-shaped distribution function as:

$$Pt = A * K / (A + (K - A) * \exp(-r * t))$$

where r = the shape parameter of the Sigmoid curve
P(t) = the prevalence of obesity and overweight at time t
A = the starting, initial, or minimum prevalence
K = the upper limit prevalence in the cohort

We fitted the obesity and overweight prevalence data from Amugsi et al. (2017) to an S-shaped distribution and used the parameters of the fitted distribution in our model. The ODD Protocol in Appendix C details calibration and the data used. In the model, we manually adjusted the prevalence at the time of initialisation (i.e., P(t) in the S-shaped distribution function) until the obesity and overweight prevalence matched the 2023 prevalence in the data from Amugsi. We used the same approach to calibrate the proportion of NHIS-insured patients and the prevalence of comorbidity in the modelled cohort (details in Appendix C).

7.5 Confidence building

Confidence building is the process of ensuring that a model is reliable, accurate, and useful for its intended purpose (Railsback and Grimm, 2019). We performed several procedures to ensure that the conceptual model was accurately programmed and that the programmed model sufficiently represented the system of DM service delivery and management in the modelled cohort and context. We validated our model based on several patterns identified from the literature, understanding from the HBM and TPB, and interactions with clinicians. We also conducted sensitivity analysis around model parameters and uncertainty analysis around the model's structure to examine how changes in model parameters and assumptions influenced the model's outcomes.

7.5.1 Model development (theory-based decisions)

Patterns based on the Health Belief Model and the Theory of Planned Behaviour:

Table 7.2 summarises the patient behaviour patterns based on the two behaviour theories.

1. The behaviour of discharged patients

We modelled discharged patients to eat healthily and take medicines from when they are discharged until after their next outpatient appointment week. HBM explains that when individuals perceive they are susceptible to a disease condition that could severely harm them, they are more likely to behave in ways that prevent it. Similarly, discharged patients have been exposed to the severity of uncontrolled DM and how susceptible they could be. The perception of susceptibility and severity reduce after discharged patients fully recover from an acute complication. Consequently, we modelled discharged patients to take medicines as prescribed and maintain a healthy lifestyle. They revert to the lifestyle trends in their community after their subsequent review appointment, when we assume full recovery from the previous acute complication.

2. Outpatient medicine adherence and health-seeking behaviour

This behaviour is influenced by medicine access and affordability, which represents the perceived barriers to engaging in health-promoting behaviours as explained in HBM and highlighted in Table 7.2. Outpatients who can afford medicines and are insured or have middle- to high-income levels can afford medicines. Those who cannot afford or have no medicines available in their communities experience a barrier to obtaining medicines and hence do not take medicines.

Outpatients with good or moderate BGC have a weak perception of DM severity and, therefore, an unmotivated attitude towards review attendance. Such patients may miss appointments. Patients with poor BGC have a strong perception of DM severity and susceptibility. Being unwell serves as a cue to seek care with or without an appointment.

3. Lifestyle of outpatients and inpatients

Based on an understanding of subjective norms in TPB, we modelled outpatients' lifestyle behaviour to follow the trend in their community. Outpatients' lifestyles are habitual and are shaped by subjective norms, culture, and the influences of close relations and their community. Inpatients follow the

treatment regimens/subjective norms of clinicians while on admission. Consequently, we modelled inpatients to live healthily and adhere to medication.

7.5.2 Verification: Verifying the programmed model

We built the model using NetLogo 6.3 and conducted experiments and analysis in the Nlrx package in R version 4.2.2. To verify the model, we performed several activities. We employed a bottom-up testing approach, incrementally integrating sub-models from the simplest low-level components to the more complex dependent ones. We then traced randomly selected patients through the inspect function in the NetLogo interface. We identified code errors using the debugger function in NetLogo and fixed them. We employed a white-box testing approach to verify the model. White-box testing is a software methodology that involves testing the internal logic and structures of the model to ensure that the application functions as intended (Henard et al., 2016). We designed test cases for which we had determined the expected outcomes before running them. We ran the test cases to confirm a match between the expected outcomes and the model outputs. Details of the test cases are in Appendix D. After making changes to the model, we retested the set of cases in the white-box testing to ensure that the modifications did not introduce new errors or negatively affect the model's existing functionalities.

7.5.3 Validation

7.5.3.1 Validating the baseline model assumptions

Patterns identified from the summary of interviews (discussed in Chapter 6) and the NHIS operations manual.

1. Outpatient appointments are scheduled considering availability and the mode of payment. Even when available, appointments in insured patients are capped at six times in 12 months, according to the NHIS operational manual. According to clinicians, patients who miss outpatient appointments are not rescheduled; they attend appointments later.

We modelled insured patients to have a maximum of 6 appointments in 12 months. Patients who missed outpatient appointments set their next appointment to any random week between the time they missed an appointment and the interval between outpatients' review appointments (i.e., 13 weeks).

2. Admissions are usually based on BGC and comorbidity status. Clinicians explained that poorly controlled glucose in patients with hypertension and cardiovascular disease conditions is admitted,

allowing for adequate care. Clinicians explained that poorly controlled blood glucose in patients with no comorbidity is usually controlled in hospitals in less than 24 hours but not admitted.

We modelled admissions in patients with poorly controlled glucose and comorbidity. Patients without comorbidity but poorly controlled glucose who attend health facilities have their glucose controlled.

3. The interval between outpatients' review appointments is mainly based on BGC and the status of comorbidities. Clinicians schedule patients who have controlled DM and no concerns with comorbidities for 13 weeks. Clinicians consider the availability of appointments and do not exceed six outpatient appointments in insured patients.

We used a 13-week interval between outpatient appointments in the model.

Patterns identified from interaction with clinicians.

We held meetings with pharmacists, nurses, physician assistants, and doctors at the Accra Regional Hospital, Ho Teaching Hospitals, Cape Coast Teaching Hospitals, and two polyclinics in Madina—an urbanised suburb of the Greater Accra Region after building the preliminary version of the model to validate the model. During these meetings, service providers reviewed the model's assumptions, schedule of activities, and model outcomes. The service providers raised specific issues that were not addressed in the initial model:

1. Clinicians considered our initial assumption that patients who do not find medicines to buy in the week they received prescriptions do not take them until their next appointment unrealistic. They pointed out that patients often search for medicines in community outlets and may obtain them before their next appointment. Additionally, prescriptions are typically valid until the next appointment, so once patients purchase the medicines, they do not search for them again until after the next prescription.

In response, we updated the model to allow patients to search for medicine every week until they have medicines. During periods when patients do not attend appointments as scheduled, we assumed patients stop taking medicines since they would have finished.

2. Clinicians noted that the assumption that increasing hospital admissions leads to fewer outpatient appointments in the preceding weeks is rarely the case. They explained that most patients with severely uncontrolled blood sugar levels are kept in the hospital for a week or two to bring their blood glucose under control and are then sent home. Only a small proportion of patients (1 out of 10) are admitted. As a result, there are few admissions each week, which does not significantly affect the number of outpatient appointments.

In response, we removed the assumption from the model. Thus, the number of admissions did not reduce the number of outpatient appointments scheduled for a week.

3. We modelled discharged patients to follow lifestyle and medicine adherence behaviours before admission. Clinicians observed that discharged patients adhered to medicines and lifestyle recommendations after discharge for fear of readmission. However, these behaviours are short-lived because clinicians are not present to motivate and monitor patients' behaviour post-discharge. According to clinicians, lifestyle behaviours are formed early in life and do not change significantly after an adverse event; however, long-term intervention could help improve diet behaviours.

In response, we modelled discharged patients to engage in healthy lifestyles and take medicine (if available and affordable) until after their review appointment preceding discharge.

4. Concerning the schedule of activities, we originally estimated weekly BGC from lifestyle and medicine adherence behaviour. Clinicians suggested that estimating BGC weekly could be misleading. They recommended using an overall control over time, like HbA1c, as a more accurate representation of blood glucose, as it represents the most occurring control over a 3–4-month period.

In response, we estimated the average BGC over three months (13 weeks) by collecting weekly blood glucose data from patients. We calculated the 13-week average as the most frequently occurring state a patient experienced. In the case of a tie, the patient was randomly allocated to one of the states.

5. Clinicians emphasised that medicines and diet are the main predictors of blood glucose in DM patients, and the relative importance of these predictors can vary based on the duration of DM. Diet is particularly effective in controlling glucose in the early stages of the disease (0 – ~5 years). While the impact of diet on BGC decreases with ageing and physiological changes, medicine is assumed to contribute significantly to control.

In response, we maintained an equal weighting for lifestyle and medicine adherence in the baseline. We explored the concept of ageing and the duration of DM in a structural uncertainty analysis.

6. We originally arranged the model operations so that blood glucose is estimated, followed by lifestyle and medicine adherence behaviour. Clinicians recommended rearrangement of the order of operations in the model. According to them, BGC reflects patients' medication adherence and diet/exercise behaviour. Thus, patients must engage in these behaviours before blood glucose is estimated.

We adjusted the order of operations so that outpatients were assessed for lifestyle and medicine intake behaviours before their blood glucose state was estimated.

7. Initially, inpatients were set to follow their prior lifestyle. However, clinicians explained that inpatients are supervised to take medicines as prescribed and eat healthily.

Consequently, we adjusted the model to reflect clinicians' opinions; inpatients live healthily and take medicines as prescribed.

7.5.3.2 Validating blood glucose and medicine adherence outcomes (comparing to empirical study results)

We ran five iterations of the baseline model, each for a year, and compared the proportion of patients with good medicine adherence and good BGC to empirical data collected in clinical surveys in Ghana, systematic reviews, and meta-analyses. The outcomes are presented in the results section.

7.5.3.3 Validating intervention Scenarios

We asked clinicians about the relationship between BGC, diet, and medicine. Clinicians explained that lifestyle effectively controls blood glucose in the early stages of T2DM. Medicine stockout affects medicine adherence but not as much as the ability to afford medicines. They explained that patients could find medicine in private pharmacies, but high prices prevent access. Clinicians perceived that expanding insurance coverage would improve medicine adherence more than increasing medicine availability. They expected that an intervention that improves affordability or a healthy lifestyle would improve cohort-level BGC more than an intervention that increased medicine availability.

After incorporating clinicians' opinions, we ran the model five times, each five years long, and asked clinicians to validate the results. We increased medicine availability (associated with Inter1) from 70% and 80% in rural and urban areas, respectively, to 100%. We also increased insurance coverage (associated with Inter2) to 100% from the initial value of ~50%. The outcomes confirming clinicians' expectations are presented in the results section.

7.5.4 Sensitivity and uncertainty analysis

7.5.4.1 Probabilistic Sensitivity Analysis

We conducted a global probabilistic sensitivity analysis (PSA) using Latin Hypercube Sampling (LHS) and Partial Rank Correlation Coefficient (PRCC). We generated 1000 sets of samples that followed

specified distributions in Table 7.3. The PRCC results describe the strength of the relationships between model parameters and outcome measures. Results of the global probabilistic sensitivity and structural uncertainty analysis are presented in the results section.

7.5.4.2 Structural uncertainty analysis

In this section, we explored uncertainty around estimating BGC and how it could influence the model outcomes. The uncertainty is related to point-estimate (fasting or random blood glucose) and average over time (glycated haemoglobin) for estimating BGC in DM, which is discussed in Chapter 3. The structural uncertainty explored relates to assessing the health impact of interventions, which is captured in Research Question 5. Specifically, we sought insights into how population-level BGC changes due to changes in 1) how we conceptualise blood glucose estimation and 2) the key factors influencing BGC.

Point estimates, including fasting or random blood glucose, indicated control at a given time. They take less time to conduct. During acute complications, these point estimates guide clinicians in making short-term treatment decisions. However, because blood glucose level flatulates over time, the point estimate cannot give a holistic picture of control. Consequently, the glycated haemoglobin test is recommended for long-term management (World Health Organisation, 2011; American Diabetes Association, 2023). HbA1c estimates average BGC over two to three months. This is especially helpful in determining a patient's risk of chronic complications including cardiovascular disease, retinopathy, and neuropathy. As mentioned in Section 7.5.3.1, clinicians suggested estimating average BGC over three months (glycated haemoglobin) rather than weekly point estimates. Moreover, Ghana's DM treatment protocol indicates the use of fasting or random blood glucose for monitoring BGC in T2DM.

Additionally, comorbidity and ageing influence BGC in T2DM (discussed in Chapter 3). Comorbidity, old age, and long duration of DM weaken the immune systems, which further compromises the body's ability to metabolise sugar and maintain a healthy state (Afaya et al., 2020; Peprah et al., 2022; Sefah et al., 2020).

Based on these insights, we varied the conceptual model used to estimate BGC to examine how robust the relative effectiveness of interventions was to changes in assumptions about how blood glucose is estimated. We explored the use of fasting blood glucose instead of HbA1c to assess BGC. We explored clinicians' perspectives on how the duration of DM and comorbidity could influence BGC, medicine adherence, and lifestyle. Table 7.4 summarises the procedures/submodels considered.

Model1: Fasting blood glucose (fbg) instead of HbA1c

We used the most frequent blood glucose state in 13 weeks, based on the concept of HbA1c averages of 3-4 months' blood glucose, to estimate a patient's blood glucose state at the baseline.

HbA1c is estimated by measuring the amount of haemoglobin bounded by glucose in the blood for the past three months. Higher blood glucose levels cause each haemoglobin molecule to carry more glucose, raising the HbA1c value. The condition implies that a patient with a higher incidence of uncontrolled blood glucose will likely have uncontrolled blood glucose over 13 weeks. Based on this logic and discussions with service providers (highlighted in the face validation section), we set the 13-week blood glucose state to a patient's frequent blood glucose state.

In uncertainty analysis, we explored changes in population-level BGC and medicine adherence outcomes using point estimates instead of three months average blood glucose. The insight from the uncertainty analysis represents a real-world scenario where health providers use fasting or random blood glucose estimates.

In the weekly estimate (Table 7.4), patients who exercised, ate healthily, and took medicine were set to have good BGC. Patients who took medicines or exercised and ate healthily were set to moderate control. Those who were nonadherent in both behaviours were set to poor control.

Table 7.4 Summary of blood glucose estimation models considered under structural sensitivity analysis (Author's own research).

Uncertainty	**Base case**	**Sensitivity**
Model1	The dominant weekly BGC (*fbg*) over 13 weeks (*HbA1c*) is reported for BGC outcome.	The 13th week's blood glucose estimate (fbg) is reported for BGC outcome.
Model2	Weekly blood glucose estimated from medicine and lifestyle, equal weight for each (i.e., FbgFxn = 0). healthy lifestyle AND took medicine = good control healthy lifestyle OR took medicine = moderate control unhealthy lifestyle AND didn't take medicine = poor control	Weekly blood glucose is estimated from medicine, lifestyle, and comorbidity, with equal weights for each (i.e., model 1 in Table 7.7). No Comorbid AND healthy lifestyle AND took medicine = good control. Two positive behaviours out of the 3 = moderate control 1 positive or none = poor control
Model3	Same as in Model2	Weekly blood glucose is estimated from medicine, lifestyle, and DM duration, with

		equal weight for each (i.e., model 1 in Table 7.7). Duration < (5 – 10) * AND healthy lifestyle AND took medicine = good control Two positive behaviours out of the 3 = moderate control One positive behaviour or none = poor control

Note: Model1 stands for conceptual model 1, which is the assumptions about how we represented a behaviour specified in the procedure column. The same applies to Model 2 and Model 3. The baseline column explains how the behaviour is represented in the baseline model, and the uncertainty column describes the changes we explored. * Selected from a uniform distribution. BGC=Blood glucose control.

Model2: Estimating BGC from medicine adherence, lifestyle, and comorbidity status.

Model 2 is based on insights from literature (discussed in Chapter 3) and clinicians' opinions, highlighted in Section 7.5.3.1 of this Chapter. The model explores uncertainty around the key factors influencing BGC in T2DM patients. It provides insight into how the negative effect of comorbidity in individual patients changes population-level BGC and medicine adherence in the modelled cohort. The model relates to real-world uncertainties about the influence of hypertension and other comorbidities on medicine adherence and BGC.

Model 2 (Table 7.4) adds comorbidity to the baseline model. A comorbid condition can cause uncontrolled blood glucose. Patients with a healthy lifestyle, a good medicine adherence behaviour, and no comorbidity are set to have good BGC. Patients with two positive behaviours are set to have moderate BGC, and those with one or no positive behaviours are set to have poor BGC.

Model3: Estimating BGC from medicine adherence, lifestyle, and the duration of DM.

Model 3 is also based on clinicians' opinions. According to clinicians, diet is most effective in controlling blood glucose in the early stages of T2DM. However, medicine becomes essential when the disease advances. We represented the concept in Model 3. Specifically, we adjusted the baseline model by the number of years patients have had DM. In patients above a given duration of DM, which is randomly selected from a range of 5 – 10 years, the weight associated with medicine adherence is

doubled compared to that associated with diet. For patients below the selected age group, the opposite is applied.

7.5.4.3 Scenario analysis

We explored several intervention scenarios to test if changes in the interventions coverage/effect make them more impactful than other interventions, consequently changing the ranking of the interventions in terms of their effectiveness and cost-effectiveness. The scenarios explored include:

1. 100% availability of medicines in rural and urban areas

MedUrban and MedRural parameters (in Table 7.3) are set to 1.0, indicating that medicine is always available to patients in the experiment.

2.10% and 20% annual reduction in unhealthy lifestyle due to the 20% SSB tax

An effect size of 0.1 is applied annually for 10 years in each of 500 simulations in an experiment. In a separate experiment, an effect size of 0.2 is applied annually.

3. A 5% annual increment in the proportion of patients actively insured by NHIS for 5 *consecutive years.*

Five per cent (0.05) is added to the insurance coverage proportion generated in our calibration model. (highlighted in section 7.4 and the ODD protocol in Appendix C). We increased the calibrated insurance coverage proportion at the end of year one through to the end of year five in each simulation. At the end of the sixth year and subsequent years, insurance coverage proportion changes are based only on the calibration model.

7.6 Experimental Design

7.6.1 Intervention modelled.

We examined the health and economic efficiency of three main PH interventions for improving DM outcomes. The interventions included: a 10% increase in the percentage of times patients found medicines in rural and urban areas (Inter1), a 10% annual increase in the active NHIS-insured patients for five consecutive years (Inter2), a 20% SSB tax (Inter3) and Inter4 which combines increased insurance coverage (Inter2) and a 20% SSB tax (Inter3). In Chapters 3 and 6, we discuss the choice of interventions to be influenced by evidence of their potential effectiveness as reported in the literature and insights from discussions with clinicians and NHIS officials. In this section, we present how we modelled the interventions and the pathway of interventions' effectiveness on BGC in the model. Figure 7.1 highlights the pathway of intervention effect on BGC and admissions in our model. Table 7.5 shows the effect we considered in experiments.

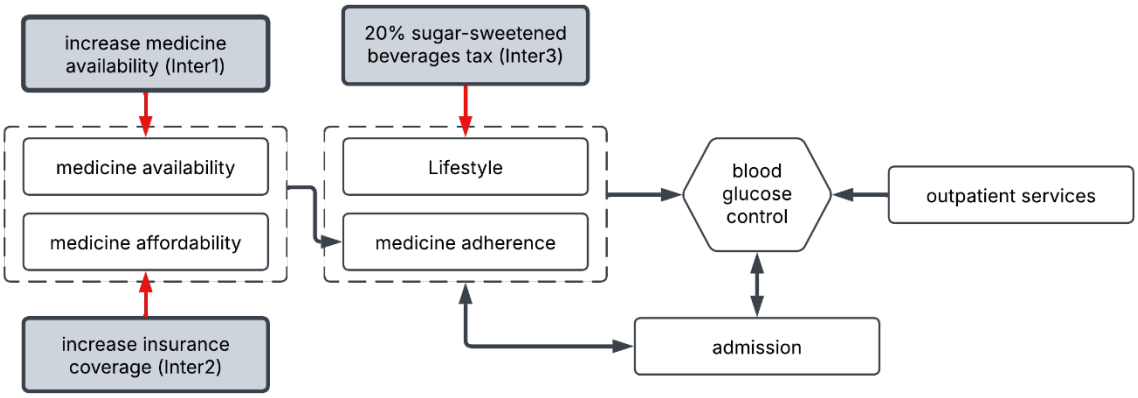


Figure 7.1 Pathway of intervention effect on diabetes treatment outcomes (Author's own research).
Note: Interventions (shaded boxes, solid red arrows) affect blood glucose control via medicine adherence and lifestyle. Providers support adherence and directly impact blood glucose control in admissions and outpatient services, while blood glucose control influences admission decisions.

Medicine adherence and a healthy lifestyle (diet and exercise) improve BGC in our model. Patients decide on lifestyle and medicine intake behaviours. In the baseline (Inter0), medicine availability and affordability directly influence medicine adherence behaviour–the decision to take medicines. Patients who can afford, yet do not find medicine to buy, do not take medicines. Inter1 increases medicine availability, addressing the challenge of unavailability for patients who can afford it. Consequently, Inter1 increases medicine adherence. To model Inter1, we increased the percentage of times patients

found medicines in rural and urban areas, MedRural and MedUrban, respectively, in Table 7.3, by 0.1 each before running the simulation.

Inter2 increases the proportion of patients who can afford medicines, which increases medicine adherence if medicines are available. To model Inter2, we added 10% to the insurance coverage percentage generated by our calibration model (highlighted in Section 7.4 and the ODD protocol in Appendix C). Specifically, we increased the calibrated insurance coverage proportion by 0.1 at the end of year one through to the end of year five in the simulation. At the end of the sixth year and subsequent years, insurance coverage proportion changes based only on the calibration model.

In Inter0, patients follow lifestyle trends in their communities. Inter3 improves the lifestyle in communities through reduced obesity/overweight resulting from tax-induced reduction in SSB consumption. To model Inter3, we reduced the prevalence of obesity/overweight prevalence (proxy for unhealthy lifestyles) in rural and urban communities by an effect ranging from 0.006 – 0.071 over 10 years (Table 7.5). The effect size (0.006–0.071) and duration of 10 years were obtained from simulation studies conducted in India and South Africa (Basu et al., 2014; Manyema et al., 2014). At the time of our study, there were no empirical studies examining the impact of SSB tax on obesity in Ghana, likely because the tax policy had been introduced only recently. Evidence from simulation studies was used because we needed to establish the link from SSB tax and obesity/overweight outcomes, rather than just to consumption changes. We applied the calculated yearly average impact of SSB taxation on obesity/overweight reduction in our model.

Specifically, at the beginning of every simulation, the model randomly selects an effect size from a uniform distribution with a range of 0.006 – 0.071. The selected value is divided by 10 (reflecting the annual effect size) and the outcome is applied to reduce obesity and overweight prevalence in urban and rural areas (UrbanProDiet and RuralProDiet in Table 7.3). There were 500 simulations in the experiment. Thus, there were 500 effect sizes drawn from the range 0.006 – 0.071 using a uniform distribution. The same effect size was applied for 10 consecutive years in a simulation.

We modelled Inter4 by applying the effects of Inter2 and Inter3, as described under each intervention. Patients receive clinical services depending on their BGC. Those with poorly controlled blood glucose may be admitted, while those with moderate to good control receive outpatient services. Admitted patients live a healthy lifestyle, adhere to medication, and have good BGC.

Table 7.5 Outline of Intervention and Effect (Author's own research).

Interventions	Description	Baseline	Experiment
Inter0	No interventions		

Inter1	10% increase in the percentage of times patients found medicines in their communities.	0.8 urban 0.7 rural	0.9 urban 0.8 rural
Inter2	10% annual increase in the proportion of patients actively insured by NHIS for five consecutive years.	Estimated from data fitted to an S-shaped distribution (see details on calibration in Appendix C)	0.1 annual increase for five years
Inter3	20% sugar-sweetened beverage tax	Lifestyle (proxied from obesity and overweight prevalence) data fitted to an S-shaped distribution	SSB tax assumed to reduce obesity and overweight by 0.006 – 0.071 over ten years.
Inter4	Inter1 & Inter3	Same as described in Inter2 and Inter3	Effects in Inter1 and Inter3

7.6.2 Simulation setup

Time horizon

Although T2DM is a chronic disease, we considered acute blood glucose complications in our model. Acute blood glucose complications, such as diabetic ketoacidosis, typically have an immediate onset and resolution. However, the time horizon must still capture all relevant clinical and economic outcomes. We considered 10 years a sufficient time to capture acute complications of poor SMB and the long-term impact of interventions on BGC, health service utilisation and NHIS cost.

Simulation runs

Due to stochasticity in ABMs, there is a range of possible outcomes for each set of parameters instead of the single outcome that deterministic models generate. Therefore, we required several simulations to understand the system's behaviour. We ran 1000 simulations, each for a year (52 weeks) and recorded 13-week outcomes. Specifically, we collected data on the proportion of patients with BGC and healthy lifestyles who took medicine as prescribed at the end of the year. We estimated the mean outcomes across all 1000 simulations. We defined the outcomes as converged for our purpose when the 95% confidence interval (CI) of the mean annual outcomes were within ± 5 incidences of good BGC. We determined the convergence of the mean outcomes after 465 simulations. However, to be conservative, we increased the number of simulations to 500 in all experiments and used 1000 runs in sensitivity analysis.

Warmup period

The warmup period is the initial simulation period that is run to get the model into a state representing the real system being modelled. We did not run a warmup period because we calibrated the model such that initial conditions and key features were representative of the real system. Specifically, we calibrated the model to represent the observed prevalence of unhealthy lifestyle behaviours (proxied from obesity and overweight) and trends in insurance coverage. We used empirical data to represent the availability of medicines in rural and urban communities.

Outcomes reported

We reported the mean and 95% CI of the difference between the mean incidence of the baseline and the interventions. For example, to compare the incidence of poor BGC in Inter0 and Inter1, we subtracted the mean incidence of Inter1 from Inter0 and then reported the mean and 95% CI of the difference in mean. We reported the difference in the mean incidence of BGC and medicine adherence, admissions, and outpatient attendance across interventions over 10 years. We only focused on poor medicine adherence, admissions and poor BGC in the main text and reported the annual incidence of BGC and medicine adherence in three categories (good, moderate, and poor) in Appendix F.

7.7 Results

7.7.1 Confidence building results.

7.7.1.1 Verification (number of outpatient appointments per insured patient)

Figure 7.2 shows the results of the distribution of outpatient appointment visits in the first year of the modelled patients' cohort. There were, on average, five OPD visits per patient; the minimum number of visits was one, occurring in 0.04% of the patient cohort. This indicates that the number of outpatient appointment visits among insured patients in our model did not exceed the NHIS limit of six visits in 12 months. The outcome indicates that our baseline model is appropriately implemented to reflect clinicians' suggestions and NHIS operational protocols.

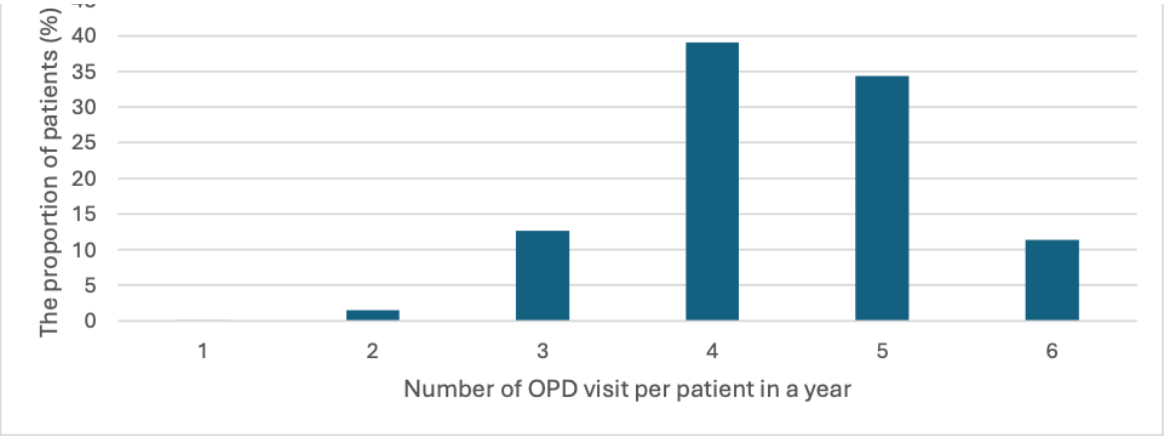


Figure 7.2 Number of outpatient visits in insured patient over 12 months in baseline (Author's own research).
Note: OPD = outpatient appointment.

7.7.1.2 Model validation results.

Baseline

Table 7.6 shows the results when we compared the prevalence of good BGC and good medicine adherence among patients in our model to empirical data. Our model predicted that ~35% of patients would have good BGC, which is lower than what Djonor et al. reported possibly because the authors used a less stringent cutoff point of 8.0mmol/L. Our model prediction of the proportion of good blood glucose is higher than Mobula et al.'s outcome possibly because of the increase in NHIS insurance coverage since 2011 when the data used by Mobula et al. were collected. Increasing insurance coverage increases medicine access and adherence, which could lead to better BGC. The model outcomes fall within the outcomes reported in the studies cited. For instance, our model predicts that a ~72% of patients to would have good medicine adherence behaviour, which falls within the range of 59%83% reported Mogre et al.'s meta-analysis. Consequently, we considered that the model outcomes reasonably compare to empirical findings reported by studies highlighted in Table 7.6.

Table 7.6 Comparing model outcomes to empirical data in published studies (Author's own research).

Empirical data	Population summary	Reference	Model estimates proportion (95% CI)
	Good BGC		
0.300	1226 patients enrolled at five health facilities in Ghana (all levels included), with an average age of 57 ±12.1years. Controlled DM is defined as HbA1c < 7.0%	Mobula et al., 2018	0.346 (0.341 – 0.352)
0.594 95% CI: 0.536 - 0.653	271 patients from a tertiary-level hospital in Ghana aged 56.6±3.8 years. Controlled DM is defined as HbA1c < 8.0	Djonor et al., 2021	
	Medicine adherence		
median = 0.71 IQR = 0.59 – 0.83	19 studies from LMICs, in a meta-analysis, adherence measure included the mean number of days patients took medicines, MMAS-8 scale	Mogre et al., 2019	0.715 (0.707 - 0.722)
*non-adherence to medications 0.434 95% CI: 0.175 – 0.694	13 studies in LMICs were used in the meta-analysis. Used the eight-item Morisky Medication Adherence Scale (MMAS-8) with a cut-off point of 80%.	Md Azharuddin et al., 2021	0.285 (0.277 - 0.292)

Note: The model estimate is the proportion of patients in the outcomes under consideration at week 52 (1 year); it does not average the proportions across the 52 weeks (about 12 months) but rather the outcome on the 52nd week. The same applies to the proportion of patients who are adherent to medication. * The study reports non-adherence; if the result is expressed as the proportion adherent, we get 56.6%, like the model's estimate.

Validation related to medicine adherence behaviour.

Figures 7.3 shows the blood glucose and medicine adherence outcomes under different intervention scenarios. Clinicians confirmed that the patterns were what they expected, increasing confidence in the model implementation and outcomes.

Specifically, the prevalence of good medicine adherence was higher when all patients were insured than when medicines were always available to patients (Figure 7.3). 100% medicine availability and 100% insurance coverage led to a higher proportion of patients with good medicine adherence behaviours than baseline.

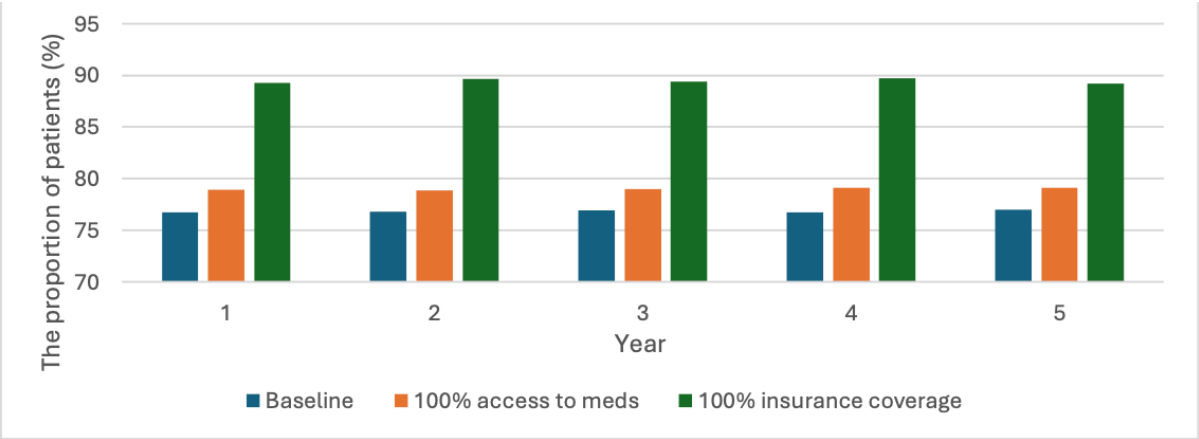


Figure 7.3 Medicine Adherence Outcomes - Face Validation (Author's own research).
Note: In baseline, the percentage of times patients found medicines in urban and rural communities was 80% and 70%, respectively. Insurance coverage in baseline was ~58% at initialisation in the baseline.

Additionally, 100% insurance coverage led to a higher proportion of patients with good BGC than a 100% medicine availability (Figure 7.4). Halving the prevalence of obesity/overweight, (proxied for unhealthy lifestyle) improved BGC more than 100% medicine availability. The 100% medicine availability intervention marginally improved BGC compared to baseline. The model outcomes were consistent with clinicians' expectations of intervention effects on blood glucose and medicine adherence outcomes.

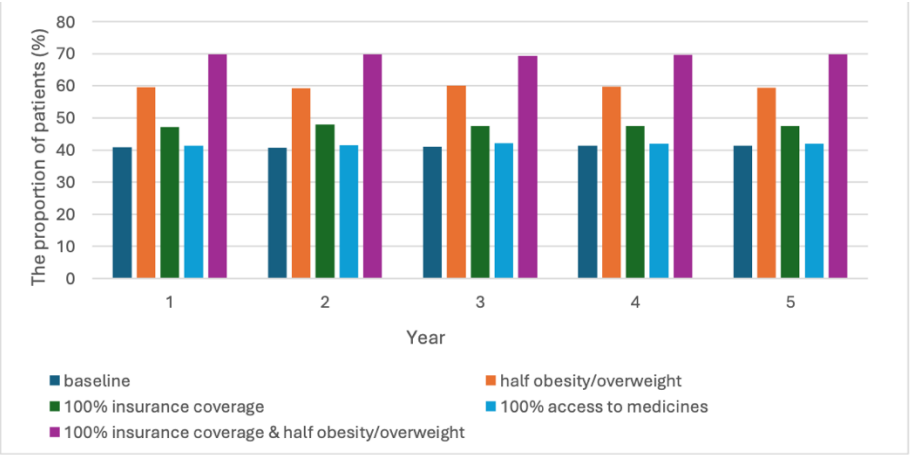


Figure 7.4 Good BGC Outcomes - face validation (Author's own research).
Note: In the baseline, the proportion of insured patients was ~58% at initialisation and obesity/overweight (proxy for unhealthy lifestyle) prevalence was ~58% at initialisation.

7.7.2 Sensitivity Analysis Results

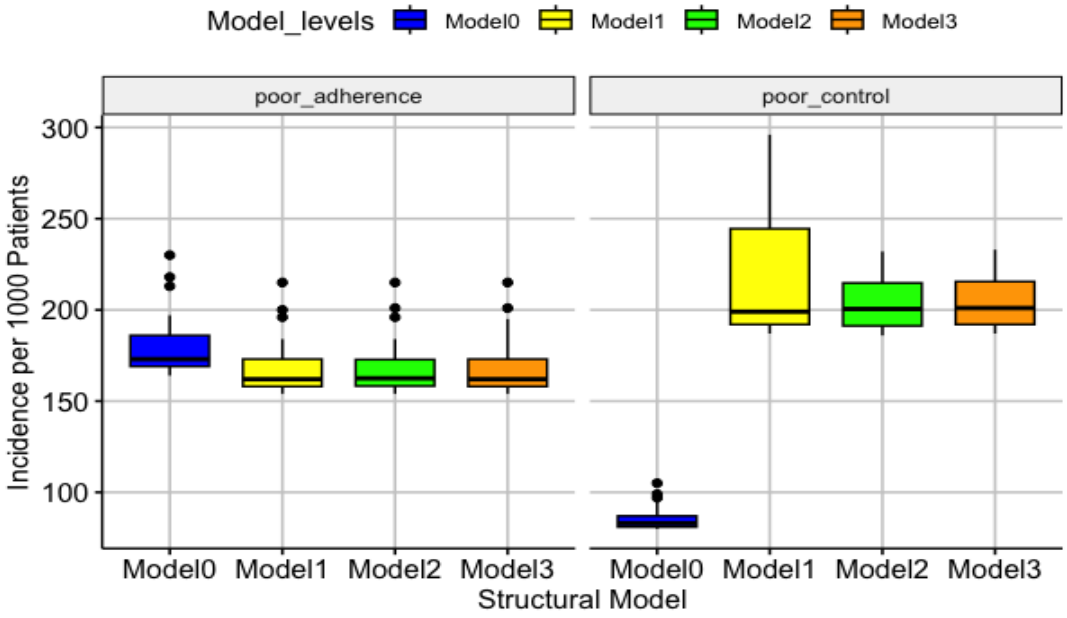
7.7.2.1 Structural uncertainty analysis

Uncertainty analysis: Treatment outcomes if blood glucose is estimated from medicine adherence, lifestyle, and comorbidity status.

As indicated in Figure 7.5, Model 1- 3 led to a significant increase incidence of poor blood glucose outcomes, admissions and outpatient attendance compared to the base case. The models reduced poor medicine adherence compared to the base case model, which estimated blood glucose outcomes from medicine adherence and lifestyle behaviours. There was no significant difference in model outcomes in Models 1 – 3.

Clinicians found the outcomes in Model 0 similar to what they observe in health facilities. According to them, about 10% or less of patients would have poor BGC leading to acute complications and admission; most patients would have moderate control. Additionally, given that there was no significant difference in the proportion of patients with poor medicine adherence in the models, we found Model 0 appropriate to use. Using Models 1–3 would initially increase poor BGC, leading to considerably high number of admissions and substantial increase in the prevalence of good BGC. The results from using Models 1-3 would not reflect reality.

A. Poor Medicine Adherence and Poor Blood Glucose Control



B. Admissions and Outpatient Attendance

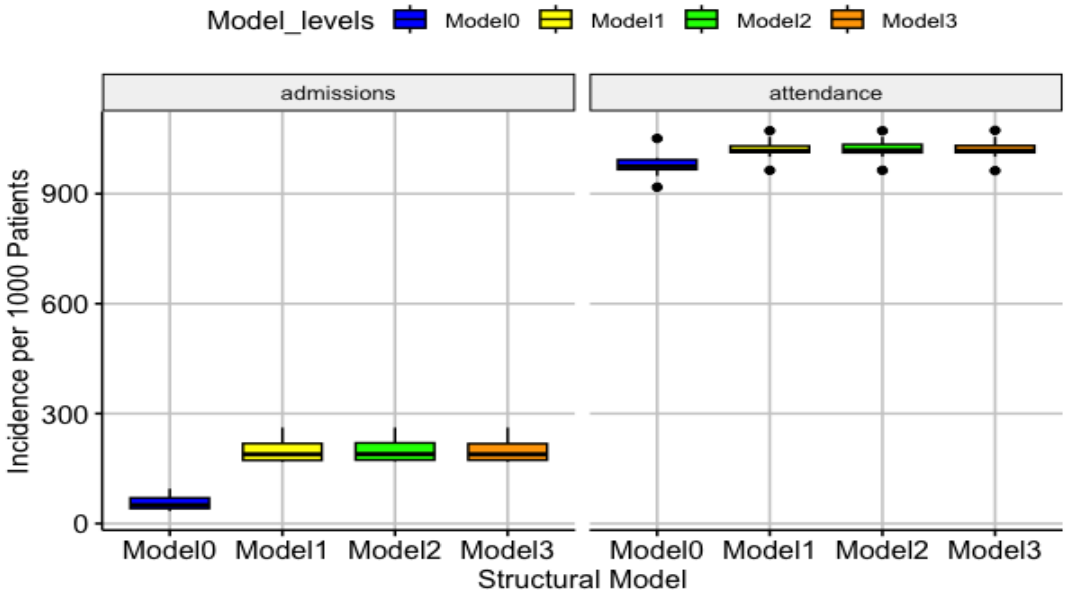


Figure 7.5 Outcomes of Structural Sensitivity Analysis on Models for Estimating Blood Glucose Control (Author's own research).

Note: Model0 represented the base case model, which estimated BGC from medicine adherence and lifestyle (diet and exercise). Model1 uses the weekly blood glucose control measure instead of a 3-month average to estimate control. Model2 estimates blood glucose control from medicine adherence, lifestyle, and comorbidity. In Model3, duration is added to medicine adherence and lifestyle to estimate blood glucose control.

7.7.2.2 Probabilistic sensitivity analysis

Table 7.7 highlights partial rank correlation coefficient of the parameters that were sensitive to the model outcomes from probabilistic sensitivity analysis. If we increase the proportion of outpatient attendance (**AttendanceProp**), there will be a corresponding substantial decrease in incidences of poor control, admissions, and poor medicine adherence. The strong influence of outpatient attendance is linked to the model structure such that patients who attend appointments obtain prescriptions without which they cannot buy medicine. Additionally, patients who attend could have their BGC directly controlled by clinicians, reducing the need for admission in cases of poorly controlled blood glucose states. If DM medicines could be bought without prescriptions, the influence of attendance on the model outcome might reduce. The understanding indicates that Inter2, which increases attendance through increased insurance coverage, would significantly improve the model outcomes. The sensitivity results indicate that refining the data on review appointment attendance could improve our model results.

Increasing the interval between review appointments beyond 13 weeks (**ReviewInterval**) moderately increases the incidence of poor blood glucose, poor medicine adherence and admissions. This insight is associated with how often patients seek care, similar to the arguments expounded for review appointment attendance.

Increasing the prevalence of unhealthy lifestyles in rural (**RuralProDiet**) and urban (**UrbanProDiet**) areas led to a moderate increase in the incidence of poor BGC. Additional results are in Appendix E. The incidence of poor medicine adherence marginally reduced if unhealthy lifestyle prevalence in rural areas increased. The parameters had a marginal effect on the model outcomes because we applied effects obtained from modelling studies in India and South Africa. We did not model the detailed chain of effect (from purchase to consumption, metabolism, and obesity/overweight prevalence) of SSB tax in the model, as our focus was not on the chain of effect but the broader effect on BGC. This implies that Inter3's effect may vary from what is observed in Ghana. Thus, contextual empirical data on the effect of the tax policy on lifestyle could improve our model outcomes.

Table 7.7 Outcomes of probabilistic sensitivity analysis (Author's own research).

Parameters	PRCC	P.value	95%CI - lower	95%CI - upper
Poor BGC				
UrbanProDiet	0.2586	0.0118	0.0595	0.5011
RuralProDiet	0.4274	0	0.2448	0.6119
AttendanceProp	-0.7841	0	-0.8894	-0.7097
ReviewInterval	0.3256	0.001	0.1323	0.5448
Poor medicine adherence				

RuralProDiet	-0.1945	0.0539	-0.4549	-0.0110
AttendanceProp	-0.8078	0	-0.8866	-0.7416
ReviewInterval	0.3237	0.0038	0.1096	0.5141
Incidence of admissions				
AttendanceProp	-0.8078	0	-0.8866	-0.7416
ReviewInterval	0.3237	0.0038	0.1096	0.5141

PRCC = Partial ranked correlation coefficient. 95% CIs of the PRCC are presented.

7.7.2.3 Scenario sensitivity analysis

Table 7.8 highlights outcomes under different scenarios. The outcomes represent the mean of the difference in incidence (95% CI) per 1000 patients over 10 years in 500 simulations.

If an SSB tax could reduce unhealthy lifestyle by 20% per year for 10 years, then it would be more effective at improving BGC and reducing admissions than a 10% increase in the proportion of patients actively insured over 5 consecutive years. A 10% reduction in obesity and overweight prevalence (for 10 consecutive years) from an SSB tax would be as effective as a 5% increase in insurance coverage for 5 consecutive years, relative to the baseline. 100% medicine availability does not change outcomes in the baseline.

Table 7.8 Outcomes of Scenario Analysis

Scenario	Blood Glucose Control Outcomes		
	Good	**Moderate**	**Poor**
100% medicine availability	1 (-1, 3)	0 (-2, 2)	1 (-43, 41)
5% annual increase in insurance coverage for 5 consecutive years	12 (10, 14)	-0 (-2, 2)	-12 (-13, -11)
10% reduction obesity and overweight (proxy for unhealthy lifestyle) over 10 years resulting from SBB tax	14 (11, 17)	3 (0, 6)	-10(-15 -6)
20% reduction obesity and overweight (proxy for unhealthy lifestyle) over 10 years resulting from SBB tax	29 (25, 33)	5 (3, 7)	-27 (-25, -29)
	Medicine Adherence		
100% medicine availability	1 (-1, 3)	0 (-1, 1)	-0 (-2, 1)
5% annual increase in insurance coverage for 5 consecutive years	47(45, 49)	-20 (-21, -19)	-27 (-29, -25)
10% reduction obesity and overweight (proxy for unhealthy	0 (-2, 0)	-1 (-3, 1)	1 (-2, 3)

lifestyle) over 10 years resulting from SBB tax			
20% reduction obesity and overweight (proxy for unhealthy lifestyle) over 10 years resulting from SBB tax	1 (-1, 3)	0 (-1, 1)	0 (-2, 1)
	Admission	**Outpatient Attendance**	
100% medicine availability	-5(-10, 2)	-2 (-4, 0)	
5% annual increase in insurance coverage for 5 consecutive years	-7 (-5, -9)	12 (10, 14)	
10% reduction obesity and overweight (proxy for unhealthy lifestyle) over 10 years resulting from SBB tax	-16 (-19 -13)	4 (-6, 10)	
20% reduction obesity and overweight (proxy for unhealthy lifestyle) over 10 years resulting from SBB tax	-29(-34 -25)	-21 (-17, 15)	

100% availability of medicines in rural and urban areas

Hundred per cent medicine availability in rural and urban areas does not make the intervention effective compared to baseline (Table 7.8). The scenario led to no significant change in all outcomes relative to baseline. This outcome is largely influenced by the model structure. In the model, medicine availability and affordability increase medicine adherence, which in turn influences BGC. Insurance coverage and wealth status (assumed to be unchanged in the model) influence affordability. However, medicine availability for patient changes weekly. Thus, patients who previously could not find medicine to buy, could find it in the following week. However, even if medicines are available, patients cannot take them if they are not affordable. Consequently, insurance impacted medicine adherence and blood glucose outcomes more than medicine availability in our model, explaining why the scenario was not effective relative to baseline.

5% annual increment in the proportion of patients actively insured by NHIS for 5 consecutive years.

Even with a reduction in the annual insurance increment from 10% to 5% (for 5 consecutive years) the intervention remained effective compared to baseline. However, the effect size was reduced from when the increase was 10%. The 5% annual increment led to a significant reduction in the incidence of poor glucose control (mean difference = -12; 95%CI: -13, -11) and an increase in the incidence of good BGC (mean difference = 12; 95%CI: 10, 14) over 10 years (Table 7.8). The scenario led to a significant improvement in medicine adherence compared to baseline. There was a significant reduction in the

incidence of admissions and an increase in outpatient service use, consistent with outcomes observed with a 10% annual increment in coverage.

10%, and 20% annual reduction in unhealthy lifestyle due to the 20% SSB tax

SSB tax became effective relative to baseline if it leads to a 10% annual reduction in unhealthy lifestyle. However, the scenario did not become more effective than a 10% increase in insurance coverage when both interventions were compared to baseline. A 10% decrease in the annual incidence of unhealthy lifestyle, due to an SSB tax, improved BGC by increasing the incidence of good control (mean of the difference in incidence over 10 years = 14; 95%CI: 11, 17) and reducing the incidence of poor control (mean of the difference in incidence over 10 years = -10; 95%CI: -15, -6).

Additionally, the scenario led to a reduction in the incidence of admissions (mean of difference -16; 95%CI: -13, -19). There was no significant difference in medicine adherence outcomes and outpatient service use when compared to baseline.

Increasing the effect of the SSB tax from a 10% to a 20% annual reduction in unhealthy lifestyles further improves outcomes. This makes the scenario slightly more effective than a 10% increase in insurance coverage over five consecutive years when both interventions are compared to the baseline. This outcome is primarily influenced by the model structure. Specifically, admissions occur if patients have poor BGC and comorbidity. Thus, improving BGC, with no significant change in comorbidity trends, reduces admissions.

7.7.3 Results of Experiments

7.7.3.1 Blood Glucose Control

In the baseline (Inter0), the incidence of good BGC increased steadily marginally, while moderate and poor control also marginally increased as the patient cohort advanced in age Figure 7.6 The cumulative incidence of poor glucose control was higher in the first five years compared to the latter five years.

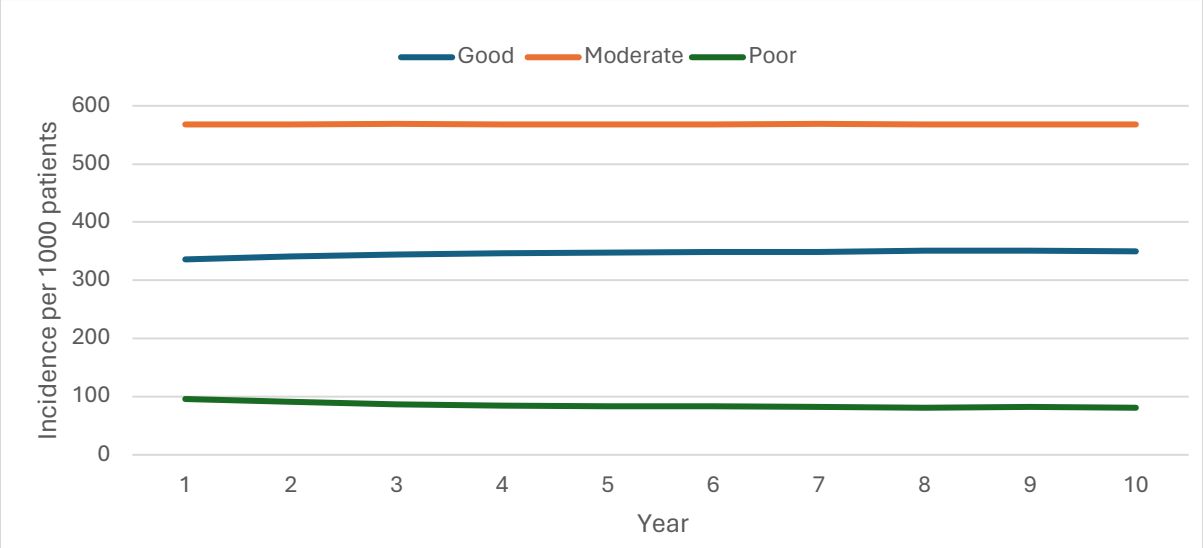


Figure 7.6 Incidence of blood glucose outcomes in the base case model (Author's own research).
Note: Good = good control, moderate = moderate control, poor = poor control. The values plotted represent the mean incidence of blood glucose outcomes per year in 500 simulations.

Figure 7.7 shows the distribution of outcomes by sociodemographic characteristics and Figure 7.8 shows the distribution of the difference in the mean incidence of poor BGC, poor medicine adherence, outpatient attendance and admissions by insurance status and residence for 1000 patients over 10 years. Uninsured patients experienced a higher incidence of poor control and poor medicine adherence than insured patients (indicated by the box plot named insured vs uninsured) compared to insured patients. There was no significant difference in the incidence of admissions between insured and uninsured patients, but outpatient attendance was significantly higher among insured patients than uninsured patients (Figure 7.7). Patients living in rural areas had a higher incidence of poor control and poor medicine adherence than those living in urban areas.

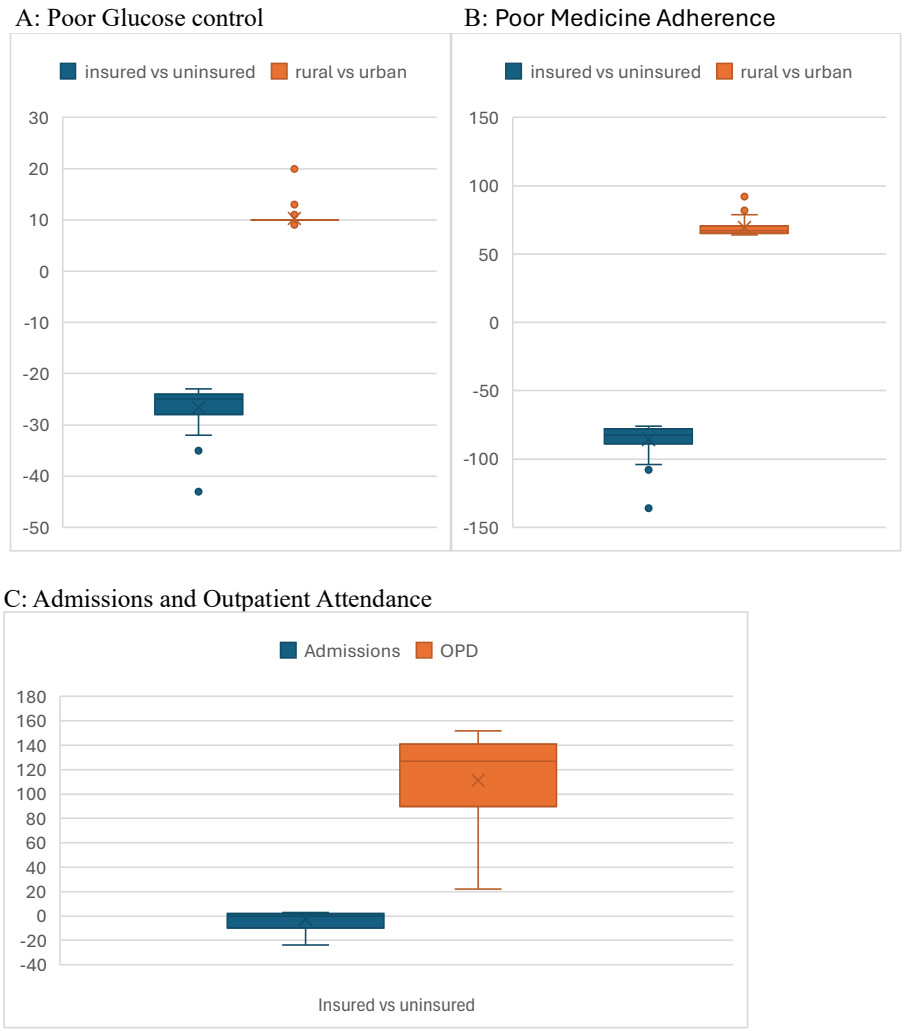
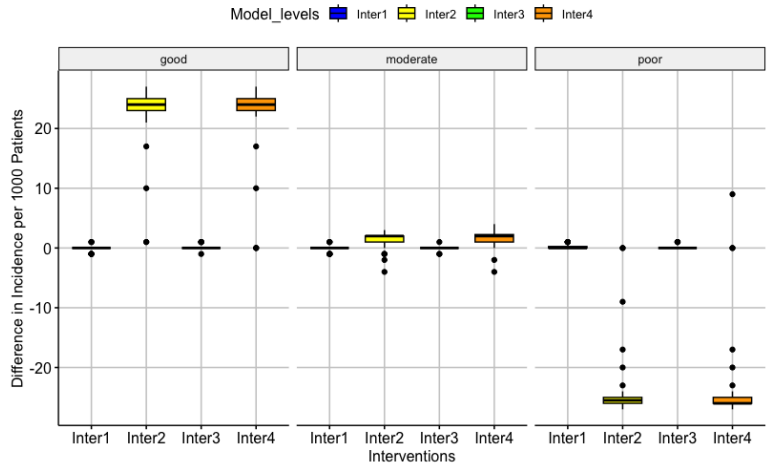


Figure 7.7 Blood Glucose Control, Medication Adherence and Service Use by Sociodemographic Characteristics in Baseline (Author's own research).

Note: OPD = outpatient department attendance. Boxplots represent the difference in mean incidence over ten years, with outcomes in insured patients and rural-resident patients being the reference; "x" represents the mean of differences, and straight lines in boxes represent the median. Rural and insured are the reference groups.

Inter2 and Inter4 more effectively improved BGC than Inter1 and inter3 when each intervention was compared to Inter0 (Figure 7.9 A). The effectiveness of Inter4, which combined Inter2 and Inter3, was largely due to Inter2. Inter2 led to a substantial decrease in the incidence of poor control and an increase in good control compared to Inter0 over 10 years (mean of the difference in poor control = 24; 95%CI of the difference 22 – 26; mean of difference in good control = 22; 95%CI of the difference 21 – 24). Inter1 and Inter3 were not more effective at improving blood glucose outcomes than Inter0.

A. Difference in Blood Glucose Control Outcomes compared to Baseline (Inter0)



B. Difference in Medicine Adherence Outcomes compared to Baseline (Inter0)

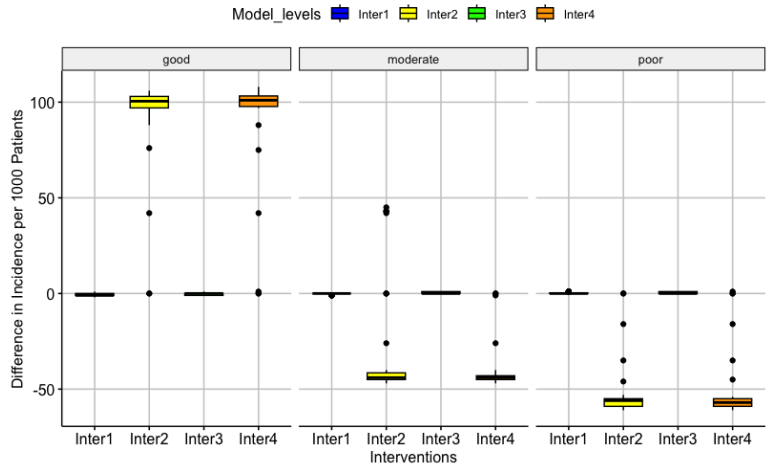


Figure 7.8 Blood Glucose and Medicine Adherence Outcomes by Interventions (Author's own research).

Note: Box plot of the outcomes after ten years under intervention scenarios. Inter0 = baseline, Inter1 = 10% increase in the percentage of times patients found medicines in rural and urban areas; Inter2 = 10% annual increase in the proportion of patients actively insured under the National Health Insurance Scheme for 5 consecutive years; Inter3 = 20% tax on sugar-sweetened beverages; Inter4 = combined Inter2 and Inter3. Good = incidence of good BGC/ medicine adherence; moderate = incidence of moderately controlled blood glucose/ medicine adherence; poor = incidence of poorly controlled blood glucose/ medicine adherence. Lower hinge: 25% quantile; lower whisker: smallest observation greater than or equal to lower hinge − 1.5×IQR; middle: median; upper hinge: 75% quantile; upper whisker: largest observation less than or equal to upper hinge + 1.5×IQR; black dot: outlier.

7.7.3.2 Medicine Adherence Behaviour

We report three categories of medicine adherence outcomes: good, moderate, and poor adherence. Good adherence is achieved if a patient takes 80% of medicines as prescribed, moderate adherence is between 50% and 79%, and poor adherence is less than 50% of prescribed medicines taken.

In Inter0, the incidence of good medicine adherence increased steadily, while moderate and poor adherence decreased steadily as the cohort grew over time. Patients who lived in urban areas had a higher incidence of good adherence and a lower incidence of poor adherence compared to rural residents (Figure 7.7). Insured patients had a higher incidence of good adherence, and a lower incidence of poor adherence compared to the uninsured.

Inter2 and Inter4 were more effective at improving medicine adherence behaviours than Inter0 (Figure7.9 B). The effectiveness of Inter4 was due to Inter2. Inter2 led to a substantial increase in the incidence of good adherence (mean of difference in incidence = 94, 95% CI of the difference: 86 - 101) and a decrease in the incidence of poor adherence (mean of difference in incidence = 52, 95% CI of the difference: 48 - 57) compared to Inter0 after 10 years. Inter1 and Inter3 did not reduce the incidence of poor medicine adherence outcomes compared to Inter0.

7.7.3.3 Admissions and Outpatient Attendance

The incidence of admissions in Inter0 decreased steadily as the cohort grew older. After 10 years, the incidence of admissions among insured and uninsured patients was the same (Figure 7.7). Insured patients attended more outpatient appointments than uninsured patients.

Inter 2 and Inter4 more effectively reduced the incidence of admissions and increased outpatient attendance compared to Inter0 (Figure 7.10). Again, the effect in Inter4 was due to Inter2. After ten years, Inter2 had an average of 14 fewer admissions (95% CI of the difference: 11 – 16) and 23 more outpatient attendances (95% CI of the difference: 20 – 27) compared to Inter0. Inter3 and Inter1 were not more effective at reducing admissions than Inter0.

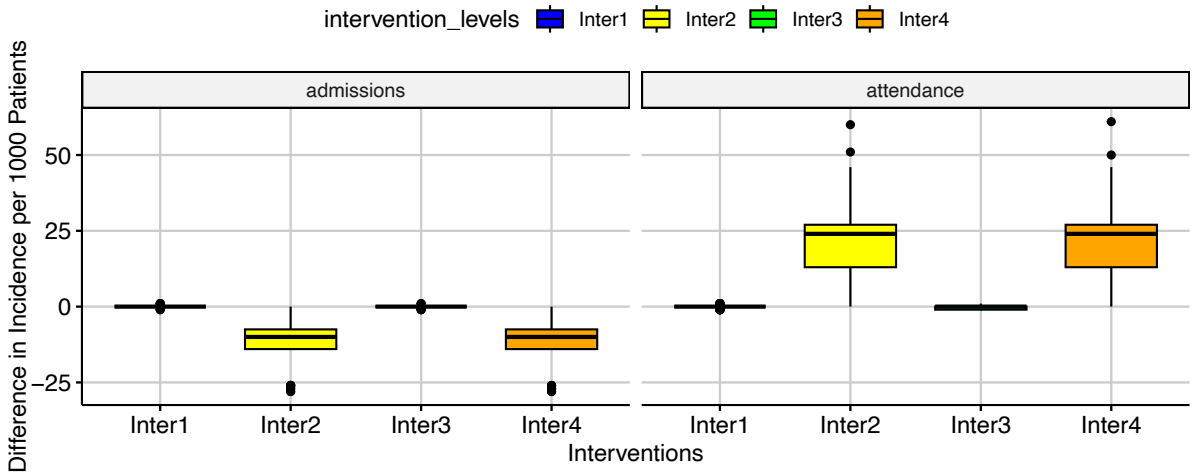


Figure 7.9 Admissions avoided and Additional Outpatient Attendance Relative to Baseline (Author's own research).

Note: Box plot of the outcomes 10 years under intervention scenarios. Inter0 = baseline, Inter1 = 10% increase in the percentage of times patients found medicines in rural and urban areas; Inter2 = 10% annual increase in the proportion of patients actively insured under the National Health Insurance Scheme for 5 consecutive years; Inter3 = 20% tax on sugar-sweetened beverages; Inter4 = combined Inter2 and Inter3. Lower hinge: 25% quantile; lower whisker: smallest observation greater than or equal to lower hinge − 1.5×IQR; middle: median; upper hinge: 75% quantile; upper whisker: largest observation less than or equal to upper hinge + 1.5×IQR; black dot: outlier.

7.8 Discussion

The simulation study sought to improve understanding of T2DM patients' treatment adherence behaviour and BGC outcomes. The study investigated the health effect of PH interventions for BGC in a cohort of T2DM patients receiving treatment within the Ghana PH system, partly addressing Research Question 5: *What is the health and economic efficiency of selected PH interventions to patients and the government?* Our analysis indicates that increasing the proportion of actively insured patients was the most effective at improving BGC. Implementing a 20% SSB tax that reduces unhealthy lifestyles (measured by obesity and overweight prevalence) by about 0.006 – 0.071 over 10 years did not further improve outcomes relative to the baseline and was less effective than a 10% annual increase in insurance coverage for five consecutive years. However, the ranking of the interventions change with an increase in the effectiveness of the SSB tax. If the SSB tax could reduce obesity and overweight prevalence by 10% each year, it would become more effective relative to the baseline. A 20% reduction in obesity and overweight prevalence from the SSB tax would make the intervention more effective than a 10% annual increase in the proportion of actively insured patients when both interventions are compared to the baseline.

Having 100% medicine availability did not further improve outcomes in the baseline scenario because the model assumes that both affordability and availability are necessary for adherence. Even with increased availability, patients cannot take medicines to improve treatment outcomes if they cannot afford them. Affordability is determined by insurance coverage and wealth, but only wealth remains largely unchanged in the model. This explains why increasing coverage is more effective than increasing medicine availability when compared to the baseline.

Using the fasting blood glucose biomarker to estimate BGC could overestimate the outcome in patients. Our model results were sensitive to these data points/parameters: prevalence of obesity and overweight in rural and urban residents, the interval between outpatients' appointments, and the proportion of patients who attended scheduled outpatients' appointments. We discussed key findings by interventions, model concept and data-related insights.

Active NHIS coverage

Our simulation results suggest that increasing the proportion of active NHIS-insured patients by 10% for five consecutive years more effectively improves BGC among T2DM patients than 20% SSB tax or increasing medicine availability. By reducing the financial barriers to care, increasing NHIS active coverage appears to increase medicine adherence and outpatient service attendance and improve BGC. Several published studies support our model findings that increasing NHIS coverage increases medicine adherence and improves glucose control and outpatient attendance. A prospective study of 109 hypertension patients in Ghana and Nigeria showed that insurance coverage was significantly associated with medicine adherence and blood pressure control. The odds of medication adherence in insured patients were 4.5 times the odds in uninsured patients. Aryeetey and colleagues (2016) examined health service utilisation before and after NHIS implementation and found that NHIS increased outpatient attendance and medicine affordability among the insured. The feasibility of this intervention is worth considering, given that the NHIS encounters operational and financial challenges. In Chapter 2, we discussed the challenges of NHIS, including delays in releasing its operational funds, claims processes, and moral hazards from service providers and insurers. The NHIS has implemented electronic claim processing to address these challenges and boost active coverage (National Health Insurance Authority, 2019a). These strategies could improve health service provision and increase active NHIS coverage.

SSB Tax

Our results indicate that a 20% SSB tax would have a limited impact on BGC compared to expanding insurance coverage. Our study is the first to examine the impact of a 20% SSB tax on blood glucose outcomes in T2DM in Ghana. Although we do not model the details of the design and implementation of the tax, our analysis can be important for health outcomes and SMB of T2DM. We applied the effect of a 20% SSB tax on obesity and overweight from modelling studies in India and South Africa (Basu et al., 2014; Manyema et al., 2014). However, the policy's effect on population-level health outcomes in Ghana may vary depending on policy design and tax pass-on rate–how manufacturers/retailers share the tax burden with consumers. Manyema et al. (2014) found from a simulation study of South Africa's population that 100-120% pass-on rates of a 20% SSB tax could result in a greater obesity reduction (range: 2.4% - 4.3%) than a 10% SSB tax with lesser pass on rates (obesity reduction range 1.1 – 2.1%). Policymakers in Ghana have identified tax evasion and noncompliance as potential barriers to effective SSB tax implementation (Singh et al., 2019), implying that the policy could be less effective than our model's predictions. Given that Ghana recently implemented a 20 % SSB tax, data collection and further studies could improve understanding of the policy's impact on food choices, consumption behaviours and obesity, which can improve our model outcomes.

Increasing medicine availability

Our model results indicated that a 10 % increase in the proportion of times medicines were available to patients in rural and urban areas did not improve BGC in T2DM any further than the current practice. This is because scaling medicine availability alone addresses the availability problem, leaving concerns about medicine costs to patients. Patients could find medicines in neighbouring communities or another day; however, they cannot have medicines if they cannot afford them. Scaling medicine availability alone partly addresses the problem, leaving concerns about medicine costs to patients. Our analysis shows that affordability influences good medicine adherence behaviours more than availability. The WHO acknowledges and addresses the challenge of medicine availability in DM control through the Global Diabetes Target, 2022, which aims to ensure everyone with DM has access to equitable, all-inclusive, affordable, and quality care (World Health Organisation, 2022b). The Ghana pharmaceutical pricing study associated medicine stockout at service delivery points with transportation from central and regional medical stores, poor inventory management and poor management of the revolving drug fund (Sarley et al., 2003).

Moreover, NHIS delays in claim payment affect health facilities' ability to pay for medicines received from central stores and medicine supply from central stores to health facilities (Sarley et al., 2003). Patients in our model take medicines if they can find and afford them. Aside from availability and affordability, other factors reported to influence medicine adherence in chronic disease management that could influence our model outcomes include, but are not limited to, forgetfulness, fear of adverse events, lack of DM knowledge/illiteracy, alternative medicines, complexity of medicine administration, low motivation, discomfort, and stress (Afaya et al., 2020b; Aflakpui et al., 2022; Ågård et al., 2016; Amaltinga, 2017; Atinga et al., 2018; Ekoru et al., 2019; Evon et al., 2015).

Model concept: Modelling Blood Glucose Estimation

Our analysis indicates that how medicine adherence, lifestyle and disease status (including comorbidity and duration) are combined to predict BGC is important for understanding the impact of interventions on BGC in T2DM. Studies have found that physical activity engagement, consumption of plant-based foods and reduced intake of sugar-sweetened beverages improve insulin sensitivity and BGC and reduce obesity and overweight (Chen et al., 2022; Navarro-Ledesma et al., 2024). However, comorbidities and long duration of DM could impede the body's immune function, insulin sensitivity and ability to metabolise sugar and fat (American Diabetes Association, 2024). Although our model does not represent the pathophysiology of long DM duration and hypertension and how it influences BGC, there is evidence to suggest that patients who have had DM for a long time are more adherent to medication, foot care and other SMB than patients in the early years of DM (Afaya et al., 2020b; Peprah et al., 2022;

Sefah et al., 2020). Given these pieces of evidence, it is possible that comorbidities and duration of DM influence BGC. However, we know little about such a relationship. Our model explored an assumption that having comorbidity or a long duration of DM (having DM from more than 5 – 10 years) reduces BGC. This assumption led to significantly different results from the baseline, which estimated control from medicine adherence and lifestyle. Our finding indicates that further clarification on the main determinants of BGC and how they combine to predict it would improve understanding of interventions' effect on DM control, contributing to intervention design.

Uncertainty in our model and its outcomes

Our model results were sensitive to these parameters: the prevalence of obesity and overweight in rural and urban residents, the interval between outpatient appointments, and the proportion of patients who attended scheduled outpatient appointments. Changes in the parameters led to significant changes in cohort-level BGC, medicine adherence, admissions, and outpatient attendance. This implies that accurate and representative data on these factors and their relationship with SMB are important for improving our understanding of PH intervention's effect on T2DM control and supporting intervention design. The Ghana Statistical Services and Ghana Health Services collect nationwide health data through the Ghana Demographic and Health Surveys and the District Health Information Management System. Academics, NHIS, and other local-based and international organisations have also collected empirical health data on Ghanaians. However, these data may be inaccessible, not presented in an accessible form and outdated. HTA and modelling studies like ours generate insights into key areas where data collection is required to support decision-making, informing researchers and clinicians to consider including such data points in routine data collection and surveillance systems. Given that Ghana has acknowledged and streamlined HTA, it needs to improve health data surveillance and make it accessible to academics.

7.9 Limitation

Although our modelling study approximates patients' SMB and outcomes within a defined scope and does not represent all the mechanisms of BGC in T2DM, it has some limitations.

First, we used data from cross-sectional studies to initialise some model parameters. These data were collected in a sample that does not represent all T2DM patients in Ghana. Also, the data may not represent current conditions as they could be outdated. For instance, the proportion of patients who attend outpatient appointments at scheduled times was taken from a cross-sectional study published in

2017; however, the data collection date was not reported. These considerations limit the generalisability of our model outcomes.

Second, our model assumes that DM patients seek care for BGC only and does not capture other clinical services for comorbidities that influence BGC. Consequently, the treatment outcome may be underestimated. DM patients may have comorbidities for which they seek care, which affect BGC. For example, an appointment for hypertension in a DM patient may provide services for controlling blood glucose. However, relaxing the model assumption to include these other related services will widen the model scope beyond what we intended.

Third, we assume a similar effect of a 20% tax of SSB on overweight and obesity in South Africa (Manyema et al., 2014) and India (Basu et al., 2014) as in Ghana, using results from modelling studies. The assumptions and limitations of these studies may apply to our model results, particularly the assumption that SSB consumption will continue to increase linearly due to secular trends and that SSB price elasticity will follow prior trends post-taxation. In the India study, for instance, the tax shifted consumption from SSB to milk, tea, and fresh fruits. In Ghana, we are uncertain about substitutes for SSB, particularly if they are healthy choices. For instance, individuals who reduce SSB consumption might increase their intake of other unhealthy, untaxed foods, leading to weight gain. Alternatively, they may compensate by exercising more, making it difficult to precisely attribute weight loss to reduced SSB consumption. The studies we used and similar studies in the literature did not account for such mediating factors affecting the impact of an SSB tax on obesity and overweight prevalence (Thiboonboon et al., 2024).

We assumed a constant rate of reduction in obesity and overweight due to the SSB tax. Basu at al. and Manyema et al. (i.e., sources of SSB tax effect used in the model) indicate a total reduction of between 0.006 – 0.071 after 10 years, but do not report on the distribution of tax-induced reduction in obesity and overweight prevalence over the period. The tax-induced reduction in the population-level overweight and obesity prevalence over time may follow a logistic growth instead of a having a constant rate of reduction, which could change the effectiveness of SSB tax in our model. A logistic growth-like distribution of the rate of reduction means that there may be a gradual reduction at the initial years of the tax policy implementation followed by large reduction (possibly when there is full policy implementation and high level of compliance) and then a decrease in the rate of reduction.

Fourth, we estimated BGC by simply combining medicine adherence and lifestyle, assuming that having more healthy behaviours leads to good BGC, while more unhealthy behaviours result in poor control. Although we conducted uncertainty analysis on the structural models for blood glucose

estimation, the complexity and dynamics surrounding metabolism and blood glucose regulation in the human body limit the generalisability of our findings.

Fifth, we assume that intentions lead to behaviour when applying behavioural theories to model patient behaviour. However, intention does not always lead to behaviour; therefore, there could be discrepancies between behaviour of the model patients and that of real patients. We also acknowledge that the HBM and TPB may not comprehensively capture individual health behaviours. Nevertheless, the HBM and TPB provided a framework for conceptualising patient behaviour in relation to DM management in low-resource settings.

Sixth, although we carried out uncertainty analysis on the structural model for estimating BGC, the diversity of the setting, including patient age, sex, comorbidities, health services received, and self-care behaviours aside from diet, exercise, and medicine adherence, limits the generalisability of our findings. Also, the model primarily represents service delivery and treatment behaviours before the COVID-19 period. However, it also explores changes to service delivery during COVID-19, specifically the lengthening of the intervals between outpatient review appointments, through probabilistic sensitivity analysis. The lengthening of intervals between outpatient due to COVID-19 is likely to persist post-pandemic due to factors, including–but not limited to–increased migration of clinicians overseas (World Health Organisation Regional Office for Africa, 2023) (leading to a reduced number of trained providers) and a rising NCD burden (resulting in greater demand for clinical services), which will likely necessitate wider intervals between review appointments to accommodate growing service demand. As a result, the model's outcome may be generalisable to the post-COVID-19 period.

Seventh, our model assumes that the proportion of Ghanaian residents who are actively insured under the NHIS is the same as among T2DM patients, which could be an underestimate. There is a discrepancy between being registered with the NHIS (having an insurance card) and having active insurance. Studies have reported that the NHIS covers over 90% of DM patients. However, the studies do not confirm whether patients are actively insured. We fitted data on active insurance coverage in the general population from the Ghana Ministry of Health report to a sigmoid distribution function to model trends in the proportion of actively insured patients. However, the proportion in the general population may differ from that of DM patients.

Eighth, we have not incorporated into the model how patients change their SMB due to social influence. For example, a patient may resume taking medicines and eating healthily after a close friend dies from DM. Also, aside from health and survival reasons, patients may eat for enjoyment, social connection, and emotional comfort (Monterrosa et al., 2020). We did not capture how such interactions would affect treatment outcomes at the cohort level. Exposure- or experience-induced changes in behaviour are often

unsustainable in the long term (Monterrosa et al., 2020). We do not expect such dynamics to significantly influence our model results.

Lastly, the model does not account for the likelihood that some DM patients may change and sustain a healthy diet behaviour during treatment. Our model assumes that patients follow general lifestyle trends, using population-wide obesity and overweight prevalence data, which we fitted to a sigmoid distribution. However, based on interviews with healthcare providers, only a few patients living with chronic disease make substantial dietary changes and maintain them. Thus, excluding from our model the few patients who transition to and sustain a healthier lifestyle may not significantly impact our model results.

7.10 Chapter Summary

This chapter has addressed the 'health effect' part of Research Question 5: "What are the health and economic efficiency of selected PH interventions to patients and the government?" We described the decision problem and context and justified the use of ABM, highlighting ABM's viability for representing individual-level behaviours and heterogeneity, which are important for the decision context we examined. We described, built, and validated a conceptual ABM model that represents individual patients' SMB, clinical service delivery, treatment outcomes, and how these components interact to produce cohort-level DM treatment outcomes.

Furthermore, we simulated selected PH interventions to examine their impact on BGC, admissions and outpatient service use. The simulation revealed that a 10% annual increase in the proportion of patients with active NHIS insurance for five consecutive years is the most effective intervention for improving BGC and medication adherence. However, increasing medicine availability and a 20% SSB tax policy did not significantly change the health outcomes observed at baseline. Combining a 20% SSB tax with expanding active insurance coverage is as effective as expanding active insurance coverage alone. The combined intervention could be optimised if medicines were more readily available to patients, especially in rural areas.

Aside from their effectiveness, PH interventions must be cost-effective to implement and financially sustainable in Ghana, where resource allocation to health is incommensurate with the burden of infectious and chronic diseases. Consequently, we build on the model's outcomes by conducting a CEA of the simulated interventions to investigate their economic efficiency, addressing the second part of Research Question 5. We present the CEA in Chapter 8.

8 Cost-Effectiveness Analysis of Non-pharmacological Diabetes Interventions

8.1 Introduction

The chapter builds on the SM studies in the previous chapter by incorporating the modelling outcomes in a CEA to investigate the economic efficiency of the interventions. The key findings from the modelling studies are that increasing insurance coverage is more effective at improving population-level BGC and reducing admissions than increasing medicine availability or a 20% SSB tax. Despite being effective, the intervention may be costly and unsustainable. This chapter investigates the cost-effectiveness of the interventions, addressing the economic efficiency part of our Research Question 5: "What are the health and economic efficiency of selected PH interventions to patients and the government?" Considering the financial challenges of the Ghana government, including the NHIS (discussed in Chapters 2 and 6), generating evidence of the financial implications of interventions will support policy decisions on implementation and sustainability. In line with our sequential mixed-methods design, the simulation study provided evidence of the quantities of resources consumed by interventions.

In Section 8.2, we briefly define and justify the choice of CEA as an economic evaluation method. Sections 8.3 and 8.4 present details on the evaluation design and cost input data. Sections 8.5 and 8.6 present the results and discussions, respectively.

8.2 Cost-effectiveness Analysis

CEA is suitable for identifying the most cost-effective alternative for achieving pre-determined effects or health outcomes, measured in natural units such as the number of patients adhering to DM medication (Drummond et al., 2015). Where the magnitude of the effect achieved varies across interventions, the result of CEA can be stated as net or incremental cost per unit of effect. The downside of CEA is the difficulty of ascertaining opportunity costs due to the specific measure of effect used. CEA compares apples to apples; it cannot compare apples to bananas. CEA inhibits comparing interventions across different health programmes that provide different health outcomes.

8.3 Justification of a cost-effectiveness approach

We employed a CEA approach in this study. The main justification for the choice of approach is that the PH intervention effects (from the ABM experiments) were measured in natural units, including the incidence of poorly controlled blood glucose and admissions. CEA supports the evaluation of alternatives where effects are measured in natural units. We considered cost-utility analysis; however, the lack of disability weights associated specifically with BGC outcomes prevented its use. The Global Burden of Disease study provides estimates of disability weights associated with chronic DM complications, such as DM retinopathy, but not acute complications like diabetic ketoacidosis, which we represent in our ABM study.

Additionally, the paucity of studies examining the cost-effectiveness of DM interventions in Ghana (discussed in Chapter 4) suggests a lack of context-specific research on interventions for improving treatment behaviour and treatment outcomes of T2DM patients. Comparing cost and health generates evidence to inform the government of the additional costs they are likely to bear should they implement the PH interventions. The evidence can guide resource allocation decisions.

Moreover, Ghana introduced a 20% tax on SSB in March 2023, aiming to reduce consumption and improve PH. The tax policy could reduce obesity and overweight prevalence and avert DM incidence, as evidenced in other countries (Nakhimovsky et al., 2016). However, we do not know the policy's effect on BGC among DM patients. Also, if invested, we do not know how much resource could make the tax policy cost-effective compared with current practice. The cost-effectiveness study examined the treatment outcomes and cost of PH interventions compared to current DM service delivery interventions. The aim was to generate evidence to support policy decision-making on DM control in Ghana.

8.4 Evaluation Design

Perspective

We used a government perspective in costing interventions because we deem the government the decision maker with control over resources and power to implement the examined interventions. We included the patient perspective to capture the cost for uninsured patients, who pay out of pocket for medicines and services. The perspective chosen in an economic evaluation defines the scope of the evaluation and what is included in the costing model, as what is considered cost in one perspective could be a gain in another view (Drummond et al., 2015). From a government perspective, we accounted

for the direct medical costs–medicines, outpatients, and inpatient services–and implementation costs in our analysis, as highlighted in Table 8.2. From a patient's perspective, we reported direct medical costs paid out of pocket. We considered a societal perspective but were limited by the lack of quality/representative data on the range of costs, such as transportation, time lost in seeking care and health services for uninsured patients. A societal perspective is more comprehensive, including costs from the health system and other sectors of society.

Unit of analysis

We used two units of analysis: 1) the insured and uninsured patients and 2) the NHIS. We reported outcomes by insurance status for individuals, providing insight into OOP expenditure. For the NHIS, we report the total cost of treatment disaggregated by type of services: medicines, outpatient services and inpatient services.

Interventions

We examined the cost and effectiveness of five interventions: the baseline (Inter0), increased medicine availability (Inter1), increased NHIS coverage (Inter2), a 20% SSB tax (Inter3), and combined Inter2 and Inter3 (Inter4). The interventions are described in detail in Chapters 6 and 7.

In the ABM simulation study, we measured health effects as the incidence of BGC and medicine adherence under interventions. The health resources used include outpatient services captured by the attendance, inpatient services captured by the number of admissions, outpatient visits, and medicines prescribed.

In all interventions, the modelled cohort consisted of 5700 hypothetical cohort of T2DM patients receiving care in NHIS-accredited PH facilities and all results were expressed per 1000 patients. The model's starting reference year was 2024. All blood glucose-lowering medicines and DM services are assumed to be covered by the NHIS. The NHIS pays for services and medicines for insured patients, while uninsured patients pay out of pocket.

Distribution of patients attending health facility types

We considered three levels of health facilities that patients attend: tertiary, secondary, and primary health facilities. Tertiary hospitals have higher bed capability, sophisticated medical technology, and expertise than secondary and primary facilities. Primary hospitals have the least capacity. Based on the

gatekeeper principle and referral systems, we assumed most T2DM patients would be managed at the primary and secondary hospitals. Tertiary-level hospitals are expected to serve complicated cases.

We used data from Mahama et al. (2023) to estimate the distribution of health facilities and assumed the distribution corresponds to the proportion of T2DM patients attending. Mahama et al. reviewed data from the Ghana Health Service and found that in 2023, 93.8%, 6.1% and 0.1% of health facilities were primary, secondary, and tertiary, respectively (Mahama et al., 2023). The proportion of primary facilities included CHPS compounds, which clinicians described as not equipped to provide DM services (in Chapter 6). We estimated from Mahama et al.'s findings that 85.5% of facilities are primary, 14.3% are secondary, and 0.2% are tertiary facilities, excluding CHPS compounds.

Time horizon

The time horizon in an economic evaluation determines how long the benefits and costs of interventions are captured (Drummond et al., 2015). While a shorter time horizon captures short-term benefits, they may fail to capture the full spectrum of benefits associated with chronic conditions accruing over a long period, potentially underestimating the cost-effectiveness of such interventions. We assessed the cost and benefits of interventions over ten years, providing insight into the long-term costs and benefits.

Outcome measures

We measured health outcomes using direct clinical outcomes from the simulation study. Specifically, we used admissions avoided and the incidence of poorly controlled blood glucose averted by interventions. Admissions avoided represent reduced admissions due to an intervention compared to the baseline intervention (Inter0). Similarly, the incidence of poorly controlled blood glucose averted is the reduction in incidences due to an intervention compared to baseline. These clinical measures are immediate, tangible outcomes directly linked to the interventions' effectiveness.

Discounting

Discounting reflects the principle that people usually prefer to receive benefits sooner rather than later and incur costs later (Drummond et al., 2015). A higher discount rate places less value on future costs and benefits, potentially making long-term interventions appear less cost-effective. In contrast, a lower discount rate increases the present value of future costs and benefits, enhancing the attractiveness of interventions with long-term benefits. We applied a 3% discount rate on cost as recommended by the Second Panel on Cost-effectiveness Analyses (Sanders et al., 2016). We applied the discount rate on

annual costs. The base year of analysis was 2024. The formula adopted for discounting:

$$C\left(\frac{1}{1+r}\right)^{t}$$

where

C = original cost

r = discount rate

t = year

Identifying and costing items

Cost items are embedded in activities along the clinical pathways for DM treatment. The ABM study established the clinical pathway(s) based on Ghana DM Treatment Guidelines 2023 and clinicians' opinions. We obtained the count of resources consumed, including medicines, outpatient attendance and admissions. Table 8.1 highlights the cost components included in the analysis.

We do not incorporate intangible costs, including emotional distress, depression, and anxiety, in our analysis because of their subjectivity and measurement challenges and the lack of quantitative data among T2DM patients in Ghana. Intangible costs are difficult to quantify consistently and objectively since they are often subjective, which could cause biases and inconsistent results in our analysis (Turner et al., 2021).

Table 8.1 Cost Components by Interventions (Author's own research).

Cost Items	**Inter0**	**Inter1**	**Inter2**	**Inter3**
Direct medical cost	Inpatient services	Inpatient services	Inpatient services	Inpatient services
	Outpatient services	Outpatient services	Outpatient services	Outpatient services
	Medicines	Medicines	Medicines	Medicines
Intervention cost	N/A	Medicine transport cost	N/A	*Tax implementation cost

Note: N/A = not applicable. *Tax implementation costs include compliance, administrative, and implementation costs for the government.

Inpatient services /admissions: the cost of managing an acute DM complication resulting from poorly controlled blood glucose in a health facility. Inpatient services include consultation fees, bed/accommodation, food, and supplies, and requested investigations, including laboratory investigations, x-rays and ultrasound scanning for inpatient care. T2DM is associated with acute complications, which require admission. Diabetic ketoacidosis (DKA) and hyperglycemic hyperosmolar state (HHS) are common acute complications of T2DM in Ghana (Sarfo-Kantanka et al.,

2016). We assumed the admission cost per patient from the NHIS Tariff. Figure 8.1 shows the cost component of NHIS tariffs, and Table 8.2 shows the NHIS tariffs per admission and outpatient services.

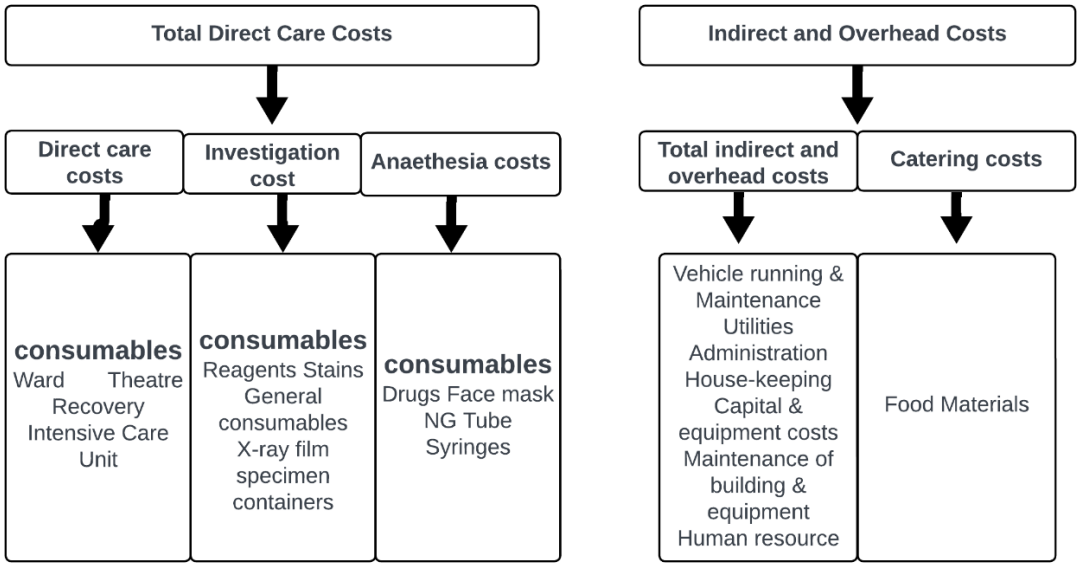


Figure 8.1 Cost components of NHIS tariff for health services (Adopted from National Health Insurance Scheme Operation Manual, 2022).

Outpatient services: the cost of clinical services during review appointments. It includes the cost of consultations—general and specialist—and investigations: laboratory tests, x-rays and ultrasound scanning, body mass index, fasting blood glucose, blood pressure, HbA1c test, lipid, and urine tests. Administrative costs, such as folders and record keeping, are also included.

Table 8.2 Cost of clinical diabetes services (Compiled from the 2019 NHIS Tariffs).

Health Facility Type	Cost per Outpatient service	Cost per inpatient service
Tertiary facilities	301.48	585.8
Secondary facilities	212.57	457.61
Primary facilities (catering)	192.89	350.29

Medicines

To estimate the cost of medicines consumed by outpatients (medicines are included in inpatient cost), we obtained a list of frequently prescribed blood glucose-lowering medicines from the Ghana National Guidelines for the Management of Diabetes (Ministry of Health, 2023) and their cost from the NHIS Tariffs (National Health Insurance Authority, 2019b, 2019c, 2019d). We also collected cost and dosage

data on medicines not included in NHIS tariffs from four clinicians using a form (in Appendix H). We triangulated information from the pharmacists and the treatment guidelines into a comprehensive medicine list, presented in Table 8.5. Glipizide was included in the list of blood glucose-lowering medicines from the treatment protocol. However, Glipizide was not included in costing medicines, as clinicians mentioned prescribing Glimepiride instead because Glimepiride was on NHIS. Moreover, both medicines had similar mechanisms of action and were equally effective. We estimated the cost per weekly dosage for all medicines.

Finally, we adjusted for multiple prescriptions per patient. We used data on the distribution of prescriptions from Mobula et al. (2018). The researchers reported the distribution of blood glucose-lowering prescriptions among 1226 T2DM patients attending five hospitals in Ghana as follows: 89.3% used metformin, 57.7% used sulphonylureas, 37.9% used thiazolidinediones, 29.4% used insulin, and 0.3% used dipeptidyl peptidase inhibitors. According to the national guidelines, metformin is a first-line blood glucose-lowering drug. Moreover, dipeptidyl peptidase inhibitors are often used as monotherapy. We found from discussions with pharmacists that insulin is generally prescribed in T2DM when most oral medicines have been ineffective for controlling blood glucose. Thus, we assumed insulin could be used as a monotherapy or combined with all oral medicines. Figure 8.2 shows how we distributed medicines among the patients' cohort, and Table 8.3 highlights the cost of blood glucose-lowering medicines included in the analysis.

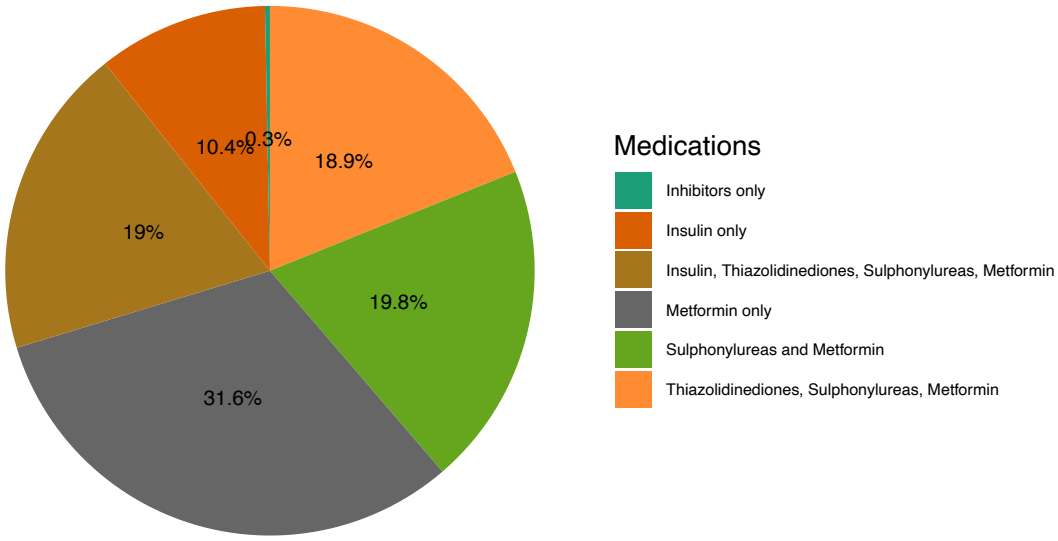


Figure 8.2 The distribution of blood glucose-lowering medicines used in T2DM in Ghana (Author's own research, compiled from Mobula et al., 2018).

Table 8.3 Cost of Frequently Prescribed Blood Glucose Lowering Medicines Covered by NHIS (Author's own research).

Medicines	Prescription Information	Weekly dose	Unit cost per tablet (in cedis)	Cost per week
1. Metformin	Dosage: 500mg Frequency: twice daily (or 800mg once daily)	14 tablets	0.11	1.54
2. Sulphonylurea: Glibenclamide:	Dosage: 2.5 mg Frequency: once daily	7 tablets	0.16	1.12
Glimepiride:	Dosage: 1 - 2 mg Frequency: once daily	7 tablets	0.21, 0.23	1.47, 1.61
Thiazolidinediones (Pioglitazone)	Dosage: 15 or 30 mg Frequency: once daily	7 tablets	0.62, 0.78	4.34, 5.46
Insulin	Dosage: 0.5 -1.0 iu/kg/day Frequency twice daily	1 vial	52.73, 52.98	52.72 - 52.98

Note: We multiplied the unit cost per tabled/vial by the weekly dose to estimate the cost per week dose.

Prices of medicines not covered by the NHIS: Consultation with Pharmacists

We asked two pharmacists we interviewed for the ABM study to provide cost data for Saxagliptin and Dapagliflozin inhibitors not covered by the NHIS. The pharmacists referred two additional pharmacists. Except for one pharmacy in Accra, a community outlet, all pharmacies were hospital-based.

We asked the pharmacists to provide the cost of medicines (as packaged by producers) and the number of tablets of vials/volume. We then used the dosage information derived from clinicians and the Ghana Diabetes Treatment Guideline, which is once daily, to estimate the cost per weekly dosage/unit. We used the cost of weekly doses because the simulation model results are presented in weekly prescriptions, highlighted in Table 8.4. All the pharmacies confirmed that the NHIS did not cover Saxagliptin and Dapagliflozin inhibitors and that patients pay out-of-pocket. We used the mean prices and explored the minimum and maximum costs in sensitivity analysis.

Table 8.4 Cost of Diabetes Medicines not on NHIS Medicines List (Author's own research).

Medicine	Price per pack	Number of tablets	Cost per week dose (GHS)
Saxagliptin:	698.50	30	162.98
	1047	30	244.30
	765	30	178.50
	1005	30	234.50
Dapagliflozin:	906	30	211.40

	845.60	28	211.40
	908	30	211.87
	850	28	212.5
Both inhibitors			Mean = 208.43 Range: 162.98 - 244.30

Cost of medicines and services to uninsured patients

During our analysis, the NHIS used the 2023 and 2019 tariffs for medicines and services, respectively. We suspected that uninsured patients pay more than the NHIS tariffs. Asiedu and colleagues (2022) reported that compared with the NHIS tariffs, the retail prices of medicines, including metformin, in community pharmacies were roughly 38.7% higher. For medicine costs to uninsured patients, we increased the NHIS medicine tariffs by 38.7 and explored a plausible range in sensitivity analysis (Table 7.5). We did not increase the cost of services for uninsured patients due to the lack of quality data on the cost of services to uninsured patients.

Interventions (implementation) cost

Inter0*:* We assumed that there would be no additional program implementation cost in the baseline scenario. Aside from the direct medical cost of services and medicines used, the baseline is a status quo, a state of no intervention or current practice. Consequently, there is no introduction of an intervention and, therefore, no additional cost to be borne. Figure 8.7 shows the health outcomes accruing from the interventions examined.

Inter1*:* The intervention involves scaling up the availability of DM medicines in rural and urban communities. The intervention may incur an additional cost for transporting medicines to purchase points. On the one hand, it can be argued that the cost of transporting medicines to communities is included in the prices of medicines. On the other hand, it can be argued that the health sector spends money from its budget allocation to transport medicines to communities.

Ghana's Ministry of Health (MoH) guidelines indicate that regional medical stores and teaching hospitals should procure medicines from the central medical store and local private suppliers. Service delivery points are expected to buy from their regional medical stores unless medicines are unavailable, in which case they can buy from the local private sector.

According to the Health Commodity Supply Chain Master Plan, the Ghanaian government uses its vehicles and third-party logistics to distribute medicines and clinical products to regional medical stores

and service delivery points. Service delivery points include public hospitals and health facilities providing DM care. Most distribution is done from regional medical stores to service delivery points, following approved distribution plans, routes, and schedules. NHIA reimburses accredited health facilities/ service delivery points for medicines, which health facilities pay to the regional stores.

Increasing medicine availability to patients would require expanding distribution routes and schedules, which would incur additional government costs. We assumed a 13% margin on medicine costs for transportation and warehousing, assuming regional medical stores receive budgets for equipment and building costs, vehicle capital, and transportation-related costs (Sarley et al., 2003).

Inter2: We assumed no additional program implementation cost associated with increasing the proportion of active NHIS-insured T2DM patients. Although patients pay premiums to remain insured, premiums are mere transfers and are not included in CEA (Drummond et al., 2015). We assumed there would be a marginal additional cost associated with subscription renewal and claim processing claims from a government perspective, considering that there are electronic claim processing and electronic subscription renewal systems.

Inter3: The SSB tax policy will incur implementation cost: monies spent on hiring additional staff for administration and compliance (World Health Organization, 2022), which we assumed from the literature review to be 1% of tax revenue (Details in Appendix H). Most of the reviewed studies that included tax implementation cost (Lee et al., 2020; Long et al., 2015; Wilde et al., 2019) assumed 1–2% of total tax revenue generated as implementation cost. Consequently, we assumed a 1% cost of the total tax revenue generated as tax implementation cost and explored a 1–2% in a sensitivity analysis.

Ghana's Ministry of Finance has estimated that the 2022 Excise Duty (Amendment) Bill, which imposes excise tax rates on sweetened beverages, would yield approximately 455,000,000 GHS (Government of Ghana, 2022). We used the Gross Domestic Product (GDP) implicit price deflator formula to calculate the present value of the estimated tax revenue (Turner et al., 2019), assuming that would be the revenue generated from a 20% SSB tax policy.

According to the International Monetary Fund, the price deflator for 2022 and 2024 (base year) was 339.077 and 555.645, respectively (International Monetary Fund, 2024).

Inflated revenue (2024) = 455,000,000 * (555.645 / 339.077)
= GHS745,607,856 per 33,475,870 people (Ghana's population in 2022).
Therefore, we applied 1% of GHS 22,273.

Inter4 combines Inter2 and Inter3; therefore, we combined cost components in both interventions. Thus, Inter4 included tax implementation costs, the cost of medicines, and the cost of inpatient and outpatient services.

8.5 Valuation of cost items

Bottom-up and top-down costing approach.

A bottom-up approach determines all the resources and their costs for each person before adding them up to estimate the total cost. Top-down methods estimate cost at a higher level (Drummond et al., 2015). While the bottom-up approach demands more extensive data collection, it provides decision makers with a more detailed cost profile, enhancing the transparency and reliability of the analysis and outcomes. We used a bottom-up approach, including direct medical costs, such as medicines and outpatient and inpatient service costs, using measurements of resources consumed from the ABM experiments in Chapter 7. We collected data on the resource quantities consumed per patient along the service delivery pathway for each intervention scenario.

Intervention Cost and Health Effect Estimation

Analysis variables include health effects, total costs, and cost-effectiveness. We considered admissions avoided and incidences of poor BGC averted as measures of health effects. We estimated the total cost by multiplying the quantities of medicines and inpatient and outpatient services consumed by their unit cost in each intervention (Table 8.5). We included implementation costs in Inter1, Inter3 and Inter4. Cost is reported as the mean present value (in 2024 Ghana Cedis) for 10 years, discounted at 3% annually, and we report OOP included in the total cost. Cost-effectiveness is measured by cedis per admissions averted and cedis per poor blood glucose incidence averted incremental to the baseline scenario. All health and cost outcomes are expressed per 1000-patient cohort.

Table 8.5 Input data for the costing model (Author's own research).

Cost item	**Base case**	**Sensitivity**	**Source**
Medicine (insured)	***cost per week's dose in GHS***		
Metformin	1.54	One type of metformin on the NHIS medicine list; no uncertainty around the cost	NHIS Tariffs
Sulphonylurea	1.40	Min = 1.12 Max= 1.61 (uniform distribution)	
Thiazolidinediones	4.90	Min = 4.34	

		Max = 5.46 (uniform distribution)	
Insulin	52.86	Min = 52.72 Max = 52.98 (uniform distribution)	
inhibitors	208.43	Min = 162.98 Max = 244.30 (uniform distribution)	
Medicine (uninsured)*	38.7% higher than insured	Min = 15% Max = 75% (uniform distribution)	
Outpatient services**	Tertiary = 301.48 Secondary = 212.57 Primary = 192.89		
Inpatients service**	Tertiary = 585.80 Secondary = 457.61 Primary = 350.29		
Intervention cost			
20% SSB Tax	1% of total tax revenue	1% - 2%	Ministry of Finance Report
Transporting medicines (Inter1)	13% of annual medicine cost	Min = 7% Max = 22% (uniform distribution)	Ghana Medicine Pricing Study
Distributions			
Distribution of medicine types	Met only = 0.316 Insulin only = 0.104 Inhibitors only = 0.003 Met & Sul = 0.198 Met & Sul & Thia = 0.189 Met & Sul & Thia & Insulin = 0.19		Mobula et al. 2018
Distribution of health facility types***	Primary = 0.855 Secondary = 0.143 Tertiary = 0.002		Mahama et al., 2023.

Note: *We increased the NHIS medicine tariffs by 38.7% for uninsured patients and explored 15% - 75% in uncertainty analysis, based on Asiedu et al. 2022. **We assumed the same cost for uninsured out-of-pocket payments. ***The distribution of patients who attended each health facility type, excluding the CHPs compound in the primary facility, was used in the base case. In uncertainty analysis, we assumed the proportion of patients attending facility types is the same as the distribution of health facilities. Met = Metformin, Sul = Sulphonylurea, Thia = Thiazolidinediones.

Sensitivity analysis

To capture uncertainty in the values of our input parameters, we conducted a Latin Hypercube Sampling (LHS) sensitivity analysis. We preferred LHS over other sampling methods because it stratifies the underlying parameter distribution, resulting in a more representative sample and reducing the number of iterations needed (McKay, 1992). We varied input parameters over a plausible range of the input parameters (Table 8.7), simulated each intervention 500 times and constructed 95% uncertainty ranges

around the mean cost. We performed the same process for health effects in the ABM simulation study (presented in Chapter 7).

8.6 Results

8.6.1 Government Expenditure

The government is estimated to spend GHS4.342 million (4.329 – 4.352 million) on DM treatment and services per 1000 patients after 10 years in the baseline scenario (Inter0). This amount constitutes 56% of the total intervention cost (Figure 8.3). After 5 years, the government is projected to spend approximately GHS 2.28 million (2.27 – 2.28 million) on medicines, outpatient attendance, and admissions in Inter0.

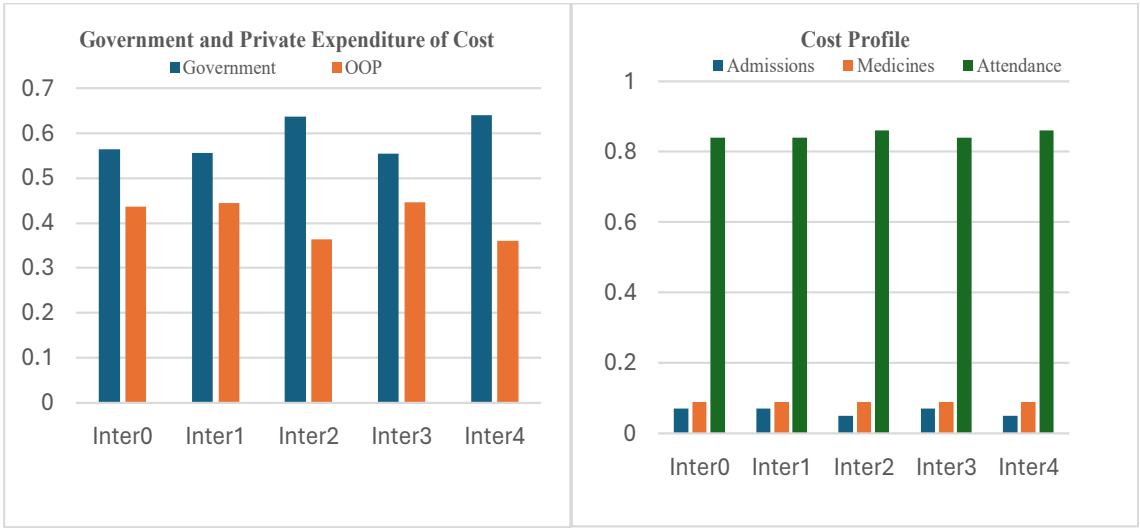


Figure 8.3 Distribution of total cost by payer and medical services/medicines (Author's own research).
Note: In the left diagram, the total cost includes medical costs (medicines, outpatient services and admissions) in 10 years over 500 simulations. Inter 1 and Inter3 include medicine transportation and tax implementation costs, respectively. In the right diagram, the cost does not include medicine transportation and tax implementation.

The sequential incremental government expenditure (including medicines, outpatient visits, inpatient services, and intervention implementation cost) per 1000 patients after 10 years is GHS49,700 (49,600 – 49,800) in Inter1; GHS2,899,000 (2,859,000 – 2,940,000) in Inter2; and GHS683,000 (681,000 – 688,000) in Inter4. Aside from medicine transport costs in Inter1 and tax implementation cost in Inter3, the government expenditure on medicines, admissions, and outpatient service does not change significantly from Inter0. In Inter2, the government saves approximately GHS59,400 (56,100 – 63,000) on reduced admissions but spends more on outpatient attendance and medicines used: GHS 1,259,000 (1,244,000 – 1,275,000) and GHS 1,236,000 (1,221,000 – 1,252,000), respectively. In all the intervention scenarios, government

expenditure is more than private OOP expenditure. The government spends a larger proportion of its expenditure on outpatient attendance, which makes up over 80% of the cost (Figure 8.3). Medicine transport and tax implementation costs constitute less than 1% of total intervention costs in Inter1 and Inter3, respectively.

8.6.2 Private, out-of-pocket expenditure

In the baseline scenario, OOP expenditure constitutes GHS 3.366 million (UR 3.357 – 3.373) of total intervention cost after 10 years per 1000 patients, which is less than 50% of the total cost. Inter2 reduced OOP by GHS1.650 million (1.618 – 1.682) per 1000 patients over 10 years. The proportion of total cost paid out of pocket reduced from 0.43 in Inter0 to 0.35 in Inter2. There is no significant change in OOP expenditure per 1000 patients after 10 years in Inter 1 and Inter3. Inter2 largely influences the reduction in OOP in Inter4 compared to Inter0. Over 80% of OOP expenditure is spent on outpatient attendance. Medicines and admissions constitute less than 20 % of total OOP expenditure. On average, approximately GHS165,000 (UR 162,000 – 168,000) OOP expenditure is averted every year in Inter2; the average annual OOP averted in the first five years (147,000 UR: 144,000 – 151,000) is less compared to what is averted in the latter 5 years (183,000 UR: 179,000 – 186,000).

8.6.3 Cost-effectiveness and cost-saving

Inter1 and Inter3 are dominated by Inter0; they cost more money and result in no significant reduction in admissions and incidence of poor BGC compared to Inter0 (Table 7.8). On average, Inter2 costs GHS4,852 more to avert one incidence of poor BGC and GHS70 (65 – 75) to avoid one admission relative to Inter0 (Table 7.9). There is no significant difference in the cost per incidence of poor blood glucose or admission avoided in Inter2 and Inter4.

Table 8.6 Incremental health and economic outcomes per 1000 patients after 10 years (Author's own research).

Intervention	Incremental cost (GHS)	Incidence of poor glucose control averted	Admissions avoided	Incremental cost/poor glucose control averted (GHS)	Incremental cost/admissions avoided (GHS)
Inter1*	49,749 (49,679 – 49,815)	-1 (-5 – 3)	-53 (-203 – 98)	Dominated by Inter0	Dominated by Inter0
Inter2	785,987 (720,364 – 852,179)	162 (159 – 167)	11,263 (11,124 – 11,401)	4,852 (4,531 – 5,103)	70 (65 – 75)
Inter3**	1,906 (1906 – 1906)	-1 (-6 – 2)	-42 (-187 – 104)	Dominated by Inter0	Dominated by Inter0

Inter4	788,431 (723,705 – 854,491)	162 (159 – 166)	11,258 (11,121 – 11,395)	4867 (4552 – 5148)	70 (65 – 75)

Note: Results are the sum of means outcomes over 500 simulations. Costs are presented in 2024 cedis, rounded to the nearest 1000 cedis and discounted annually at 0.3%. Inter0 represents the baseline. All intervention scenarios cover the annual medical costs (medicines, outpatients, and inpatient services). Inter 1 and Inter3 include transportation and tax implementation costs, respectively. In Inter1, the proportion of times patients found medicines available in community pharmacies increased by 10% each in rural and urban areas compared to baseline. In Inter2, there is a 10% annual increment in the proportion of patients actively insured by NHIS for the first 5 consecutive years. In Inter3, a 20% SSB tax reduced obesity and overweight (a proxy for unhealthy lifestyle) over 10 years compared to baseline. Inter4 combines Inter2 and Inter3. * Aside from medicine transport cost, reported in the table, Inter1 incremental cost relative to Inter0 is -1854 (UR: -50036 – 90,281). **Aside from the tax implementation cost of GHS1,906 per 1000 people over 10 years, medical cost is 22 (-62623 – 60852).

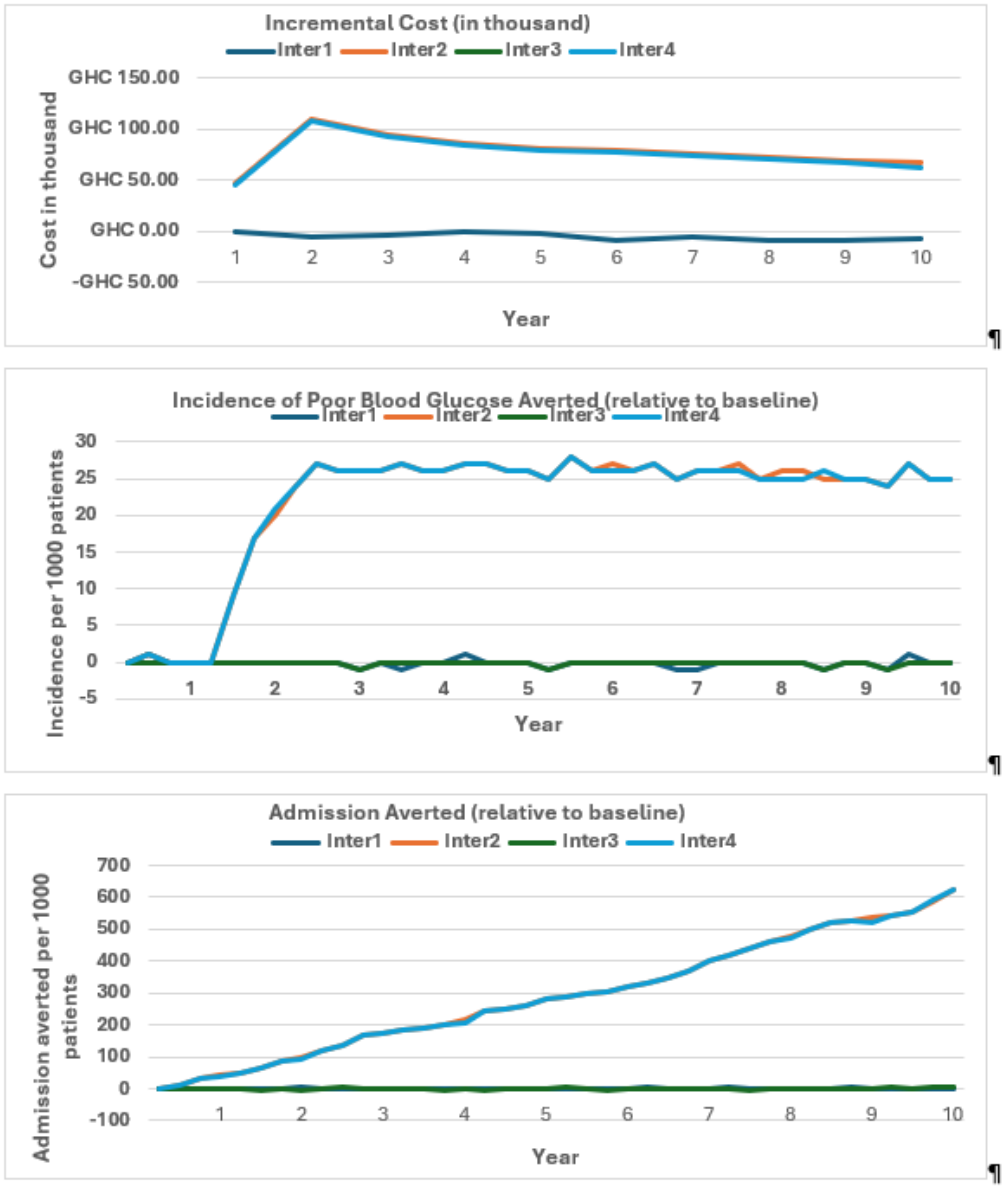


Figure 8.4 Cost-effectiveness. Results are over 500 simulations and 10 years (Author's own research). Note: Row 1 shows the mean undiscounted total costs of interventions presented in 2024 cedis, rounded to the nearest 1000 cedis. The cost included government and private out-of-pocket expenditures for

medicines, outpatients, and inpatient services. Inter 1 and Inter3 included transportation and tax implementation costs, respectively. Rows 2 and 3 represent the mean incidence of poor blood glucose averted and mean admissions avoided in a 1000-patient cohort. In Inter1, the proportion of times patients found medicines available in community pharmacies increased by 10% each in rural and urban areas compared to baseline. In Inter2, there is a 10% annual increment in the proportion of patients actively insured by NHIS for the first 5 consecutive years. In Inter3, a 20% SSB tax reduced obesity and overweight (a proxy for unhealthy lifestyle) over 10 years compared to baseline. Inter4 combines Inter2 and Inter3.

8.6.4 Sensitivity analysis results (CEA Acceptability Curve)

Figure 8.5 shows the proportion of times that each intervention is cost-effective (compared to Inter0/baseline) at reducing admissions when we varied health and cost parameters across a plausible range over 1000 simulations for 10 years. We estimated that Inter1, Inter3, and Inter4 were over 60% of the time more costly and less effective than Inter0. Inter3 was 70% more costly and less effective than Inter0. At a threshold of GHS2,000 per admission avoided, the choice of the most cost-effective interventions is uncertain, as the probabilities that Inter1 – Inter4 offer the highest net benefit are very close: 0.140, 0.123, 0.109, and 0.135, respectively. Inter1, Inter2 and Inter4 are more likely to be cost-effective at avoiding admissions compared to Inter3 as the cost-effectiveness threshold increases.

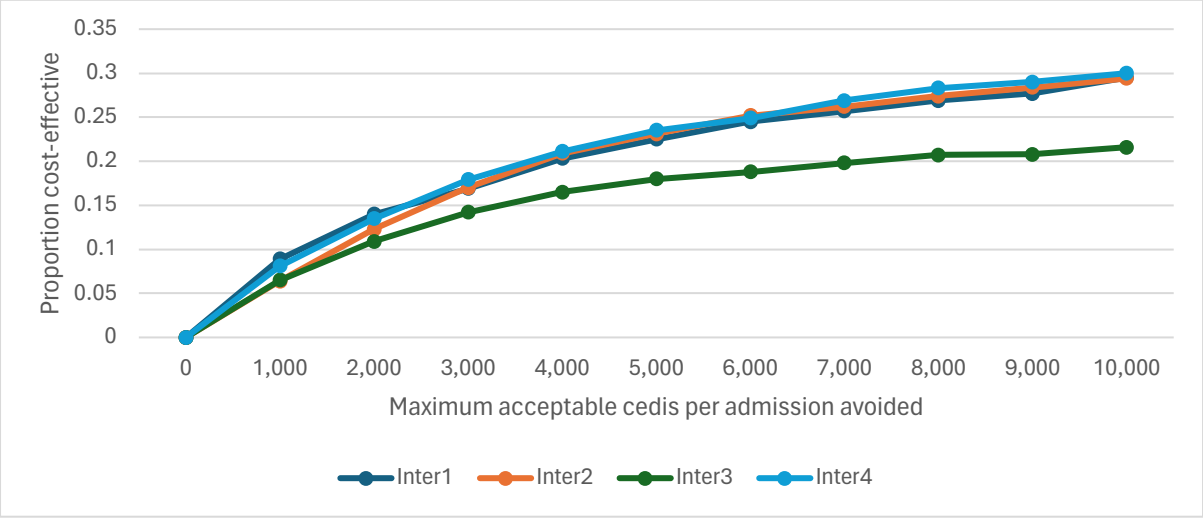


Figure 8.5 Cost-effectiveness acceptability curve (Author's own research).
Note: Cost-effectiveness from a government perspective. Results represents 1000 simulations over 10 years per 1000 patients. In Inter1, the proportion of times patients found medicines available in community pharmacies increased by 10% each in rural and urban areas compared to baseline. In Inter2, there is a 10% annual increment in the proportion of patients actively insured by NHIS for the first 5 consecutive years. In Inter3, a 20% SSB tax reduced unhealthy lifestyle (using obesity and overweight prevalence as a proxy) over 10 years compared to baseline. Inter4 combines Inter2 and Inter3.

8.7 Discussion

We estimated the cost and cost-effectiveness of DM PH interventions to support policy decision-making on DM control in Ghana. Our analysis indicates that a 10% annual increase in the proportion of actively insured NHIS patients for five consecutive years reduces the OOP, admissions and the incidence of poor BGC. Implementing a 20% SSB tax and increasing medicine availability to patients cost the government more money but does not improve clinical outcomes compared to the baseline intervention. We discussed key findings by interventions, model concept and data-related insights.

We estimated the cost and cost-effectiveness of DM PH interventions to support policy decision-making on DM control in Ghana. Our analysis indicates that a 10% annual increase in the proportion of actively NHIS-insured patients for five consecutive years reduces out-of-pocket (OOP) expenses, hospital admissions, and the incidence of poor blood BGC. In contrast, increasing medicine availability and implementing a 20% SSB tax, which reduces unhealthy lifestyles (using obesity and overweight prevalence as a proxy) by 0.006–0.071 over 10 years, results in higher government costs without improving treatment outcomes compared to the baseline. From the modelling study (Chapter 7), we found that increasing the effect that SSB tax has on obesity and overweight prevalence (i.e., from about 0.006 – 0.071 over 10 years to 0.2 per year for 10 consecutive years) makes the tax intervention more effective than the insurance intervention relative to baseline. Also, increasing medicine availability is not cost-effective because the model assumes that both affordability and availability are essential for adherence. Even if medicines are widely accessible, patients cannot use them to improve treatment outcomes if they cannot afford them. While affordability depends on insurance coverage and wealth in our model, wealth mostly remains unchanged in the model. Consequently, expanding insurance coverage proves to be a more effective strategy than simply increasing medicine availability.

Active NHIS coverage

Our analysis shows that increasing the proportion of NHIS active membership saves the government money from reduced admissions. However, the government spends more money on outpatient service utilisation. Our finding confirms a number of studies' results (Alhassan et al., 2016; Aryeetey et al., 2016; Okoroh et al., 2018; van der Wielen et al., 2018). These authors found that NHIS increased health service utilisation and reduced OOP payments. Aryeetey et al. (2016) reported a 64% and 51% increase in outpatient and admissions, respectively, and a general improvement in medicine availability after NHIS implementation. Increasing active insurance coverage may require substantial government investment in NHIS promotion campaigns and health infrastructure, including beds, equipment, and workforce, to improve service quality, subscriber satisfaction and, incentivise active membership while

supporting the scheme's operations (Awoonor-Williams et al., 2016; Fenny et al., 2016; Wang et al., 2017).

In our analysis, we account for NHIS costs for medicines, outpatient attendance, and inpatient service but not NHIS operational costs; therefore, the intervention costs are low. In the first five years of Inter2, the government would spend GHS 2.58 million per 1000 patients and an additional GHS 2.424 million in the following five years. The annual progressive increase in active NHIS coverage is likely feasible, and in reality, the additional operational and administrative costs can be substantial (National Health Insurance Authority, 2019a). Even if active membership remains stable, aggressive increases in tariffs could significantly affect government NHIS expenditure (National Health Insurance Authority, 2019a). Health provider behaviours, delays in claims payment and poor subscriber experience of service quality and membership renewal contribute to low enrolment in the NHIS (Aryeetey et al., 2016; Awoonor-Williams et al., 2016; Wang et al., 2017). The electronic renewal and claim processing combined with promotion campaigns could help improve active membership and retain subscribers on the scheme (National Health Insurance Authority, 2019a; Nsiah-Boateng et al., 2017b).

We find that increasing active insurance coverage (Inter2) improves DM outcomes and substantially reduces OOP expenditure compared to baseline intervention. The finding is similar to those reported in other studies (Guindon et al., 2022; Mann et al., 2014; Sinnott et al., 2013). These studies provide evidence that expanding public insurance coverage for DM treatments improves BGC and reduces the financial burden associated with treating the disease. Our study provides evidence that can support discussion on achieving the WHO Global DM targets of increasing BGC and access to medicines among DM patients (World Health Organisation, 2022b). Our analysis shows that increasing active insurance coverage reduces poor BGC and increases access to medicines by making them affordable to patients.

SSB Tax

Our analysis indicates that the government spends additional money to implement a 20% SSB tax. However, the intervention does not improve DM clinical outcomes any more than the baseline, which contradicts the findings of Manyema et al. (2014) in South Africa and Basu et al. (2014) in India. These authors used nationally representative data on SSB consumption and price elasticity, energy intake and expenditure equations, DM risk and disability weights, and DM cost estimates in a Markov model to examine the effect of a 20% SSB tax on DM control. These studies modelled the chain of effects of SSB tax: reducing consumption leads to reduced obesity and overweight and consequently improved BGC. We do not represent these details in our model. Instead, we applied the SSB tax effect from

Manyema et al. and Basu et al., which could explain why the intervention was not cost-effective compared to the baseline.

Our results show that if the tax implementation cost is excluded from the intervention cost, a 20% SSB tax intervention's cost and health effect are not significantly different from the baseline cost and health effect. Tax compliance is a key consideration in SSB tax policy as non-compliance could make the intervention ineffective at influencing healthy behaviours (World Health Organisation, 2017a). There are concerns that close ties between politicians and the beverage industry leaders in Ghana could influence non-compliance with Ghana's 20% SSB tax and lead to potential increases in illicit trade and negative economic effects (Singh et al., 2023). In our analysis, we do not explore tax compliance behaviours. However, non-compliance could increase monitoring costs, reduce tax revenue generated, and reduce the impact on obesity and overweight prevalence.

Increase medicine availability.

We found that a 10% increase in the proportion of times patients found medicines in their communities is more costly but does not improve health outcomes and OOP expenditure relative to baseline. The additional cost is incurred due to transporting medicines.

Persistent medicine stockouts, especially in rural areas, have been reported in Ghana's PH system. According to the Ghana Pharmaceutical pricing study, the lack of effective transportation from regional medical stores to points of service contributes to the persistent medicine stockouts (Sarley et al., 2003). One of the recommendations by the study and WHO (World Health Organisation, 2022b) is to increase medicine availability. However, our analysis shows that, despite the additional cost of transporting medicines, increasing availability does not significantly reduce admissions and poor BGC for one main reason: availability does not mean patients can afford the medicines. Patients who are insured or belong to the middle to highest wealth quintile can afford medicines in our model, as evidenced by studies (Aryeetey et al., 2016). In instances of non-availability, patients who can afford medicines are able to find them in other NHIS-accredited pharmacies. Uninsured patients and those in low-wealth quintiles may be able to afford generic medicines, which are more affordable than originators if made more available (Babar et al., 2019; Ewen et al., 2019). Thus, increased availability could increase access and potentially improve adherence and DM outcomes.

Our analysis indicates that a 10% increase in the proportion of times patients found medicines in communities does not substantially change OOP expenditure in uninsured patients. This is because we do not account for the cost of travel in search of medicines. DM patients in Ghana are reported to spend substantial money OOP on medicines and travel (Amissah and Dunyah, 2016; Amon and Aikins, 2017).

If we had accounted for travel costs incurred by patients, increasing medicine availability would have reduced the cost as patients would find medicines more frequently and would not need to travel as often in search of them. However, additional expenses would shift towards transporting medicines to hard-to-reach communities.

8.8 Limitation

Aside from the limitations of our ABM studies (discussed in Chapter 7), which provided evidence of health effects, our CEA analysis has some limitations. We do not capture all possible covariates in our analysis. A combined ABM and CEA allow for evaluating prospective national PH intervention costs and health benefits to the government and DM patients. However, the accuracy and level of detail possible in our analysis are restricted by the quality of input parameters. Thus, improving the ABM and cost input parameters would improve our cost-effectiveness results.

First, our use of clinical outcomes rather than DALYs reduces the comparability of our results with the outcomes of other cost-effectiveness studies. The recommendation for using DALYs and QALYs hinges on the ability to compare outcomes of various policy interventions, giving decision-makers a broader range of alternatives (Drummond et al., 2015). We found no DALYs directly associated with acute complications due to poor blood glucose in T2DM patients from the GDB study and the Global Health CEA registry's online DALY calculator. DM conditions for which both sources report DALYs include uncomplicated DM, DM neuropathy, vision impairment, blindness and chronic kidney disease in DM. Extrapolating DALYs for these conditions to represent health states during acute DM complications could be misleading. The paucity of research focused on acute complications and BGC in T2DM could explain the lack of data on DALYs. Nevertheless, our use of clinical outcomes, specifically admissions and the incidence of poorly controlled blood glucose, is informative for clinical service planning and delivery and NHIS budget considerations.

Second, the costs included in the analysis do not represent an exhaustive list of costs associated with interventions. We do not account for direct non-medical and intangible costs, including travel costs to and from health facilities, which could be substantial OOP expenditures (Amissah and Dunyah, 2016; Amon and Aikins, 2017). Also, adverse drug reactions, chronic DM complications and comorbidities such as retinopathy and hypertension, which are common among DM patients in Ghana, but not captured in our analysis, impact clinicians' prescription choices and health facility referrals, among other care decisions, which tend to affect OOP expenditure and medicine costs for NHIS.

Third, we assume that wealth quintiles and treatment costs will be constant over 10 years. We also assume the same cost of inpatient and outpatient services for insured and uninsured patients, which may not be the case. Ghana's economic challenges, including high inflation rates and the depreciation of its currency against the USD, contribute to erratic fluctuation in medicine prices, as evidenced by Asiedu et al. (2022). The authors found that the average percentage increase in medicine prices rose from 26.2% in February 2022 to 178.6% by October 2022; the rate was 151.3% for medicines used in the treatment of chronic disease. Also, inpatient and outpatient service costs could be higher for uninsured patients than for insured, as Asiedu et al. (2022) found a 38.7% average disparity between NHIS medicine costs and the average prices of medicines in community pharmacies. Accounting for medicine price increases over time and higher OOP expenditure for inpatient and outpatient services would increase intervention costs in our analysis.

8.9 Chapter Summary

This chapter has addressed the economic efficiency component of Research Question 5: "What is the health and economic efficiency of selected PH interventions to patients and the government?" We described the decision problem, highlighting insufficient funding for health and multiple health demands as necessitating hard choices. We outlined economic evaluation methods and justified our use of CEA as a means of generating evidence to support decision-makers in making hard choices. We described the CEA study design, highlighting our use of a government perspective, health effect evidence from the ABM study presented in Chapter 7 and costing data mainly from the NHIS.

The CEA study has revealed that compared to the baseline, increasing active NHIS coverage is cost-effective for reducing admissions and the incidence of poorly controlled blood glucose. A 10% increase in the proportion of times patients found medicines available in communities and a 20% SSB tax could prove be more costly and less effective than the baseline.

Furthermore, we examined uncertainty around cost and health input parameters using CEAC. The uncertainty analysis revealed that the probability that a 20% SSB tax would be cost-effective at reducing admissions and improving BGC is lower than the probability of: 1) increasing medicine availability and 2) increasing insurance coverage. Evidence from the CEA can support policy discussions and decision-making for DM control in Ghana.

In the next chapter, we summarise the overall body of research and present its key contributions and limitations.

9 Conclusion

9.1 Introduction

The chapter presents the research agenda and summarises the main conclusions reached from this body of research. It describes the research's theoretical, methodological, empirical, and policy contributions to DM control, management science, operational research, and policy decision-making. Furthermore, the chapter outlines the implications of the research conclusions for practice and policy. The limitations of the research are presented, and finally, opportunities for further research are suggested.

9.2 Research Summary

In Chapter 1, we presented the research background, motivation, aim, and research questions. Based on a narrative literature review, we briefly discussed the DM burden in Ghana and other LMICs, highlighting the impact of socioeconomic factors and the COVID-19 pandemic on the disease burden. We presented five research questions addressed within the overall research thesis structure.

Chapter 2 presents a non-systematic narrative literature review on the burden of T2DM in Ghana and other LMICs, as well as international and national policies and programmes to address the burden. It also discusses how clinical DM services are organised and delivered and the challenges they face. We identified the first and second research objectives: to improve understanding of the pathway to DM service delivery in Ghana and to describe interventions and barriers to DM control in the country. The chapter addresses research question 1: "*What is the state of DM service delivery in Ghana and DM interventions in Ghana and LMICs?"*

Chapter 3 is based on a non-systematic narrative literature review. It discussed PH interventions for DM control interventions, partly addressing research question 1. The Chapter focuses on PH interventions, including education and fiscal policies, for their wide-reaching impact on non-DM populations. The chapter also examined patient SMBs in the scope of health behaviour theories, addressing research question 2: "*How do patients' behaviour influence health service delivery and DM treatment outcomes?"* The review of patient behaviour and health behaviour theories helped identify broad areas of concern in treatment adherence for chronic health conditions: provider and health system factors, DM and medicine-related factors, patient-related factors, socio-cultural environment and logistics and finance-related factors. The review discussed the relationship between SMB and treatment

outcomes. The literature on interventions informed the selection of interventions examined in the simulation study.

Chapter 4 discussed SM approaches commonly used in health intervention research, providing insights for addressing research question 4: "*What is an appropriate modelling approach for representing the system of DM treatment in Ghana?"* The chapter also presented a systematic review of the application of DAMs for DM intervention studies in LMICs, focusing on ABM, SD, DES, and Markov cohort models. The systematic review addressed research question 3: "*How have SM and economic evaluation methods (DAM) been applied to evaluate PH DM interventions in LMICs?"* The review provided insights into how studies modelled DM outcomes, issues of data limitation, model calibration, validation, and reporting. It enabled the identification of the research gap explored in this research: a lack of ABM approaches for investigating T2DM patients' SMBs and how these behaviours influence treatment outcomes.

Chapter 5 presents critical realism as the philosophy underpinning this research. It discussed the mixed methods research design and methodology. This chapter presents the methods applied to address the research questions and discusses sequential analysis as the approach to integrating findings from different studies to address the research questions.

Chapter 6 presents our first original study: a qualitative interview with clinical DM service providers in Ghana, further addressing research questions 1 and 2. The study focused on understanding the DM service delivery system, changes that may have occurred due to the COVID-19 pandemic, patients' SMBs and challenges to treatment adherence. The interviews with clinicians helped establish rapport and collaboration, which facilitated the modelling process, especially model scoping and validation. The interview highlighted vital lifestyle and medicine adherence behaviours as key factors influencing BGC and emphasised the importance of representing patient behaviour in a simulation model of T2DM control. The interviews helped refine interventions investigated in the simulation study.

Chapter 7 presents the case study of an agent-based SM of T2DM patients' behaviour regarding medicine adherence, diet and exercise and health-seeking. The chapter addresses the health part of research question 5: "*What are the health and economic benefits of selected PH interventions to patients and the government?"* The model contains patients who have been diagnosed and are receiving treatment in Ghana's PH facilities. The model captured how medicine access and affordability, admissions of acute complications, and decisions on diet and exercise behaviour influenced BGC. Using ABM helped capture patients' stochastic behaviour and agency in the treatment process, which are difficult to achieve using SD, DES, or Markov cohort modelling. The modelling approach provided

evidence of the effectiveness of PH interventions: increasing medicine availability, increasing national insurance coverage and 20% SSB tax for BGC in T2DM.

Chapter 8 presented a CEA of the PH interventions examined in Chapter 7, addressing the economic efficiency part of research question 5. The CEA addressed the research objective of evaluating the health and economic benefits of PH interventions for patients and the government. It provided evidence of the interventions' cost-effectiveness to support policy decision-making for controlling T2DM in Ghana. The chapter reviewed common economic evaluation methodologies in the health economic literature and justified our use of the CEA methodology. Costing was conducted from a government perspective using data from the NHIS, peer-reviewed articles and clinicians. The analysis used evidence of health effects from the ABM study. It provided insights into the additional cost associated with avoiding admissions and the incidence of poor blood glucose.

9.3 Key Contributions

9.3.1 Theoretical Contribution

This research makes two main contributions from a theoretical perspective. First is **the development of a conceptual model of individual patients' SMB using the theory of planned behaviour and the health belief model to improve understanding.** Health behaviour is complex and mutually influenced by multiple factors in the physical and policy environment (American Diabetes Association, 2024; Brown, 2024; World Health Organisation, 2020). Theories can help improve understanding of behaviour. We applied HBM and TPB to conceptualise individual patient's SMB. Our study represents patients' SMBs using decision rules formulated from health behaviour theories–HBM and TPB and clinicians' opinions. We applied the understanding of TPB and HBM tenets to design individual patients' SMB. The decision rules incorporate dynamic socioeconomic factors in patients' environments, such as insurance coverage and lifestyle trends. For instance, based on perceived barriers (HBM) and actual behavioural control (TBP), we conceptualised that patients who cannot afford prescriptions and those who cannot find medicines in their communities do not take medicines. We used Ghana's DM treatment guidelines, NHIS operational tariffs, and clinicians' opinions to define the rules for clinical service delivery. Our conceptual model provides clarification of patients' SMB, which can serve as a foundation for further research on adherence behaviours and DM treatment outcomes.

The second theoretical contribution of this research is the development of an **agent-based model for improving our understanding of the interaction between patients' SMB, the socioeconomic environment, and the clinical service delivery system and how such interactions influence BGC**

outcomes among T2DM patients. There is evidence that SMB significantly influences treatment outcomes, especially in chronic disease management, where patients are left on their own most of the time to manage the condition (American Diabetes Association, 2024; Magliano and Boyko, 2021; World Health, 2016). There is also an understanding that the socioeconomic environment and lifestyle, including but not limited to access to and affordability of health services and medicines, and food environment, influences patients' SMB and consequently affects BGC and other DM outcomes condition (American Diabetes Association, 2024; World Health, 2016). However, there is little evidence of the theoretical explanations underlining how socioeconomic factors, lifestyle choices and health service delivery systems interact with individual-level behaviours to explain blood glucose outcomes in T2DM patients.

We used an ABM model to improve understanding of the interaction between patients' behaviour, socioeconomic environment, and clinical service delivery. Many existing simulation studies in LMICs have used compartmental, microsimulation models, and cohort models to simulate the progression to chronic DM complications, including DM retinopathy and kidney failure (Mukonda et al., 2021; Twumwaa et al., 2022; Watson et al., 2014). Compartmental and Markov cohort models represent the pathway of an average person from a population with similar characteristics rather than representing individual-level variability. Microsimulation does not represent how a patient decides to take medicines, seek care, or change their SMB following acute blood glucose complications. These simulation approaches mask the fundamental concept of patient SMB affecting poor BGC and the progression to chronic complications and mortality. The flexibility of ABM to capture agency and behaviour of individual patients and the dynamic PH environment helped us to represent patients' decision-making processes, incorporating key factors that influence patients' decisions and how these decisions tend to influence the clinical services and BGC outcomes. Our model explicitly represents the individual-level behaviours and heterogeneity. Each patient in our model has unique demographic and socioeconomic characteristics reflecting empirical data.

Our model provides insights into the relationship and feedback between individual patients' SMB, patients' socioeconomic environment, clinical service delivery, and BGC. Specifically, our model indicates a nonlinear and mutually influential relationship between patients' SMB, health service delivery, and the socioeconomic environment. For example, our model shows that increasing insurance coverage (in the socioeconomic environment) increases patients' access to medicines, which improves medicine adherence, reduces admissions, and improves BGC. Admissions foster healthy dietary behaviours as clinicians monitor inpatients to ensure they consume nutritious food and adhere to medication. The understanding of the mutual nonlinear relationship between the individual patients' SMB, the socioeconomic environment, and clinical service delivery can serve as a foundation for future modelling and empirical research.

9.3.2 Methodological Contributions

This research makes two key methodological contributions to the field of modelling and simulation in management science.

First, we **applied ABM to implement a dynamic and stochastic SM of T2DM patients' SMB and clinical service delivery within Ghana's socioeconomic environment, which is useful for experimenting with PH intervention's health impact.** SMs are built to represent decision problems, considering decision variables, objectives, constraints, and uncertainties. They provide a systematic approach to analysing decision scenarios, enabling decision-makers to better understand the potential outcome of alternatives. Although SMs can be a viable approach to investigate health policy interventions, their application in health policy research is scarce in Africa, including Ghana, for reasons including, but not limited to, technical capacity and difficulty accessing quality data (Koduah et al., 2023; Mukonda et al., 2021; Twumwaa et al., 2022). To the best of our knowledge, our research is the first in Ghana to apply SM to investigate DM PH interventions. The first national attempt of SM in HTA in Ghana was the collaboration of iDSI and MoH on hypertension management under NHIS. The study adopted an Excel-based state-transition model to examine policy scenarios on prescription patterns under NHIS (Koduah et al., 2023). We applied ABM to represent individual-level variability and behaviour, which state-transition models cannot represent. Our ABM captures the dynamic and nonlinear relationship between patient-level behaviour, clinical services, and cohort-level blood glucose outcomes. The model improves understanding of cohort-level blood glucose outcomes and generates evidence of the impact of PH interventions to support policy and resource allocation decision-making in Ghana. Our modelling methodology could guide other researchers in Ghana aiming to apply ABM to health policy. Also, engaging with clinicians and hospital management in the modelling processes helped validate the model and could facilitate it buy-in to support the implementation of model recommendations.

Second, we **applied HBM and TPB as a conceptual framework, rather than for designing a survey, to model patient SMB**. We modelled patients' medicine adherence and health-seeking behaviour based on the HBM's tenets: perceived barriers, perceived susceptibility and severity, and the tenet of actual behavioural control from the TPB. We do not quantitatively measure the tenets of HBM and TPB like Edwards et al. (2021), Maiman et al. (1977), Mabotja et al. (2021), Kim et al. (2024), Wallén Warner (2023) and McEachan et al. (2011). These studies used scales and questionnaires to collect data on specific tenets in relation to health behaviours. The authors used regression models and structural equation modelling to examine the relationship between tenets and health behaviour and explain the predictive ability of each tenet. However, we do not quantify the tenets. Instead, we applied the theories

as a framework to design patient behaviour rules. For example, we represented medicine adherence behaviour using a perceived barrier (HBM) and actual behavioural control (TPB) such that patients who had no prescriptions or could not afford or access medicines locally were set to not adhere to medication. In applying HBM and TPB tenets as a conceptual framework, our model makes a key assumption that intentions translate into actual behaviour, which is not always the case. The discussion on the gap between intention and behaviour is extensively explored in the behavioural psychology literature, with mixed opinions (Conner and Norman, 2022; Koole et al., 2023). Although there is agreement that not all intentions are translated into action, it is unclear which intentions materialise as behaviours. Our model contributes to applications of TPB and HBM as a framework for describing the health behaviour of T2DM patients.

9.3.3 Empirical Contribution

This research makes two empirical contributions to the field of T2DM management. First, the ABM model has **improved the understanding of how the interaction of patient-level behaviour, clinical services and the socioeconomic environment influences the effectiveness of PH interventions for BGC at the cohort level.** NCD management in Ghana has focused mainly on pharmacological and clinical services to slow the progression of chronic complications and achieve blood glucose and blood pressure control (Ministry of Health, 2022a). Our model demonstrates that PH interventions influence patients' SMB, which consequently impacts treatment outcomes. Thus, focusing on clinical services alone could lead to suboptimal control of the disease burden. Furthermore, at the time of the ABM study, no other published study had considered how PH interventions could impact clinical service use and blood glucose outcomes in T2DM in Ghana. Our model predictions suggest that a 10% increase in medicine availability is no more effective at improving cohort-level blood glucose outcomes and does not significantly reduce admissions than the baseline intervention. This is largely because, while holding income levels and active insurance coverage proportions constant, an increase in medicine availability does not mean patients can afford medicines. Increasing the proportion of active NHIS coverage in our model improves medicine adherence as more patients can afford medicine. The intervention significantly reduced admissions and the incidence of poorly controlled BGC. Our model results predict that a 20% SSB tax is no more effective at improving BGC than the baseline intervention. We applied the SSB tax effect on obesity and overweight from studies in India and South Africa (Basu et al., 2014; Manyema et al., 2014). We do not model the detailed chain of effects of SSB tax on dietary behaviours and BGC, which could explain why the tax intervention is ineffective in our study. However, it has been reported as effective for DM control in other countries.

Second, the sequential CEA in our research has **shed light on the effectiveness in comparison to the cost implications of selected PH interventions to support resource allocation decision-making.** Our study is the first to examine the health and economic benefits of the recently introduced 20% SSB tax for BGC in T2DM in Ghana. The literature on the economic evaluation of PH DM interventions in Ghana is limited. We found 22 articles relating to either cost or DM in Ghana from the Web of Science. Many of the studies were interview- and survey-based studies investigating medicines and service delivery pathways, patients' experiences, quality of life and coping strategies. Only two of the papers estimated the cost of DM to patients (Pei, 2015; Quaye et al., 2015). Unlike our analysis, which compared clinical outcomes and medical costs, these two studies only estimated the medical costs associated with the cost of DM management. Our study adds to the literature by examining Ghana's PH interventions' cost and clinical outcomes. We also expand the argument on the cost-effectiveness of PH interventions for DM control, as suggested by WHO Best-Buy Policy Objective 4: strengthen and orient health systems to address the prevention and control of NCDs and the underlying social determinants through people-centred primary health care and UHC. Our analysis affirms that increasing insurance coverage (which constitutes UHC) improved medicine adherence, reduced admissions, and improved BGC in T2DM. Our study provides evidence that can contribute to policy discussions and interventions to support Ghana's achievement of the WHO Global DM target of 80% of patients having BGC (World Health Organisation, 2022b).

9.3.4 Practical and Policy Implications and Implementation

The ABM model in this research **improved our understanding of how clinical service delivery and PH interventions modify patient SMB and what PH interventions work well within the Ghanaian PH context**, which could contribute to supporting policymakers' and clinicians' decision-making. The model provided insights into the interaction of key factors within the system of DM management and examined the effect and cost-effectiveness of selected PH interventions. For instance, our study provided insight into how scaling up active NHIS insurance coverage increases access to medicines, outpatient service use and medicine adherence, improving blood glucose outcomes and reducing admissions. This insight could inform the planning of health service delivery while considering trends in active insurance coverage. Specifically, it could inform discussions on re-evaluating resource allocation for inpatient and outpatient services in response to increasing NHIS coverage. Insights from our CEA could support discussions on how the government can operationalise NHIS for UHC. For instance, our model findings suggest that implementing a 20% SSB tax alongside expanding active NHIS coverage is no more effective than expanding active NHIS coverage only. Although our model does not account for SSB tax revenue, a 20% SSB tax generates revenue, which could be invested into the NHIS to sustain its financial operation.

9.4 Limitations and Future Research

We reflect on the research's limitations relating to its design and the generalisability of its contributions. We also discuss future research opportunities to address these limitations and other research opportunities that could build on our research's contributions.

9.4.1 Design and Generalizability

We have encountered challenges in obtaining relevant high-quality data to develop the ABM in this research and to determine cost input parameters in Ghana.

We triangulated pockets of data relating to the characteristics of T2DM patients, the socioeconomic environment and intervention effects from multiple sources. However, we appreciate that such data only revealed part of the whole picture of BGC in T2DM in Ghana. Several uncertainties have led to various assumptions in the models. A number of studies in Ghana report the challenge of obtaining high-quality and nationally representative datasets on health and how that continues to hinder research, planning and effective management (Koduah et al., 2023; Mukonda et al., 2021). The discussion in this section is limited to data gaps relevant to intervention effectiveness and cost-effectiveness.

First, individual-level data on the sociodemographic characteristics and clinical outcomes of NCD patients are essential but unavailable in one nationally representative study or dataset in Ghana. The Demographic and Health Survey gathers data on NCDs, while the District Health Information Management System collects high-level data on health-facility-based NCD prevalence and cases diagnosed. These national surveillance systems do not monitor NCD treatment outcomes. The ABM model in this research has captured the heterogeneous characteristics of patients in terms of age, residence, wealth, and insurance status. These characteristics influence individual patients' SMBs and decisions that could affect cohort-level treatment outcomes. However, the data we used to populate patients' characteristics were sourced from individual studies, most of which were conducted in among Ghanaian residents at different times, using different sampling methods, assumptions, and limitations. Although triangulating data from these unique studies provided insights, they may not account for all the heterogeneity in the characteristics of T2DM patients in Ghana.

Second, NCD patients' SMB is not well understood. Medicine adherence behaviours, for instance, are highly heterogeneous and dynamic and are influenced by multiple correlated factors, aside from medicine access, affordability, and patients' clinical state (in good control, acute complication state, or admitted), which we represented in our model. The SMBs of individual patients have a significant

impact on cohort-level BGC outcomes. We have tried to capture some of these important factors and behaviours and their influence on clinical outcomes in our model by applying health behaviour theories, reviewing literature, and interviewing clinicians in different roles. However, further empirical research, such as trend analysis of nationally representative survey data (e.g., the GDHS), can improve our understanding of the single and combined influence of the factors and provide high-quality representative data to improve our model outcomes.

Third, how SSB taxes influence consumption behaviours and reduce overweight and obesity within Ghana's food and cultural environment has not been well understood. There is mixed evidence on the effect of SSB taxes on overweight and obesity incidence and prevalence from several countries, including LMICs, but not in Ghana. Studies that found a reduction in obesity prevalence and incidence reported a shift from SSB consumption to healthy alternatives, such as milk (Nakhimovsky et al., 2016; Tönnies et al., 2021). We assumed a 20% SSB tax in Ghana would have the same effect as that reported in simulation studies in India and South Africa's populations. The food industry and culture in these countries vary from Ghana, and therefore, the effect of an SSB tax in these countries could differ from that in Ghana. Although we used a distribution of the effect size in these studies to cover a range of the effect size, we do not know if the 20% SSB tax in Ghana would reduce SSB consumption and influence the consumption of healthy food alternatives among T2DM patients. Improving such knowledge through empirical studies now that Ghana has implemented a 20% SSB tax will help improve our model outcomes regarding the policy's impact.

Fourth, the lack of disability weights associated directly with blood glucose outcomes in T2DM patients hindered our use of DALYs in the CEA. The Global Burden of Disease (GBD) study is often cited for disability weights. The Global Health Cost-effectiveness Analysis Registry also provides a web-based DALY calculator. GBD estimates disability weights for chronic T2DM complications by combining mortality and morbidity associated with the complications and comorbidities. The GBD leverages data from published studies, expert consultation, large-scale population surveys, evidence of clinical states and progression of DM, and modelling to estimate utility weights. GBD 2021 and the DALY calculator report disability weights for T2DM with no complication, vision loss, neuropathy, amputation, kidney complications and cardiovascular complications. However, they do not report disability weights associated with acute DM complications. Using disability weights estimated for DM without complications could be misleading because acute DM complications, such as a hyperglycemic hyperosmolar state, are associated with some discomfort and a reduced health state, which is not the case with DM without complications.

Fifth, the completeness of factors influencing BGC in T2DM patients and how these factors interact to determine BGC are poorly understood. Our model captures key factors—medicine adherence and

lifestyle behaviours- and explores incorporating comorbid status and the duration of DM into the factors that determine BGC in a T2DM patient. We combined these factors using logical reasoning such that healthier characteristics lead to good BGC and vice versa, as suggested by clinicians. However, we appreciate that our model does not capture other factors, including adverse drug reactions and ageing, that could influence BGC. We also appreciate that our model does not explore other ways of combining influencing factors to determine BGC (e.g., an exponential model). Further empirical studies, such as observational and clinical studies, can offer a better understanding of additional ways influencing factors interact to determine BGC.

9.4.2 Future Research Opportunities

Future research can extend the lifestyle submodel by modelling food consumption patterns in individual patients and their impact on body mass index and, consequently, BGC. Such an extension could explore the influence of urbanisation, household composition and social networks on patients' food choices and SMB. It can help identify whether patients' interaction with non-DM people could modify SMB and the cost-effectiveness of PH interventions. It could also support the design of peer/community interventions for DM control.

Our model can be extended to explore how the heterogeneity of patients' behaviours following admission for poorly controlled blood glucose influences medicine adherence, lifestyle, and BGC outcomes. Such an extension could incorporate instances where patients change and sustain healthy SMB after experiencing acute complications and how such changes influence the lifestyle of patients' social networks. It could help identify the unintended effects of PH DM interventions on non-diabetic and at-risk populations.

The medicine adherence submodel in our ABM model could be extended to incorporate other factors influencing the decision to take prescribed medicines aside from access and affordability, such as forgetfulness due to an absence symptoms and use of traditional medicines. Such an extension could include the medicine supply chain within Ghana's PH sector, especially bottlenecks and behaviours in the distribution of medicines from central medical stores to health facilities. Aside from changes in insurance status, our model does not incorporate dynamics in patients' ability to afford DM medicines and care. For example, we do not model changes in the wealth status of patients and instances of family members funding the treatment of DM patients. Thus, considerations for extending the medicine adherence submodel include representing patients' changing income/wealth status and the financial support patients could receive from close contacts. The influence of caregivers and close contacts on medicine adherence and SMB could be captured using their knowledge levels.

Future studies could link the incidence of poor BGC to transition probabilities associated with chronic DM complications and DM-specific deaths for which disability weights exist or collect data on weights that patients are willing to place on poorly controlled blood glucose. The disability weights can be used to estimate DALYs averted due to reduced acute complications resulting from PH interventions. Policymakers could then compare the cost-effectiveness of PH interventions with pharmacological interventions using the DALYs averted.

Appendix A: Systematic Review of the Application of Decision Analytical Models in Non-pharmacological Diabetes Intervention.

Author(s), year	Country of Research	Modelled/ target population	Intervention(s) studied	Outcomes Assessed	Model Type	Sensitivity Analysis (approach: parameters involved)	Parameterisation and Calibration	Valida-tion	Soft-ware	Data Sources	Economic Evaluation	Policy implication
Abu-Rmeileh et al., 2013	Palestine	At-risk population	Reduction in obesity prevalence	Diabetes prevalence	Markov model	Multi-way analysis: clinical parameters	National survey, validated model from published studies	Historical data from national surveys	Micro-soft Excel	National demographic and health survey	Benefit analysis	Set lower obesity reduction targets initially and increase over time as this is realistic and feasible compared with a straight 35% reduction recommended by WHO.
Basu et al., 2014	India	At-risk population	Increasing taxes on sugar-sweetened beverage	Overweight and obesity prevalence, type 2 diabetes incidence	Micro-simulation	One-way and PSA: intervention parameters	Standard microeconomic equations, validated hazard calculation method	Historical data from international organisation	MAT-LAB	National survey, subpopulation studies	Benefit analysis	Sugar-sweetened beverage price increase is likely to reduce overweight and obesity prevalence, and type 2 diabetes incidence
Basu et al., 2015	India	At-risk population	Performance of alternative screening instruments	Screening results, i.e., true positives and false negatives; cost per case screened, total cost of screening	Micro-simulation	One-way and PSA: intervention parameters	Mixed-effects meta -regression, standard " inverse-variance" methods, Monte Carlo methods	Historical data from international organisation	R v.3.1.0	Cohort studies conducted in India; UKPDS South Asian specific disease progression data validated in India	Cost-analysis	Survey-based screening tools are less specific (many false positives) and more expensive compared with glucometer-based testing. The health system may be less capable of mass screening, subsequent confirmatory testing and treatment.

Basu et al., 2016	LMICs: Ghana, China, India, Mexico and South Africa	Adults with type 2 diabetes	Target-to-treat versus benefit-based tailored treatment	Diabetes complications averted, cost per DALY averted, cost-effectiveness ratio	Micro-simulation	One-way and PSA: clinical parameters	Meta-analysis of RCTs, validated UKPDS equations	Not stated	R v.3.2	International Diabetes Federation, WHO SAGE 2007-2010, United Nations database	Cost-effectiveness analysis: societal perspective, 3% discount rate on cost and effect, life course of population within a 10-year horizon	Benefit-based prescribing (focusing on reducing risk of complication based on sex, age and biomarker) avert more complication at less cost compared with "target to treat" strategy if insulin availability is guaranteed
Ben et al., 2020	Brazil	40+ years old type 2 diabetic without diabetes retinopathy	Diabetes retinopathy screening strategies	Cost, QALYs and ICER of the screening strategies	Markov model	One-way and PSA: clinical and costing parameters	Published studies	Historical data from literature review	Tree-Age software	National health survey, statistics from Public Health England	Cost-utility analysis; Public health system's perspective, 40-year time horizon, A discount rate of 5% on utility and cost	Increasing coverage of teleophthalmology-based screening among could be more costly and more effective—reduces waiting time and increases QALYs than usual practice
Chao et al., 2014	China	Adults with type 2 diabetes	18-month community-based health management: education, biomarker monitoring, exercise and diet therapy	Complication averted, death averted,	Markov model	Not reported	Published studies	Not stated	MAT-LAB 7.0	RCT conducted in Southeast China; cohort studies, UKPDS	Benefit analysis	Community-based health management averts, by about half, diabetes complications and mortalities in the long term compared to usual practice
Javan-bakht et al., 2018	Iran	At-risk population	Increasing dairy food consumption	Type 2 diabetes incidence, healthcare cost savings	Microsimulation	PSA: clinical and costing parameters	Published studies	Code verification, internal validation with domain experts, cross-validation: compared with	Tree-Age Pro 2014	Tehran Lipid and Glucose Study; medical expenditure registries; national studies.	Cost-analysis	Increasing dairy food consumption levels to that recommended by the food-based dietary guidelines in Iran could significantly reduce healthcare cost

								similar models				
Lui et al., August 2013	China	At-risk population 25 years and above	(1) one-time undiagnosed diabetes and impaired glucose tolerance screening alone, (2) 1 plus diet intervention, (3) 1 plus exercise intervention, (4) 1 plus combined diet and exercise	Survival year remaining at initiation of intervention, cost of intervention, cost savings, QALYs and incremental QALYs	Hybrid: decision tress and Markov model	One-way: intervention, costing and clinical parameters	Markov chain Monte Carlo	Not stated	Tree-Age 2011	Cohort studies conducted among Chinese and Asian population and Census data	Cost-effectiveness analysis: societal perspective, 40-years horizon, 3% discount on cost and effect	All interventions in 25–40-year-olds prolongs life expectancy, increase QALYs and delays the onset of diabetes. These interventions are cost-saving with high screening compliance rate
Luo et al., 2019	China	At-risk population	Lifestyle interventions: (1) Improving diet, (2) controlling smoking and (3) increasing physical activity levels	Diabetes incidence	Agent-based model	One-way: assumptions around interventions	Meta-analysis of previous studies,	Code verification, internal validation with domain experts, cross-validation: compared with similar models	Not stated	National Sample survey, Health and Nutrition survey, NCD Risk Factor Collaboration, WHO Global Health Observatory	Benefit analysis	Diabetes incidence reduces the most with improved physical activity levels
Wang et al., 2019	China	Over-weight and obese type 2 diabetes patients	Lifestyle intervention: Cities Changing Diabetes Program (CCD)	Cost per QALY, ICER	Markov model	One-way: costing parameters	Empirical data from an intervention program	Not stated	Tree-Age Pro 2018	Data on participants, cohort studies	Cost-utility analysis; societal perspective, a 5-year time horizon were applied. A 3% discounting	The CCD program improves lives at less cost especially for young males and elderly females if policymakers are willing to pay 3 folds the GDP for a QALY.

											rate on costs and utilities.	
Wong et al., 2016	China	At-risk population	(1) SMS intervention plus usual practice and (2) usual practice only	Intervention cost, diabetes onset prevented and associated cost-savings, cost per QALY, ICER	Markov model	One-way and multi-way: clinical, costing and intervention parameters	Published studies	Not stated	Tree-Age Pro 2013	Estimates from other cost-effectiveness models, cohort studies and RCTs	Cost-effectiveness; health provider perspective, annual discount rate of 3% on cost and health outcomes, 50 years' time horizon	2-years SMS intervention for newly diagnosed IGT reduces the onset of diabetes in the short and long term compared to usual care. Cost-savings from reduced diabetes incidence could compensate for the SMS intervention cost.
Basu et al., 2018	Palestine	At-risk population 20–79-year-olds	Approaches to delivering food aid	Incidence and complications of type 2 diabetes, hypertension, and cardiovascular diseases, DALYs averted, cost averted	Micro-simulation	PSA: input parameters	United Nations Relief and Works Agency database, the Risk Equations for Complications of Type 2 Diabetes.	Not stated	R v. 3.3.3	United Nations data on registered Palestinian refugees, the World Food Program, health record system of the UN Relief and Works Agency	Cost-effectiveness; health systems and societal perspective. Life course analysis for persons alive during a 10-year policy planning horizon, 3% discount on cost and effect.	An alternative food parcel would be more effective than transitioning from traditional food aid to either debit card or cash delivery from the perspective of reducing chronic disease. But compensatory increases in consumption of less healthy foods may neutralize the improvements from an alternative food parcel unless total aid funding were increased substantially.

Feldhaus et al., 2021	Cambodia	Diabetes patients	Strategies providing financial coverage for diabetes care through Health Equity Fund in Cambodia.	DALYs averted and financial risk protection was analyzed in terms of cases of catastrophic health expenditure averted.	Markov model	PSA: cost and effect parameters.	Published studies	Not stated	R (versio n 3.6.1)	National survey, published literature, the 2017 Global Burden of Disease (GBD) Study, The WHO Global Health Observatory report, the GBD Study 2017	cost-effectiveness analysis, societal perspective,4 5-years horizon, cost discounted at 3%	Coverage for medications would be cost-effective. Increasing the number of individuals eligible for financial coverage could improve the value of the intervention. Efforts to increase the availability of services and capacity of primary care facilities to support diabetes care could have far-reaching impacts on the burden of diabetes and contribute to long-term health system strengthening.
Kaur et al., 2022	India	At-risk population aged 30 years old.	Population-based screening strategies for diabetes and hypertension.	incremental cost per QALY	Markov model and decision tree	One-way, multi-way and PSA: cost and effect parameters	The United Kingdom Prospective Diabetes Study clinical trial	Not stated	Not stated	Primary data were collected from two Indian states, meta-analysis of published literature, natural survey,	Cost-utility analysis, societal perspective, lifetime horizon, 3% discount on cost and effect	Population-based screening for diabetes and hypertension in India could potentially reduce time to diagnosis and treatment and be cost-effective if it is linked to comprehensive primary health care through health and wellness centres for provision of treatment to patients who screen positive.
Rachapelle et al., 2013	India	Type 1 and 2 diabetes	Different retinopathy screening strategies interval strategies	QALY, incremental cost-effectiveness ratio	Markov model	One-way and PSA: cost and effect parameters	Population-based survey	Not stated	Tree-Age Pro 2009	Published literature and primary data collection, population-based survey, Indian life tables	Cost-utility, health provider and societal perspectives, 25-years horizon, 3% discount rate on cost	Depending on the administrative costs of establishing and maintaining screening at regular intervals and on achieving sufficient coverage, 2-years or 5-years frequency of screening could be cost-effective from a health and societal perspective.

Basu et al., 2021	67 LMICs	Diabetes patients	Achieving different targets of diagnosis, treatment, and control of diabetes	DALYs lost and healthcare costs	Micro-simulation	One-way: intervention parameters	Multiple imputation with chained equations plus a classification and regression tree algorithm to impute missing data, 2019 WHO cardiovascular disease risk equations, Risk Equations for Complications of type 2 Diabetes	Not stated	Not stated	National survey, the Institute for Health Metrics and Evaluation, the Institute for Health Metrics and Evaluation,	Cost-utility analysis, health system perspective, 10-year horizon, 3% discount on cost and effect	Increasing blood pressure and statin medication treatment initiation and blood pressure medication titration could reduce diabetes complication in LMICs compared to increasing screening to increase diagnosis, blood glucose treatment and control.
Basu et al., 2019	South Africa residents	Persons with diabetes, hypertension, and cardio-vascular diseases	Various treatment levels for hypertension, dyslipidemia and diabetes (1) WHO's package of essential non-communicable disease interventions and (2) South Africa's Primary Care guidelines	cardiovascular disease burden per 1000 population per year, DALYs, ICER, cost savings	Micro-simulation	PSA: clinical and costing parameters	Monte Carlo sampling, chained equations imputation, WHO and International Society of Hypertension equations	Not stated	R v 3.4.3	South African National Health and Nutrition Examination Survey, census data	Cost-effectiveness: health systems perspective, 10-years horizon, 3% discount on cost and effect	South African clinical treatment guidelines is more cost-effective, in terms of DALYs

Note: QALYs = quality-adjusted life years. DALYs = disability-adjusted life years ICER = incremental cost-effectiveness ratio PSA = probability sensitivity analysis. LMICs = low- and middle-income countries

Appendix B Health Provider Interview Outline

Participant information Sheet

Study Title: Pathway and Barriers to Diabetes Service Delivery in Ghana

Principal Investigator's Name and Address	Itamar Megiddo Associate Professor (Senior Lecturer) Department of Management Science University of Strathclyde 199 Cathedral Street Glasgow, G4 0QU United Kingdom
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Study Background and Purpose

Ghana, where nearly one-third of the population has diabetes, is ranked sixth in diabetes prevalence in Africa. The National Health Insurance Scheme (NHIS), which aims to increase utilization and affordability of services and medications, particularly among vulnerable and poor populations is under financial threat. Supply- and demand-side barriers lead to inequitable access and outcomes when interventions are rolled out.

This study seeks to clearly define the current pathways and challenges to clinical diabetes service delivery and financing, which is a first step to developing strategies to improve the current diabetes service delivery and financing structures.

Participants involvement

The study is intended to last four months, and interviews will take on average 45 minutes. Participants include individuals involved in clinical diabetes service delivery in Ghana.

As a participant, you will first be taken through the consent process where we send you the study details with you ahead of the interview date and then answer all question and clarifications you may have. You will be asked to sign and return a written consent form, which will be sent ahead of the interview to confirm your voluntary participation.

If you consent to participate, you will be asked questions on pathway and barriers to diabetes service delivery. You will be asked to confirm the information provided after the recorded interview has been transcribed.

Potential Risk

There is no foreseen risk associated with participating in this study.

Benefits

There is no direct benefit to study participants; however, the project outputs will form a foundation to designing efficient strategies for delivering diabetes service in Ghana. We will discuss outputs with relevant stakeholders and publish an article based on our findings to inform the global efforts towards diabetes management.

Costs

Researcher and the participants will individually bear the cost of internet or phone calls.

Compensation

There is no compensation for participants' time loss to this study.

Confidentiality and Anonymity

You are not required to mention your name. We will ask you to tell us about your role, position and the organisation you work with to help us situate your responses in context. However, we will not associate findings with you.

After interviews, the transcribed data will be shared with you to confirm your views are appropriately represented and your identity is not revealed; you have the right to withdraw your statement(s).

All interview recordings will be permanently deleted after transcription. Typed transcribed data and signed consent forms will be kept (password word protected) in StrathCloud, which is the University of Strathclyde approved data storage platform until the end of the study and then permanently deleted.

Voluntary participation/withdrawal

The decision to participate should be out of your free will after reading and seeking clarity on the study. You have the right to withdraw from this study at any time and withdrawal will not affect your job or relationship with the researcher.

Outcome and Feedback

We will use this study as part of thesis submission and also publish an article based on our findings to increase learnings in the global health community. This outcome will be an important step to designing strategy to improve diabetes service delivery in Ghana.

Funding information

This project is funded by the by the University of Strathclyde through the Student Excellence Award.

Sharing of participants Information/Data

Information generated from this study will be jointly owned by the principal investigator and the funding organisation.

Provision of Information and Consent for participants

You will be sent this information sheet and signed consent form and a copy of the transcribed interview session for reference.

For more information kindly contact:

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Topic guide for interviews

Pathway and barriers to diabetes service delivery in Ghana
[Assume participants have read PIS and so have a background to the study, and have completed consent]

Access to diabetes services

Can you tell me about your role and expertise with diabetes service delivery and policy decision-making? Can you tell me about the diabetes services your facility provides?

Can you explain the routes patients could use to seek care in your facility? What are the gatekeeping requirements for accessing diabetes care in your facility? How has this route changed since the COVID-19 epidemic?

Diabetes service organisation

Can you briefly describe the procedures involved in diabetes services delivery in your facility? Can you tell me how these services are organised (e.g., clinic days and scheduling appointments and reminders and patients' data management)?

Can you briefly tell me which procedure you are primarily involved with and the challenges you encounter organising and delivering diabetes services? How have these challenges evolved with COVID-19? Can you tell me about any other challenges your colleague providers encounter while providing diabetes care?

Medicines and supplies

Can you tell me about how your facility obtains medical supplies and drugs for diabetes care? Can you briefly describe the challenges your facility encounters with medical supplies and diabetes medicines? How has the COVID-19 epidemic affected the supply of medicines and logistics you require to deliver diabetes services? How do these challenges affect your work?

Diabetes service referrals

Can you briefly explain when and how your facility refers people with diabetes to other hospitals/ resources? Can you tell me about any referral challenges and how that affects the delivery of diabetes care? Can you tell me how COVID-19 has affected the way your facility refers patients to other health facilities?

Service provider expertise

Can you tell me about the level of staffing for diabetes care in your facility and how the COVID-19 epidemic influences the staff available to provide diabetes services? What or which expertise would be needed for sufficient staffing?

Diabetes service delivery cost

Can you tell me how patients pay for the diabetes services your facility provides? Can you tell me briefly what diabetes services/procedures/medication most patients cannot afford? Can you tell me how your facility manages patients who cannot pay for services? Can you tell me how the COVID-19 epidemic influences patients' ability to afford diabetes services? How does this challenge affect their treatment outcome?

Are there any other challenges we have not discussed that you would like to mention?
What do you recommend for improving diabetes service delivery in Ghana?

Consent form

Study Title: Pathway and Barriers to Diabetes Service Delivery in Ghana

Participants' Statement

I have carefully read the study purpose and content of the participant information sheet and have had all my questions answered satisfactorily. I understand the potential implication of the study and my rights to withdraw contributions at any stage of the study without any negative effect.

I voluntarily agree to be interviewed as part of this research.

Name of Participant: ……..
Participants' Signature: ……...
Date: …….

Statement of Witness

I witnessed the consenting process where the researcher shares the study details (participant information sheet) with participant ahead of the interviews time. The researcher answered all the participant's study-related questions.

I testified that the participant was given the opportunity to ask questions and given clarification before voluntarily agreeing to be interviewed.

Name:…….
Signature……..
Date:……..

Investigator's Statement

I declare having given participants ample time to read and ask all questions about this study. All questions and clarifications raised by the participant have been adequately addressed.

Researcher's name……
Signature ……..
Date……

Appendix C: ODD Protocol of the Agent-based Model

Purpose and Patterns

See Chapter 7, section 7.4.1

Entities, State Variables, and Scales

See Chapter 7, Section … 7.4.2

Process Overview and Scheduling

BGC is the main model outcome resulting from patients' behaviours and interactions with health services. A time step in the model represents a week. Not all procedures occur weekly, and not all patients perform a given procedure. Figure 1 shows the scheduling of procedures, Table 2 shows the outcomes of model procedures, and Figure 2 shows the transition between blood glucose states.

check-clinical-state

The procedure is performed by discharged patients at the start of a time step to check their *clinical-state.* This procedure checks if a discharged patient has fully recovered from the event leading to admissions. The procedure changes the clinical state of discharged patients (*clinical-state* = 1) who have fully recovered from an acute diabetes (DM) complication (recovery-period = ticks (current week)) to outpatients (*clinical-state* = 0) and the patients set their *lifestyle* through the **set-diet (**see submodel section for details of this procedure). The *clinical-state* determines subsequent procedures a patient can perform. For all other patients, clinical-states remain unchanged.

record-diet

All patients perform this procedure weekly (every time step) to update the weekly record (*my-lifestyle*) of their lifestyle. Patients simply update their *my-lifestyle* list by appending the current *lifestyle* to the end of the list.

check-med

The procedure constitutes two sub model, **check-affordability, and check-med-in-com**, in the order of performance. The procedures determine outpatients who have medicines (i.e., could afford, found medicine, and bought them). Factors such as medicine availability and affordability influence patients' medication adherence decisions. Only outpatients with prescriptions perform these procedures. We define prescription as a clinician-authorised instruction directing the issue of medicines. First, outpatients with prescriptions (*clinical-state* < 2 and *prescription* > 0) perform the **check-affordability** procedure to determine if they can afford prescribed medicines. The procedure updates the *prescription* of patients who cannot afford (set *prescription* -1, indicating that the patient could not afford and does not have medicines). **check-med-in-com** checks medicine availability in communities. The procedure updates patients' *med-in-com* and *prescription* state variables. Once medicine is available (*med-in-com* = 1) *prescription* is set to 0, indicating that the patient bought the medicines and there is no outstanding prescription. If medicines are unavailable (*med-in-com* = 0), *prescription* is set to *-1,* indicating the patient has no medicines. More details of the procedure are in the sub model section.

take-meds

Depending on their *clinical-state*, all patients perform some part of this procedure every week. Outpatients, including those discharged who have medicines at hand (*med-in-com = 1 and prescription = 0* and *clinical-state* < 2) are set to take medicines (the *med* = 1). Outpatients without medicines do not take medicines (*med* = 0). Inpatients take medicines (*med* = 1). All patients update their *my-med* list by appending their current *med* behaviour to the list.

attend-review

Outpatients who have review appointment in the present week and outpatients who have acute complications perform this procedure every week to decide on review attendance.

Among the former set of outpatients (clinical-state < 2 and appointment = tick (the current week)), those with uncontrolled blood glucose in the previous week (*fbg* > 1) attend review while those with controlled perform the **decide-attendance** procedure which uses stochasticity.

Patients who decide to attend a review appointment do not update any state variable but proceed to perform the **treat** procedure, a sub model of the **attend-review** procedure. Patients who decide not to attend update their *appointment* to any time between 1 and 13 weeks. They also increase the *nonattendance* global variable by 1, indicating the number of missed appointments.

Outpatients have acute complications if their blood glucose has been uncontrolled for the last 13 weeks, they have uncontrolled blood glucose in the current week, they have not taken medicines, and they have comorbidity. Such patients increase the *emergencies* global variable by one and proceed to perform the

treat procedure.

The treat procedure determines the type of care a patient who attended a health facility received. Patients could be admitted or prescribed medicines and rescheduled for a later appointment. Admitted patients perform the **admit** procedure to update their *discharge-time* among other state variables presented in Table 2. Patients perform the schedule-appointment procedure to **reschedule a later appointment**. Details of the **treat** procedure and its sub models are in the sub models section, and the variables updated in the procedures are in Table 2.

discharge

This is an inpatient procedure performed weekly at the same time to determine inpatients who are discharged. Patients with discharged-time, same as the current week, are discharged. Such patients update their *discharge-time, clinical-state*, *recovery-period* among other state variables listed in Table 2. Details of the procedure is in the sub model section.

get-weekly-control.

All patients perform this procedure weekly, at the same time, to determine their BGC during the week. Figure 2 shows the outcomes of this procedure. There are four sub models for estimating weekly BGC; one is set at initialisation and other sub models are used in sensitivity analysis. Details of each are in the sub model section The procedure uses patients' *lifestyle, med, comorbidity,* and *duration* to update patients' *fbg*.

get-three-months-outcomes.

All patients perform this procedure every 13 weeks at the same time to determine their most frequent BGC states, lifestyle, and medicine adherence behaviour over the period. The procedure updates patients' *HbA1c* variable by setting *HbA1c* to the frequent *fbg* in the 13-week period. It also updates patients' *lifestyle-ave* and *med-ave* state variables to the frequent occurrence. Details of the procedure are in the sub model section.

update-age

All patients perform this procedure weekly to increase their *age* and *birthweek*. Age affects patients' time in the model (*life-expectancy*).

Patients with *birthweek* < 52 increase their *birthweek* by 1. Patient with *birthweek* = 52, perform the following action in order:
1) set *birthweek* to 0
2) increase their *age* by 1
3) **check-life-exp** (a procedure to check if they die/exit the model, explained below)
4) perform the **set-age-group** to update their age-group
5) increase duration by 1

The **check-life-exp** procedure involves patients comparing their age to their life expectancy (assigned at initialisation). If age = life-expectancy, the patient increases deaths (a variable for recording deaths in the model) by one and then dies/exists in the model. Otherwise, the patient remains in the model and performs steps 4 and 5 above.

update-obesity

This is an annual procedure that updates the **PDiet** global variable (the prevalence of obesity and overweight in the patient cohort). Once the **PDiet** is updated, patients update their *lifestyle* by performing the **set-lifestyle** procedure. Details of the procedure are in the sub model section.

update-insurance

An annual procedure performed by patients that updates the **InsuranceCoverage** variable, which is the prevalence of insurance coverage in the patient cohort, using an optimisation function. Using the undated **InsuranceCoverage** variable, patients update their *insurance* state variable. The procedure also updates the **AttendanceProp** variable. Details of the procedure are in the sub model section.
estimate-crude-death

Patients perform this procedure every year (52 weeks) to determine if they remain or exit the model. All patients perform the procedure at the same time. As shown in Figure 2, patients exit the model from crude mortality, which includes deaths from DM and non-DM causes. The procedure updates the *deaths* global variable.

Table 2: Model procedures and outcome

Procedure name	(submodel) Outcomes	Variables updated
check-clinical-state	0 = outpatient 1= discharge patients	recovery-period clinical-state
check-meds	(check-affordability) prescription = -1 (check-med-in-come) med-in-com = 1 prescription = 0 reduced prescription increase **insuredMeds** increase **uninsuredMeds**	 prescription med-in-com **insuredMeds** **uninsuredMeds**
take-meds	meds = 0 meds = 1	med
attend-review	(decide-attendance) increase **missedappointment** my-appointment (treat) Increase **insuredAttendance** Increase **uninsuredAttendance** med-in-com = 0 (admit) appointment = 0 clinical-state = 2 increase discharge-time meds = 1 lifestyle = 1 fbg = 1 increase **insuredAdmissions** increase **uninsuredAdmissions** (schedule-appointment) increase appointment increase prescription	 my-appointment, prescription med-in-com clinical-state appointment my-appointment discharge-time med lifestyle fbg
discharge	clinical-state = 1 med = 1 increase recovery-period (schedule-appointment) increase appointment increase prescription	clinical-state, med appointment, recovery-period prescription
get-weekly-control	fbg = 1 fbg = 2 fbg = 3	fbg
get-three-months-outcomes	HbA1c = 1 HbA1c = 2 HbA1c = 3 lifestyle-ave = 1 lifestyle-ave = 0 med-ave = 1	HbA1c lifestyle-ave med-ave

	med-ave = 2 med-ave = 3	
update-age	increase birthweek increase age (check-life-exp) Increases deaths	birthweek age age-group
estimate-crude-mortality	patients die/exit the model. deaths increase	Patient variables are deleted
update-obesity	changes **PDiet** (set-lifestyle) lifestyle = 1 lifestyle= 0	**PDiet** lifestyle
update-insurance	**InsuranceCoverage** changes **AttendanceProp** changes insurance = 1 insurance = 0	**InsuranceCoverage** **AttendanceProp** insurance
update-comorbidity	**HypertensionPrev** changes **HyperInc** changes comorbidity = 1	**HypertensionPrev** **HyperInc** comorbidity

Note: Global variables are in bold.

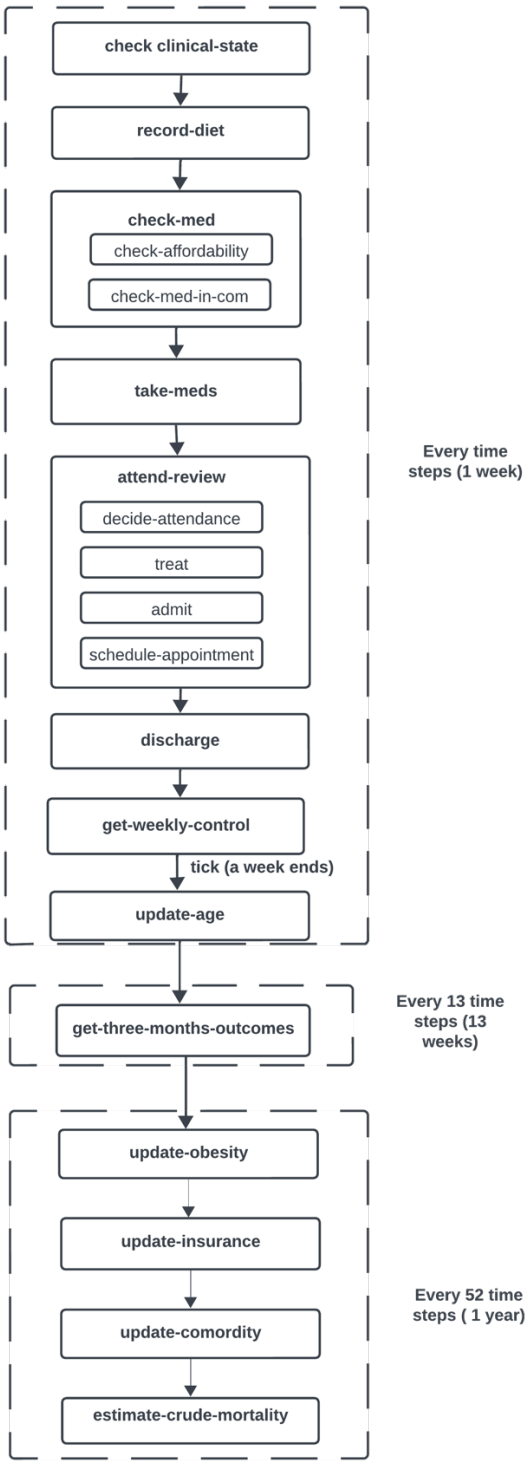

Figure 1: Overview and scheduling of model procedures. **check-med-in-com** and **check-affordability** are sub-sub models in the **check-med** sub model. The same applies to processes in the **attend-review** sub model. Procedures are run in the order they appear in the Figure. Patients update birth week at the end of a week, as shown in the Figure.

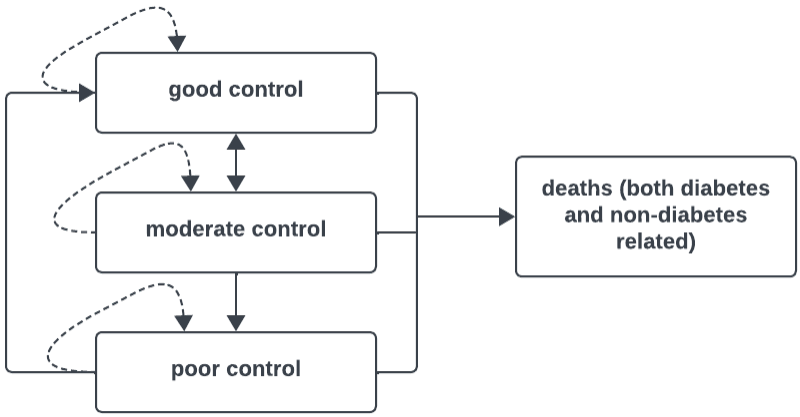

Figure 2: Transition between diabetes treatment outcomes.

After a cycle (one week), patients who initially had good BGC could remain or transition to moderate control, and vice versa. Patients with poor BGC could be admitted, where they transition to good control. Patients with moderate control could get worse by transitioning into poor control. Patients in all states can die from DM or non-DM-related causes.

Basic principles

System-level concept:

This model addresses a key PH management question: how do various PH interventions affect treatment outcomes for T2DM in a low-resource setting? Specifically, it explores how factors such as medicine availability, insurance coverage, and sugar-sweetened beverage taxes influence BGC, lifestyle, and medicine adherence at a population level in Ghana.

Theoretical foundation:

At the agent level, the model is grounded in the Health Belief Model (HBM), a well-established psychological theory explaining health-related behaviors (Strecher et al., 1997) and the Theory of Planned Behaviour (TPB) (Ajzen, 1991). The HBM's constructs–perceived severity, perceived susceptibility, perceived barriers, perceived benefits, cues to action and self-efficacy– and the TPB constructs–subjective norms, attitudes, and perceived behavioural control–are used to inform patient decision-making processes regarding treatment adherence and health-seeking behaviors.

Table 3 summaries how we use the theories to represent patients' behaviour. Perceived barriers in HBM and perceived behaviour control in TPB are similar; they refer to the individuals' assessment of obstacles, including cost and availability of resources. Implementing the construct, patients do not take medicines when they are not available in communities, cannot afford medicines or do not have a

prescription. Cues to action are external or internal stimuli that trigger a decision to engage in recommended health behaviours. Using the concept of perceived severity and clues to action in HBM, patients with poor BGC, have unhealthy lifestyle and did not take medicine seek care regardless of having an appointment. Poor treatment behaviours in such patients result in acute complication which triggers the decision to seek care. Patients who have good to moderate BGC may miss review appointment as they do not feel unwell and therefore have a low perception of severity, susceptibility, and triggers. Perceived susceptibility is the perception of the likelihood of experiencing a health threat. Perceived severity describes the perception of how serious a disease or health condition is and the medical, clinical, and social consequences of leaving it untreated. Perceived susceptibility and Perceived severity influence an individual's evaluation on a behaviour, which represents *attitude* in TPB. Discharged patients have a high perception of susceptibility and severity of DM after experiencing acute DM complications that led to their admission. Therefore, such patients live healthy lifestyle and take medicines if they could access and afford them. Inpatients live healthily and take medicines. Perceived benefit describes the belief in the effectiveness of a recommended behaviour in reducing the severity of the health condition. Patients perceive the effectiveness of clinical services in resolving acute complications and therefore seek care in such a condition. Subjective norms in TPB described perceived social pressures to conform to a behavior. Patients follow the lifestyle trends in their communities.

Table 3: Application of HBM and TPB to Conceptualise Patient Behaviour

Behaviour	HBM	TPB	example
Lifestyle (diet and exercise)	N/A	subjective norms	Patients follow unhealthy lifestyle of people in their community.
Medicine intake (patient have prescription)	perceived barriers of access and affordability	actual behavioural control: cost and availability that hinder medicine intake	Patient is not insured and have low income to buy medicines or medicines are out of stock. Therefore, patient do not take medicines.
Medicine intake (patients have no prescription)	perceived barriers	actual behavioural control: no prescription to buy medicines	DM medicines need prescription to buy. Patient missed appointment and therefore have no prescription to buy and no medicine to take.
Review appointment attendance	perceived severity and cue to action	Attitude towards the disease	Patient is feeling well, no signs of illness, therefore may miss an appointment.
Seeking care in acute complication state	Perceived severity and susceptibility of DM perceived benefit of clinical services	Attitude	Patients' glucose in poor controlled, feels unwell. Patients' belief health facilities can manage their condition and therefore seeks care.
Inpatients' behaviour	Perceived severity and susceptibility	subjective norms	Patients experience the severity of DM and their vulnerability to it and therefore adhere to recommended

			treatment. Patients follow instructions of clinicians.
Discharge patients' behaviour	Perceived severity and susceptibility, perceived benefit	attitude	Patients experience the severity of diabetes and their vulnerability to it and appreciate the benefit of adherence therefore adhere to recommended treatment.

Note N/A means not applicable. DM= diabetes

Novel approach:

This model uniquely combines patient behavior, clinical service delivery, health system factors, and policy interventions. It aims to provide insights into how system-level changes due to PH interventions can influence individual patients' behaviors and, consequently, population-level health outcomes.

Integration of clinical and behavioral aspects:

The model integrates clinical aspects of DM management (such as BGC) with behavioral factors (such as lifestyle and medicine adherence). This integration allows for a more comprehensive understanding of the complex dynamics involved in T2DM management in real-world settings.

By simulating the effects of different PH interventions, the model serves as a framework for evaluating potential policy decisions. This approach allows for the exploration of intervention impacts without the need for costly and time-consuming real-world trials.

Emergence

Patient-level and cohort-level treatment outcomes (e.g., the proportion of patients with poor, good, moderate BGC, medicine adherent and admissions) are the main model outcomes that emerge from patients' decisions on medicine adherence, health seeking, lifestyle and how they interact with clinical services, medicines' availability, and affordability in communities and community-level lifestyle trends. Deaths from all causes, including DM, are imposed.

Adaptation

The decision to attend outpatient appointment or seek care is an adaptive behaviour of patients. Patients decide to attend or not attend based on their state variables: appointment date (*appointment*), comorbidity (*comorbidity*) BGC (*fbg*), medicine adherence (*med*), and lifestyle (*lifestyle*). The **AttendanceProp** variable affects the decision. Outpatients who have appointments in the present week and poor BGC (*fbg* = 3) decide to attend appointments. Outpatients who do not have appointment in the present week but experience poor BGC, engaged in unhealthy lifestyle, did not take medicine, and

have a comorbidity decide to attend. Outpatients who have an appointment in the present week but have moderate to good BGC (*fbg* = 2 or *fbg* = 1) decide to attend or miss appointment using the stochasticity and the **AtttendanceProp** parameter. The patient selected a random number between 0-1 and attends if the selected number is less than **AtttendanceProp.** Otherwise, the patient does not attend.

The decision of when to schedule an outpatient appointment an adaptive behaviour of patients that changes their *appointment* state variable. Patients who attended appointment and were not admitted set their next appointment based on their BGC, insurance status and the availability of appointments. Those with good control blood glucose set next appointment to any week between 9 – 14 weeks, moderate control set to any week between 7 – 9 weeks. Insured patients ensure they have no more than 6 appointments in a year. Patients who missed appointment set the next appointment using stochasticity.

The decision about whether a patient is admitted or scheduled for appointment is affected by patients' blood glucose, medicine adherence, lifestyle, comorbidity. The decision changes patients *clinical-state* variable. Patients with poor control (fbg = 3), medicine non-adherence (med = 0), and unhealthy lifestyle (lifestyle = 0) and comorbidity (comorbidity = 1) get admitted. Patients in other states, included the mentioned states but no comorbidity get glucose controlled and scheduled for appointment.

Patients' decision to check or not check if medicine is available in their community is affected by patient-level variables: *prescription* and environment variables: **MedUrban** and **MedRural**. The decision changes patient's *med-in-com* variable. If there are an outstanding prescriptions (*prescription* > 0) patients checks for medicines. Otherwise, patients do nothing.

Medicine intake in patients is an adaptive behaviour. Patients decide to take medicines as prescribed or not based on access to and affordability of medicines. Patients-level variables that affect medicine access is *prescription* and *med-in-com* while *wealth* and *insurance* affect affordability. Medicine availability in the community (**MedUrban** and **MedRural**) affect the decision. Inpatients take medicines as prescribed.

Lifestyle that represents decision to exercise and eat healthily or not is an adaptive affected by lifestyle trends in patients' community, represented by Pdiet, ruralProDiet and urbanProDiet. Patients select a random number and compares it to the lifestyle trend in their community (**Pdiet * ruralProDiet** in rural residents otherwise **Pdiet * urbanProDiet**). If the selected number is less than the comparator, the patients set an unhealthy lifestyle. Otherwise, the patient sets a healthy lifestyle.

The decision to be covered by insurance or not, and to develop comorbidity or not is affected by trends in patient's environment, represented by **InsuranceCoverage** and **HypertensionPrev**, respectively.

Patients used the same behaviour rules when deciding on lifestyle to decide on insurance and comorbidity. The decision update patients' *insurance* and *comorbidity* state variables.

Patients remain or exit the model based on their *age, sex* and *life-expectancy* and the environment variables: **female-crude mortality** and **male-crude-mortality**. First, patients who have lived to the expected age (*age* = *life-expectancy*) exit the model. Second, patients use stochasticity sex and age as well as **female-crude mortality** or **male-crude-mortality** to decide if they exit the model for other reasons aside age.

Patients' decision to remain in admission, discharged or recovered is an adaptive behaviour affected by *recovery-period* and *discharge-time.* If *discharge-time* is same as the present week, inpatients change to discharged patients (change *clinical-state* from 2 to 1). Otherwise, patients remain in admission. In discharged patients, if recovery period is same as the present week, patients change to outpatients (change *clinical-state* from 1 to 0). Otherwise, patients remain in recovery state.

Aside the decision to admit patients, patients simply follow rules in all the adaptive behaviours described; they do not seek to directly increase some form of utility.

Objectives

Outpatients who have no appointments in the present week but experience an acute complication due to poorly controlled blood visit health facilities. This is an adaptive behaviour that seeks to improve BGC. Good medicine adherence, healthy lifestyle and clinical procedures improve BGC. Such patients simply set their blood glucose to controlled (change from *fbg* = 3 to *fbg* = 1). Among such patients, those who have comorbidity get admitted. The adaptive behaviour that seeks to improve BGC and reduce the risk of another complication soon. The objective behaviour is modelled to represent the real-world clinical DM service delivery.

Prediction

Outpatients with acute DM complications seek care and get admitted to health facilities (not explicitly modelled but in the patients' environment) are based on implicit predictions that they will get better on admission. According to clinicians in the study setting, these predictions are mostly correct. Patients implicitly predict that taking medicines will improve their DM condition.

Sensing

We model DM patients receiving treatment in health facilities; therefore, all patients know they have DM, prescribed medicines and recommend lifestyle. Patients know the following characteristics about themselves: review appointment, BGC state, when they recover from acute complication, when they are discharged, their clinical state, age, sex, insurance status, comorbidity status and life-expectancy. They sense the date of their review appointment *(*via their state-variable *appointment*) and implicitly know their BGC.

Interaction

There are no interactions in the model.

Stochasticity

The model initialises age, sex, lifestyle, and residence stochastically, as these features are used to reproduce variability in the modelled population as observed in data. Patients' lifestyle, wealth and insurance are randomly assigned to reproduce observed patterns in observed data. Wealth and insurance affect patients' access to medicines, influencing medicine adherence and BGC outcomes. Patients' first review appointment is assigned randomly. The duration of DM in patients was set using stochasticity. Details of how randomness is used in these procedures are in the sub model section of the ODD protocol in Appendix 7.1.

Collectives

There are no collectives in the model.
Learning

There is no learning in the model.

Observation
We collect data on treatment outcomes (the count of patients with poor, moderate and good BGC, medicine adherent and healthy lifestyle) from the model for analysis. The data is collected directly in R, and a copy is saved in a CSV file for analysis outside R. We displayed weekly and three-month outcomes of BGC, lifestyle, and medicine adherence behaviour using graphs in the model interface. We also used graphs to visualise trends in insurance coverage, the distribution of patients in various clinical states (inpatients and outpatients) and the prevalence of comorbidity in the patient cohort.

Initialisation

The model initialisation has two main procedures: **set-globals** and **set-patients**, in the order of execution.

set-globals procedure

Table 4 shows the values of global variables at initialisation, while Table 1 shows their meaning and rationale. Figure 3 shows the order in which the global variables are initialised and whether the variable is present in the model interface or the NetLogo application's code section.

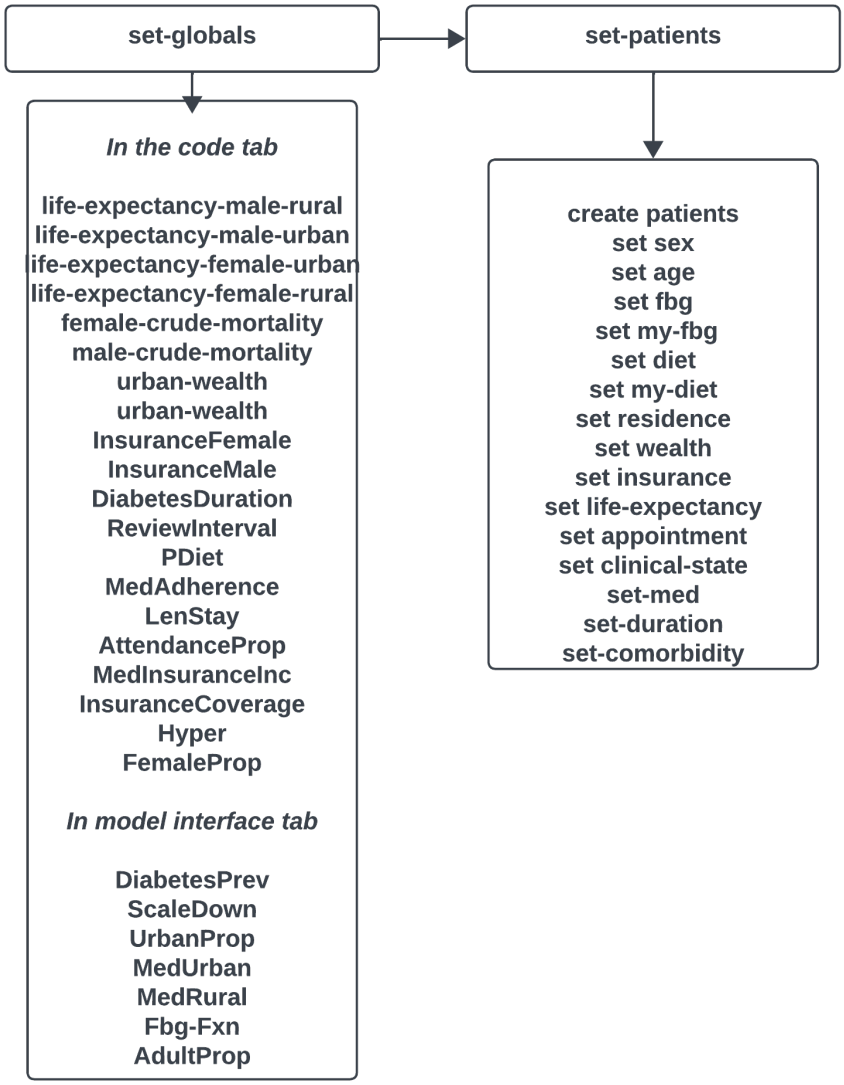

Figure 3: The order of procedures in model initialization.

set-patients procedure

We initialised the model with 5700 patients, which is a 0.5% (**ScaleDown**) of the prevalence of DM (**DiabetesPrev**) in the adult population (**Adult-pop**) of Ghana at the time of model building. Patients draw randomly from a uniform distribution with a range of 0 – 1 and compare their choice to **FemaleProp** to set their *sex*. Patients draw randomly from a normal distribution (parameters in Table 4) to set age. Patients set their *birthweek* to a randomly selected number from a uniform distribution with a range of 1 – 51. Details on how patients' *wealth, life-expectancy, duration, insurance, med* and *comorbidity* are initialised are in the sub model section. Patients set *appointment* by randomly selecting a number between 1 – 52 from a uniform distribution. Patients set their *my-lifestyle, my-fbg*, *my-med* to empty lists to collect weekly outcomes. Parameters in Table 4 that are not mentioned in the initialisation section are used in sub models, which are detailed in the sub models sections.

Table 4: Model Parameters

Parameter name	Meaning and rationale	Default value	Sensitivity analysis	Source
age	Age of patients. used at initialisation to populate patients' age	Mean = 59 Standard deviation = 12 Min = 27 Max = 88		Osei-Yeboah et al. (2018)
PDiet	The prevalence of obesity and overweight (used as a proxy for diet and exercise behaviour). Used to increase the prevalence of poor diet and exercise behaviours among patients).	Estimated from an S-shaped distribution (details in **update-obesity** sub model section Appendix C)		Amugsi et al.
ruralProDiet	The proportion of the national prevalence of obesity and overweight in rural communities.	0.4		Yussif et al. (2024)
urbanProDiet	The proportion of the national prevalence of obesity and overweight in urban communities.	0.6		Yussif et al. (2024).
InsuranceFemale	The proportion of female patients who are NHIS-insured by wealth quintile. Used to adjust insurance coverage in females by wealth. Used in **set-insurance** sub model.	Poorest = 45.4% Second = 49.3% Middle = 53.0% Fourth = 55.8% Richest = 70.1%		Ghana Multiple Indicator Cluster Survey 2017/2018 (Ghana Statistical Services, 2018)
InsuranceMale	The proportion of male patients who are NHIS-insured by wealth quintile. Used to adjust insurance coverage in males by wealth. Used in **set-insurance** sub model.	Poorest = 32.2% Second = 28.1 Middle = 36.2% Fourth = 40.0% Richest = 59.8%		Ghana Multiple Indicator Cluster Survey 2017/2018 (Ghana Statistical Services, 2018)
MaxInsuredAppointment	The maximum number of weeks between outpatient appointments in insured patients.	9		Assumed based on NHIS operational tariff. (National Health Insurance Authority, 2022)

UrbanProp	The proportion of the population living in urban areas. Used at initialisation to populate patients' residence	0.52	0.50 – 0.58	Ghana Multiple Indicator Cluster Survey 2017/2018 (Ghana Statistical Services, 2018)
MedUrban	The percentage of times DM medicines are available to patients in urban communities. Used in setting **med-in-com,** which indicates if the patient found medicines. Details in **check-meds** sub model in Appendix C.	0.8	triangular distribution (min= 0.6 mode= 0.8 max= 1)	Assumed based on (Masters et al., 2014)
MedRural	The percentage of times DM medicines are available to patients in rural communities. Used in setting **med-in-com,** which indicates if the patient found medicines. Details in **check-meds** sub model.	0.7	triangular distribution (min= 0.4 mode= 0.7 max= 1)	Assumed based on (Masters et al., 2014)
rural-wealth	The proportion of rural-resident patients falling in wealth quantile. Used at initialisation to populate patients' wealth in **the set-wealth** sub model.	Patients in rural areas: 0 = poorest 33.5% 1 = second 27.3% 2 = middle 19.7% 3 = fourth 12.2% 4 = richest 7.2%		Ghana Multiple Indicator Cluster Survey 2017/2018 (Ghana Statistical Services, 2018)
urban-wealth	The proportion of urban-resident patients falling in wealth quantile. It is used at initialisation to populate patients' wealth in **the set-wealth** sub model.	Patients in urban areas: 0 = poorest 4.2% 1 = second 11.4% 2 = middle 20.4% 3 = fourth 29.1 % 4 = richest 34.9%		Ghana Multiple Indicator Cluster Survey 2017/2018 (Ghana Statistical Services, 2018)
female-crude-mortality	The probability of female patients dying from all causes by age. Used in the **estimate-crude-mortality** sub model.	Drawn for each female patient from an empirical distribution: 80+ years old: 6.8% 75 – 79 years: 4.0% 70 – 74 years: 4.0% 55 – 59 years: 1.4% 50 – 54 years: 1.1% 45 – 49 years: 0.8% 40 – 44 years: 0.8% 35 – 39 years: 0.5% 30 – 34 years: 0.4%		Ghana Demographic and Health Survey (Ghana Statistical Service et al., 2015)

		65 – 69 years: 2.5% 60 – 64 years: 1.9%	25 – 29 years: 0.3% 20 – 24 years: 0.2%		
male-crude-mortality	The probability of male patients dying from all causes by age. Used in the **estimate-crude-mortality** sub model.	Drawn for each male patient from an empirical distribution: 80+ years old: 4.4% 75 – 79 years: 2.2% 70 – 74 years: 1.7% 65 – 69 years: 1.5% 60 – 64 years: 1.1%	55 – 59 years: 0.8% 50 – 54 years: 1.0% 45 – 49 years: 0.8% 40 – 44 years: 0.8% 35 – 39 years: 0.6% 30 – 34 years: 0.5% 25 – 29 years: 0.3% 20 – 24 years: 0.3%		Ghana Demographic and Health Survey (Ghana Statistical Service et al., 2015)
AttendanceProp	The proportion of patients who attend outpatient appointments at scheduled times. Used in the **attend-review** sub model.	0.6923		uniform distribution min= 0.38 max= 1.00	Amaltinga (2017)
life-expectancy-male-urban	The average number of additional years a male patient in an urban area is expected to live. Used to initialise how long male patients in urban areas stay in the model. Also used in the **update-age** sub model.	Drawn for each patient from an empirical distribution: 80+ years old: 5.9 75 – 79 years: 7.9 70 – 74 years: 10.4 65 – 69 years: 13.3 60 – 64 years: 16.1	55 – 59 years: 20.2 50 – 54 years: 23.9 45 – 49 years: 27.8 40 – 44 years: 31.9 35 – 39 years: 36.0 30 – 34 years: 40.1 25 – 29 years: 44.1 20 – 24 years: 48.1		Ghana Demographic and Health Survey (Ghana Statistical Service et al., 2015)
life-expectancy-male-rural	The average number of years a male patient in a rural area is expected to live is used to initialise how long they live in the model. It is also used in the **update-age** sub model.	Drawn for each patient from an empirical distribution: 80+ years old: 6.0 75 – 79 years: 8.0 70 – 74 years: 10.5 65 – 69 years: 13.4 60 – 64 years: 16.7	55 – 59 years: 20.4 50 – 54 years: 24.1 45 – 49 years: 28.1 40 – 44 years: 32.1 35 – 39 years: 36.2 30 – 34 years: 40.5 25 – 29 years: 44.5 20 – 24 years: 48.5		Ghana Demographic and Health Survey (Ghana Statistical Service et al., 2015)
life-expectancy-female-urban	The average number of years a female patient in an urban area is expected to live is used to initialise how long they live in the	Drawn for each patient from an empirical distribution: 80+ years old: 6.5	55 – 59 years: 22.2 50 – 54 years: 26.2 45 – 49 years: 30.4		Ghana Demographic and Health Survey (Ghana Statistical Service et al., 2015)

	model. It is also used in the **update-age** sub model.	75 – 79 years: 8.7 70 – 74 years: 11.4 65 – 69 years: 14.7 60 – 64 years: 18.3 40 – 44 years: 34.6 35 – 39 years: 38.9 30 – 34 years: 43.3 25 – 29 years: 47.6 20 – 24 years: 52.0		
life-expectancy-female-rural	The average number of years a female patient in a rural area is expected to live is used to initialise how long female patients in rural areas stay in the model. It is also used in the **update-age** sub model.	Drawn for each patient from an empirical distribution: 80+ years old: 6.4 75 – 79 years: 8.6 70 – 74 years: 11.3 65 – 69 years: 14.5 60 – 64 years: 18.1 55 – 59 years: 21.9 50 – 54 years: 25.9 45 – 49 years: 30.1 40 – 44 years: 34.2 35 – 39 years: 38.5 30 – 34 years: 42.8 25 – 29 years: 47.1 20 – 24 years: 51.4		Ghana Demographic and Health Survey
FemaleProp	The proportion of patients who are female. Used at initialisation to populate patients' sex variables.	0.60		Sarfo-Kantanka et al. (2016)
DiabetesPrev	The prevalence of DM in the adult population in Ghana. At initialisation, it is multiplied by adult-pop to estimate the number of patients to model.	0.06	uniform distribution min= 0.046 max= 0.074	Asamoah-Boaheng et al. (2019)
AdultProp	The total number of adults (20+ years old) living in Ghana; used at initialisation to estimate the number of patients to model	19 million (0.617 * 30.8 million)		Estimated from the Ghana Demographic and Health Survey (Ghana Statistical Service, 2022b)
ReviewInterval	The average number of weeks between outpatient appointments is used in the **schedule-appointment** procedure within the **treat** sub model to populate patient appointment weeks.	13	uniform distribution min= 8 max= 18	Estimated from clinicians' opinion
recoveryPeriod	The number of weeks the patient adheres to treatment following discharge for an acute DM complication that led to admission. Set the weeks between	The weeks between when a patient is discharged and the patient’s next appointment		Assumed based on clinicians' opinion.

	discharge and the next appointment. This is used in the **discharge** and **check-clinical** procedures.			
HypertensionPrev	The annual prevalence of hypertension and overweight (used as a proxy for comorbidity). Used to increase the prevalence of comorbidity among patients).	Estimated from an S-shaped distribution with equation and parameters. (details in sub model section)		Opoku et al. (2020) Adeloye and Basquill (2014)
DiabetesDuration	The proportion of patients who have had DM for a given number of years. used at initialisation to populate patients' *duration* state variable in the **set-duration** sub model.	1 – 5 years = 46.7% 6 – 10 years = 29.3% >10 years = 24.0 %		Osei-Yeboah et al. (2018)
LenStay	The number of weeks a patient stays in admission. used in the **admit** sub model.	2	uniform distribution min = 1, max = 3	Sarfo-Kantanka et al. (2016)
InsuranceCoverage	The proportion of the cohort actively insured under the NHIS. Used at initialisation in the **set-insurance** procedure and the **update-insurance** sub model.	Estimated from an S-shaped distribution with equation and parameters (details in sub model section)		Ministry of Health, 2023
MaxInsuredAppointment	The maximum number of outpatient appointments that the NHIS covers for insured patients.	6		Assumed based on NHIS operational tariff (National Health Insurance Authority, 2022)
ScaleDown	Used to estimate patient cohort size at initialisation.	0.5%	0.1 and 1%	Modeller's assumption.

Note: DM = diabetes

Input data

This model does not include input data.

Sub model:

In this section, we discuss the procedures that are represented as sub-models.

Sub models In Initialisation:

set life-expectancy

All patients perform this procedure once during initialisation to set their *life-expectancy.* They use their *age-group*, *residence*, and *sex* in the procedure.
First, patients choose from the list of life expectancies that match their state. For example, female patients in urban communities choose the

life-expectancy-female-urban list, while male patients in rural communities select the *life-expectancy-male-rural* list. There are four list summaries below. Each list contains 13 values corresponding to life expectancy from age group 1 to 13. Table 4 shows the band for each age group.

life-expectancy-male-urban – male urban-resident patients
life-expectancy-male-rural - male rural-resident patients
life-expectancy-female-urban - female urban-resident patients
life-expectancy-female-rural - female rural-resident patients

Second, patients set their *life-expectancy* to the sum of their *age* and the life-expectancy corresponding to their *age-group.* All patients approximate life-expectancy to the nearest whole number, e.g., 65.7 = 66, 52.3 = 52. For example, for a 25-years-old female patient residing in an urban, their *life-expectancy* is (round 25 + 47.6) 47.6 is the life expectancy at age 24 – 29 in female urban residents, in Table 4.

set-age-group
Patients set their age group using the bands shown in Table 4. For instance, a 24-years-old patient sets age-group to 1. Age-group is updated anytime age increases.

set-duration

All patients perform this procedure once at initialisation to set their *duration* state variable. Patients use their age-group and the DiabetesDuration variable in the procedure.
First, all patients set *duration* to 0. The DiabetesDuration variable specifies the proportion of the cohort who have had DM for 1-5 years, 6 -10 years and 10-15 years. We estimated the count of patients expected in each duration period by multiplying the proportions in the DiabetesDuration list by the cohort size (count of patients)

[0.467, 0.293, 0.24] * cohort size

0.469 = 1 - 5 years of DM
0.293 = 6 – 10 years of DM
0.24 = 11 - 33 years of DM

Second, we estimated the maximum expected age for a patient who has had DM for at most five years to be 34 by adding 5 to the minimum age of the cohort (MinAge = 27, in Table 4).

We then calculated the difference in the count of patients in age-group 2, corresponding to age 34, or less and the expected counts to be:

(0.469 * cohort size) – (count in age-group 1 – 2)

Given the age distribution, we had a positive difference (surplus). All patients in age-group 1 – 2 set duration to a random number between 1 – 5 years, with all numbers having an equal chance of selection. Third, we estimated the minimum expected age for a patient to have had DM for 33 years, given a maximum age of 84 in the patient cohort to be 51, corresponding age-group 6 and above.

Given the age distribution, the expected count (0.24 * cohort size) is less than the actual count (number of patients in age group >= 6). Consequently, we randomly selected the expected count (0.24 * cohort size) of patients in the age group to set their duration to any random number in a uniform distribution with a range of 11 - 33 years.

Fourth, we expected the number of patients with durations between 6 and 10 years to be 0.293 * cohort size. We then asked the expected number of patients who have yet to set their *duration* (*duration* = 0) to set their duration to any random number in a uniform distribution with a range of 6 to 10 years.

We confirmed that the remaining number of patients whose *duration* = 0 matches the difference (surplus) in the second step. We then asked these patients to set *duration* to a random number between 1 – 5 years.

set-wealth

All patients perform this procedure once at initialisation to set their *wealth.* Depending on their *residence,* they use the urban-wealth or rural-wealth variable *(in Table 4).*

urban-wealth = 0.042, 0.114, 0.204, 0.291, 0.349
rural-wealth = 0.335, 0.273, 0.197, 0.122, 0.072

First, all patients choose a random number from a uniform distribution with a range of 0–1 and a precision of 3 (approximated to 3 decimal places). All urban-resident patients who selected numbers below the first item on the *urban-wealth* list set their wealth to 0, meaning poor. Rural resident patients do the same but compare their choice to the first item on the rural-wealth list to set their wealth.

Specifically, urban residents with choice < 0.042 set wealth 0, while rural residents with choice < 0.335 set wealth 0.

Second, patients whose choices are greater or equal to the value of the first item but less than the sum of the first and second item on their respective lists set wealth 1. Thus, if
residence = 1 and choice >= 0.042 and choice < (0.042 + 0.114), set wealth 1
residence = 0 and choice > = 0.335 and choice < (0.335 + 0.273), set wealth 1
Third, patients whose choices are greater or equal to the sum of the first two items but less than the sum of the first three items in their respective lists set wealth 2. Thus, if
residence = 1 and choice >= (0.042 + 0.114) and choice < (0.042 + 0.114 + 0.204) set wealth 2
residence = 0 and choice >= (0.335 + 0.273), and choice < (0.335 + 0.273 + 0.197) set wealth 2

Fourth, patients whose choices are greater or equal to the sum of the first three items but less than the sum of the first four items in their respective lists set wealth 3. Thus, if

residence = 1 and choice >= (0.042 + 0.114 + 0.204) and choice < (0.042 + 0.114 + 0.204 + 0.291) set wealth 3
residence = 0 and choice >= (0.335 + 0.273 + 0.197), and choice < (0.335 + 0.273 + 0.197 + 0.122) set wealth 3

Finally, all other patients whose choices are greater than the first values in their respective list but have their wealth = 0 set wealth 4. We run a line of code in the model interface to verify the proportion of patients with wealth 4 matches the proportion in the lists.

set-insurance

All patients perform this procedure at initialisation to set their *insurance* state variable and then update their insurance status annually. The procedure uses InsuranceCoverage, InsuranceFemale and InsuranceMale global variables.

First, all patients set *insurance* 0. We multiply each item in the InsuranceFemale list by the count of patients in the corresponding wealth quantiles and store the result in a list (LIST A-expected). The values in the list represent the expected number of female patients to be insured per wealth quantile. We do the same for male patients using the InsuranceMale list. We then created a list of male and female patients currently in the model by their wealth quantile (LIST B-available).

Second, for each item on List A, we compared it to the corresponding item in List B and created a third List C using this rule:

item A > item B set the corresponding item C = B
item A <= item B set the corresponding item C = A

We generated two list Cs, one for males and the other for females.
Third, we asked randomly selected patients to be insured by wealth quantiles; using the sex-specific list, we asked patients *x* number of patients in the corresponding wealth quantile to set their insurance to 1 (insured), where *x* is the value on the list.

set-med

All patients perform this procedure once at initialisation to set their medicine adherence behaviour (*med*). Patients use their insurance, lifestyle, wealth and comorbidity in the procedure. We estimate the proportion of patients expected to be adherent using the MedAdherence variable to be:

Y = MedAdherence * cohort size

First, all patients set their med to 0. We assumed that patients with insurance, those with moderate to high wealth, or those who eat healthily take medicines. Consequently, we estimated the total number of patients in such states (X). Using conditional statements, we asked patients to set their *med.* If

Y = X, all patients insured or have moderate to high wealth or ate healthily set *med* 1

Y > X, all patients insured or have moderate to high wealth or ate healthily set *med* 1; the difference is randomly selected from other patients.

Y < X, Y randomly selected patients from the group of patients insured or have moderate to high wealth or ate healthily to set *med* 1

All patients append their *med* to their *my-med* list.

set-comorbidity

All patients and the modeller perform this procedure at initialisation to set their *comorbidity* of DM using the **HypertensionPrev** variable. First, all patients set their *comorbidity* to 0.

The modeller estimated **HypertensionPrev** using parameters (in Table 4) and an equation (detailed in Submodels in Model Run section). Then, a randomly selected number of patients corresponding to **the HypertensionPrev * cohort** size was used to set their *comorbidity* to 1.

Submodels In Model Run

check-clinical-state

The procedure checks if a discharged patient has fully recovered from an acute blood glucose complication that led to admission. It then updates such patients' clinical state, which determines the procedures patients perform in the model. Procedures for inpatients vary from those for outpatients in the model.

To perform the procedure, discharged patient (*clinical-state* = 1) checks their *clinical-state* using conditional statements (if *recovery-period* = ticks (current week), change *clinical-state* from 1 to 0). The recovery period is the period when a patient adheres to treatment following discharge for an acute DM complication that led to admission. Outpatients and inpatients do nothing, while discharged patients (*clinical-state* = 1) who have completed their recovery periods (*recovery-period* = ticks (the current week)) change to outpatients (*clinical-state* = 0). Discharge patients who have not completed their recovery-period (*recovery- period* > ticks) do nothing.

check-meds

Outpatients with prescription (*clinical-state* = 0 or *clinical-state* = 1) perform the procedure to decide medicine availability in their community and whether they can afford medicines. The procedure constitutes two sub models: **check-affordability** and **check-med-in-com**, in the order of execution. Inpatients are assumed to take medications regardless of medicine availability in their communities.

Outpatients perform the check availability procedure immediately after attending a review appointment and receiving a prescription. We define prescriptions as clinician authorised instructions directing the issue of medicines.

First, the patients perform the **check-affordability** procedure to determine whether they can afford prescribed medicines. The procedure changes the patients' *prescription* state variables.

Patients use *insurance* and *wealth* state variables to check affordability. Specifically, patients who are insured (*insurance* = 1) or fall within the middle to richest wealth quintiles (*wealth* > 1) or both can afford medicines and therefore proceed to check medicine availability in their community (**check-med-in-com**), still having their *prescription* > 0. No state variable is updated at this point. Patients with neither insurance (*insurance* = 0) nor wealth (*wealth* = 0) cannot afford it. Such patients set *their prescription* to -1, indicating they could not afford medicines. They do not take medicines (set *med* to 0).

Second, the outpatients with prescriptions (*clinical-state* < 2 and *prescription* > 0) who can afford medicines perform the **check-med-in-com** procedure to check medicine availability in communities.

To check medicine availability, the patients draw a random number between 0 and 1 from a uniform distribution and then compare the choice to the proportion of times medicines are available in their residence (MedUrban or MedRural, in Tables 1 and 4), depending on the patient's residence. If the choice falls within the proportion of times medicines are available, the patient sets *med-in-com* = 1, indicating medicines are available and bought. Otherwise, the patient 1) sets *med-in-com* = 0, indicating medicines unavailable, 2) reduces the value of *prescription* by one week, and 3) does not take medicines (sets *med* 0). Such patients do nothing until the next time step to perform the **check-med-in-com** procedure again. Figure 4 shows the decision process.

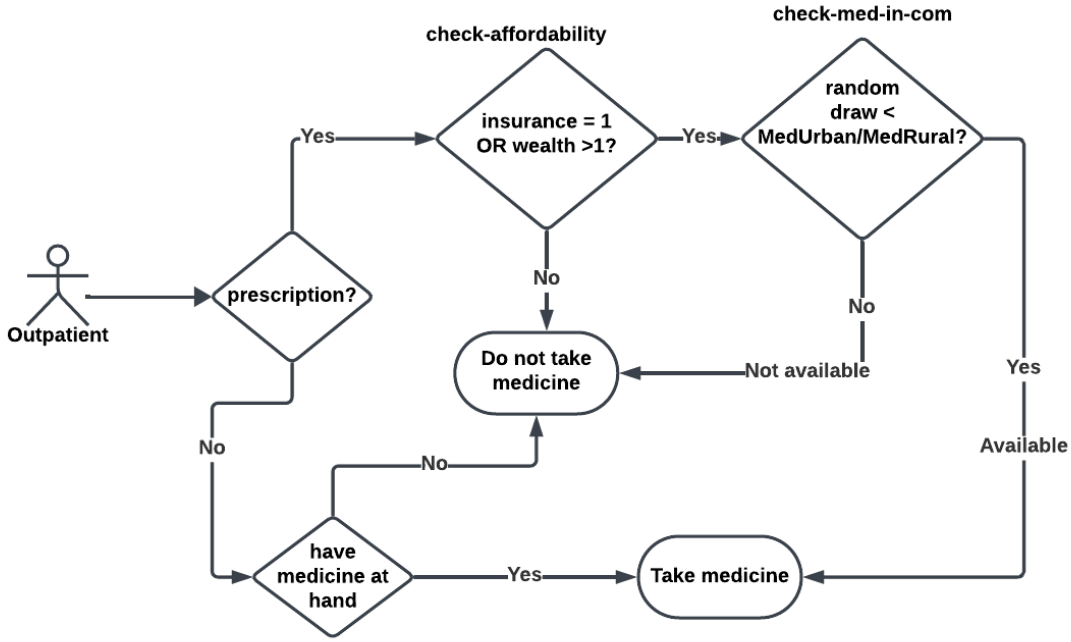

Figure 4: Patients medicine adherence behaviour. MedUrban and MedRural represent the proportions of times medicines are available in urban and rural areas, respectively.

attend-review

The procedure constitutes four submodels: **decide-attendance, treat, admit** and **schedule-appointment.** Figure 5 shows the decision-making process.

The procedure starts with outpatients deciding on review attendance (**decide-attendance**). At model initialisation, all outpatients have appointment weeks. Outpatients who have an appointment in the current week decide on attendance using **AttendanceProp** and BGC state (*fbg*).

Patients who have an appointment in the current week and poorly controlled blood glucose (*fbg* = 3) attend based on the perceived severity of HBM (details in the Basic Principles section).

Patients with an appointment in the current week and moderate or good BGC decide on attendance using the **AttendanceProp** (details in Table 4) and stochasticity. Specifically, such patients select a random number between 0 – and 1 from a uniform distribution and compare their choice to **AttendanceProp**. If their choice falls below **AttendanceProp**, they attend the appointment or do not attend. Patients who miss appointments set their next appointment to any random number between the next week and **ReviewInterval**, and set *prescription* -1, indicating procession of medicines. Because clinicians

prescribe medicines for the duration between review appointments, patients who miss appointments are assumed not to have medicines. Each patient that attends an appointment updates the **insuredAttendance** or **uninsuredAddtendance** global variable increase depending on the patient's insurance status.

Patients have emergencies if they have poorly controlled blood glucose (*fbg* = 3), healthy lifestyle (*lifestyle* = 0), and do not take medicines (*med* = 0). Such patients attend health facilities regardless of having an appointment in the current week.

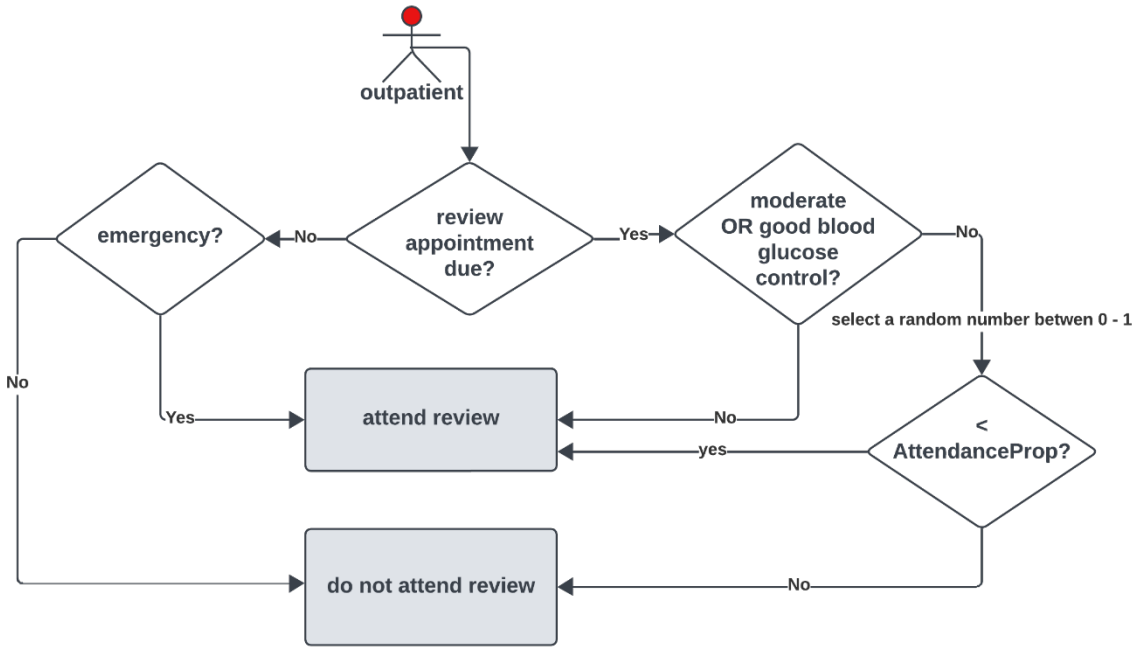

Figure 5: Patients review attendance behaviour. Note: **AttendanceProp** is the proportion of outpatients who attend review appointments obtained from the literature.

treat

Patients seeking care through review appointment attendance or emergencies are treated through the **treat** procedure. First, the patients set their med-in-com 0, indicating that they have no outstanding prescription and have yet to receive one.

The patients with good or moderate BGC (*fbg* = 2 OR *fbg* = 1) have their next appointment scheduled through the **schedule-appointment** procedure and receive prescriptions. Next appointments are scheduled based on patients' glucose control and availability of appointments. Patients who have good control (*fbg* = 1) are seen between 9 - 13 weeks, while those who have moderately controlled glucose

(*fbg* = 2) are seen between 4 –9 weeks. When an appointment week is set, patients update their appointment to the *appointment* week. The patient then gets a prescription. Prescriptions are given for the duration patients will be at home (*appointment* – the current week (*ticks*)).

Those with poor BGC (*fbg* = 3) are admitted through the **admit** procedure. Clinicians monitor patients' treatment behaviour, ensuring that they take medicines, eat healthily, and maintain their blood glucose while on admission. In the week of admission, admitted patients have controlled blood glucose (*fbg* = 1), take medicines (*med* = 1), live healthy lifestyle (*lifestyle* = 1), change their clinical-state to inpatients (*clinical-state* = 2), and set their *discharge-time* to one or two weeks (draw from a uniform distribution between 1 and *LenStay* (in Table 4)).

discharge

Inpatients (clinical-state = 2) set their next *appointment* to a randomly selected number of weeks between 1 and 4 (within one month after discharge) in the week of discharge (when discharge-time = ticks). After the patient sets their *prescription* to the weeks between the current week and the next *appointment*, the prescribed medicines are for the weeks until the next *appointment*.

Then, the patients set a *recoveryPeriod* (details in Table 4) the same as their next *appointment*, indicating that they remain in recovery between discharge and the next review appointment.

In the week of discharge, patients have controlled blood glucose (*fbg* = 1), taken medicines (*med* = 1), changed from inpatients to discharged patients (*clinical-state* = 1), and cancelled their *discharge time (discharge-time = 0).*

get-weekly-control

All patients perform the procedure to estimate their BGC in a week. In the base case, patients have good control if they took medicines as prescribed and ate healthily in the current week. Table 5 shows how we estimated BGC in the base case and the conceptual models we considered in uncertainty analysis.

Table 5: Models of BGC estimation

Model	Behaviour Element	Function (*Sum behaviour elements.*)	The outcome of blood glucose
Base case (fxn-0)	lifestyle med	If Sum = 2	Good BGC *(fbg = 1)*
		Sum = 1	Moderate BGC *(fbg = 2)*
		Sum = 0	poor BGC *(fbg = 3)*
Conceptual model 1 (fxn-1)	lifestyle med comorbidity*	Sum = 3	Good BGC *(fbg = 1)*
		Sum = 2	Moderate BGC *(fbg = 2)*
		Sum <= 1	poor BGC *(fbg = 3)*
Conceptual model 2 (fxn-2)	lifestyle med duration	If duration >= CutOffDuration 2*med 1*lifestyle If duration < CutOffDuration 1*med 2*lifestyle Sum >= 2	Good BGC *(fbg = 1)*
		Sum = 1	Moderate BGC *(fbg = 2)*
		Sum = 0	poor BGC *(fbg = 3)*
Conceptual model 3 (fxn-3)	Randomly select one of the above models		

*In the model, patients with comorbidity set comorbidity 1. However, in the estimation, patients with comorbidity (comorbidity = 1) score 0, while those without (comorbidity = 0) score 1 point.

get-three-months-outcomes

Patients perform this procedure every 13 weeks to estimate their average blood glucose. We derived the logic of estimating 13 weeks of BGC from the principles used in estimating HbA1c in the medical literature. A1C is estimated by measuring the amount of haemoglobin in the blood that has been bound to glucose during the previous three months. Higher blood glucose levels cause each haemoglobin molecule to carry more glucose, which raises the HbA1c value, implying that a patient with more incidence of uncontrolled is likely to have uncontrolled blood glucose over the 13 weeks.

Patients set their 13-week blood glucose (*HbA1c*) to the frequent blood glucose state. For example, a patient with 6 occurrences of good control (*fbg* = 1), four occurrences of moderate control (fbg = 2), and three occurrences of poorly uncontrolled (*fbg* = 3) sets *HbA1c* to 1. This is because he/she has more occurrences of good control. Where there is a tie, the patient randomly selects one of the states in the tie.

We applied the same logic to determine patients' lifestyle behaviour over 13 weeks (*lifestyle-ave*). Patients set their lifestyle behaviour to the most common behaviour in the previous 13 weeks.
To estimate medicine adherence behaviour over 13 weeks (*med-ave*), we ranked medicine adherence outcomes into good adherence, moderate adherence and poor adherence. We used an 80% cut-off for good adherence.

Patients first sum the values in *my-med.* Patients who took medicines 70%+ of the time (the sum of my-*med* >= 9) are considered to have good adherence; those who took medicines 69% - 50% of the time (sum my-*med* >= 5 but < 9), the rest (sum my-*med* >= 4) have poor adherence.

update-obesity

We adapted the sigmoid function/ logistic growth curve to model the prevalence of overweight and obesity in the cohort using data from the literature. The sigmoid function is a mathematical model that illustrates how a population expands when subject to environmental and resource limitations. It is frequently used to describe growth processes that show initial exponential growth followed by a levelling down as the population approaches a maximum capacity in various domains, including biology, ecology, economics, and epidemiology. We used prevalence data from Amugsi et al., 2017. Detailed in the Table 6.

Table 6: Trends in Obesity and Overweight in Ghana

Year	**Over weight**	**95%CI**	**Obesity**	**95%CI**	**Total**	**95%CI**
1993	17.9	17.9 – 18.2	7.7	7.0 – 8.5	25.6	24.9 – 26.7
1998	17.0	13.6 – 21.1	13.8	10.6 – 17.8	30.8	24.2 – 38.9
2003	24.8	21.3 – 28.7	17.9	14.7 – 21.5	42.7	36 – 50.2
2008	26.2	24.2 – 28.3	14.2	12.7 – 15.8	40.4	36.9 – 44.1
2014	30.4	26.3 – 34.9	22.0	18.3 – 26.3	52.4	44.6 – 61.2

We defined the logistic growth curve function (S-curve) as:

Pt = A * K / (A + (K - A) * exp(-r * t))

where r = the shape parameter of the Sigmoid curve

P(t) = the prevalence of obesity and overweight at time t

A = the starting, initial, or minimum prevalence

K = the highest prevalence there can ever be in the cohort

Using data in Table 6, we specified

A = 0.256, minimum prevalence rate

K = 0.524, maximum prevalence rate

r =.01, set using a heuristics numerical approach

Using the non-linear least squares function in the R "stats" package, we obtained the following parameter and fitness measures. The fitness of the predictive model is show in Table 7:

Estimate Std. Error t value Pr(>|t|)

A 0.24770 0.04515 5.486 0.0317 *

K 0.63985 0.34690 1.844 0.2064

r 0.08702 0.08320 1.046 0.4054

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04463 on 2 degrees of freedom

After fitting the data to the S shape distribution, we included the code in our ABM NetLogo model.

Prevalence at time t = (A * K / (A + (K - A) * exp (- r * t)))

Where:

A = 0.24770

K = 0.63985

r = 0.08702

t = (31 + (year in the model)), 31 brings the time from 1993 to 2024.

The plot in Figure 6 shows the fitted model and the original prevalence:

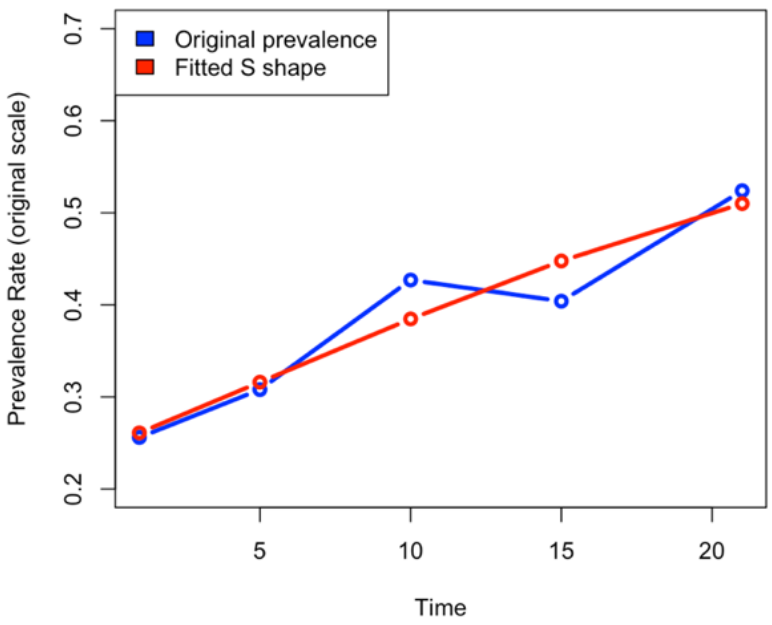

Figure 6: Predicted and observed overweight and obesity prevalence.

Table 7: Observed and predictive prevalence of obesity and overweight prevalence

Time point	Original prevalence	Predicted prevalence	Absolute percentage error
1	0.256	0.261	1.95
2	0.308	0.316	2.60
3	0.427	0.385	9.84
4	0.404	0.448	10.89
5	0.524	0.509	0.00

Mean Absolute Percentage Error (MAPE) = 5.06%

Figure 7 is a prediction of 70 years, starting from 1993; the dotted line shows prevalence in 2024.

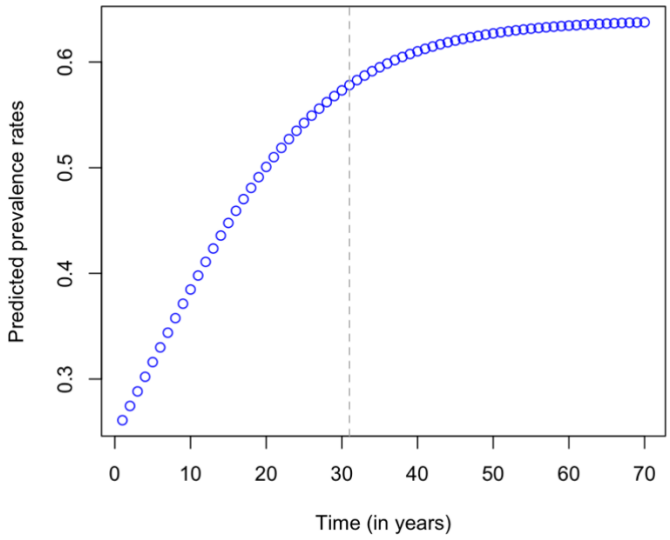

Figure 7: Predicted overweight and obesity prevalence.

update-insurance

We used the same approach to predict obesity and overweight prevalence, using data from Ghana's National Health Insurance.

The data in the Table 8 shows trends in NHIS active Membership coverage. We used the same procedures to estimate the s-shaped function for obesity and overweight people to estimate the parameters of an s-shaped function for NHIS active membership.

Table 8: Active NHIS coverage in Ghana

Year	% coverage
2019	40
2020	42
2021	52.6
2022	57
2023	57

Source: Ministry of Health, 2023. Medium Team Expenditure Framework for 2023 – 2026

% coverage is the number of active NHIS members divided by the total population of Ghana and then multiplied by 100. 2018 – 2020 % coverage is the target; we found no actual/achieved percentage coverage for these years from the NHIS programme of work at the time of the study.

Parameters:

Estimate Std. Error t value Pr(>|t|)

A 0.31195 0.06777 4.603 0.0441 *

K 0.64493 0.14274 4.518 0.0457 *

r 0.46415 0.38030 1.220 0.3467

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.03221 on 2 degrees of freedom

After fitting the data to the distribution, this is the code we included in our ABM Netlogo model.

Prevalence at time t = (A * K / (A + (K - A) * exp (- r * t)))

Where :

A = 0.31195

K = 0.64493

r = 0.46415

t = (5 + (year in the model)), 5 brings the time from 2019 to 2024.

Figure 8 shows the fitted model and the original coverage proportion, and the Table 9 shows the fitness of the predictive model:

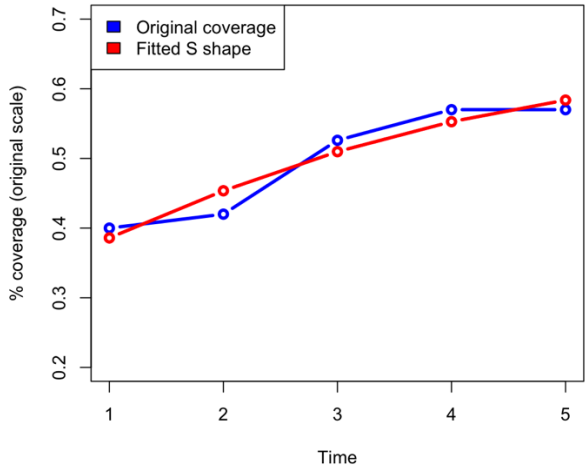

Figure 8: Predicted and observed active NHIS coverage.

Table 9: Observed and predictive proportion of active NHIS coverage

Year	Original coverage	Predicted coverage	Absolute percentage error
2019	0.400	0.386	3.5
2020	0.420	0.454	8.095238095

2021	0.526	0.509	3.231939163
2022	0.570	0.553	2.98245614
2023	0.570	0.584	2.456140351

MAPE = 4.05%

Below is a prediction for 30 years, starting from 2019, and the dotted line shows prevalence in 2023.

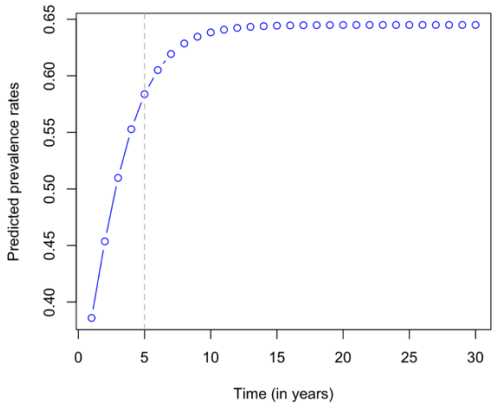

Figure 9: Predicted values of active NHIS coverage

After estimating the percentage of the cohort insured under NHIs, we estimated the effect of insurance coverage on medicine adherence using the MedInsuranceInc parameter. Specifically, we

1) insurance coverage $_{t}$ - insurance coverage $_{t-1}$ (estimated the difference in insurance coverage)
2) MedInsuranceInc * difference (in step 1)
3) increase MedAdherence by the product of step 2

update-comorbidity

We applied the same approach to predict obesity and overweight prevalence, using data from Davies Adeloye, 2014- (1990 – 2010 prevalence) and GDHS 2014 dataset in Sampson Opoku et al., 2020. (2017 prevalence), shown in Table 10.

Table 10: Hypertension Prevalence Trends in Ghana

year	Hypertension prevalence
1990	0.197

2000	0.274
2010	0.308
2017	0.3043

Parameters:

Estimate Std. Error t value Pr(>|t|)
A 0.184235 0.007562 24.363 0.0261 *
K 0.310071 0.006497 47.723 0.0133 *
r 0.169631 0.032609 5.202 0.1209

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.006285 on 1 degrees of freedom

Number of iterations to convergence: 6
Achieved convergence tolerance: 7.405e-06

The plot below shows the fitted model, and the original prevalence proportion and Table 11 indicates the fitness of the predictive model.

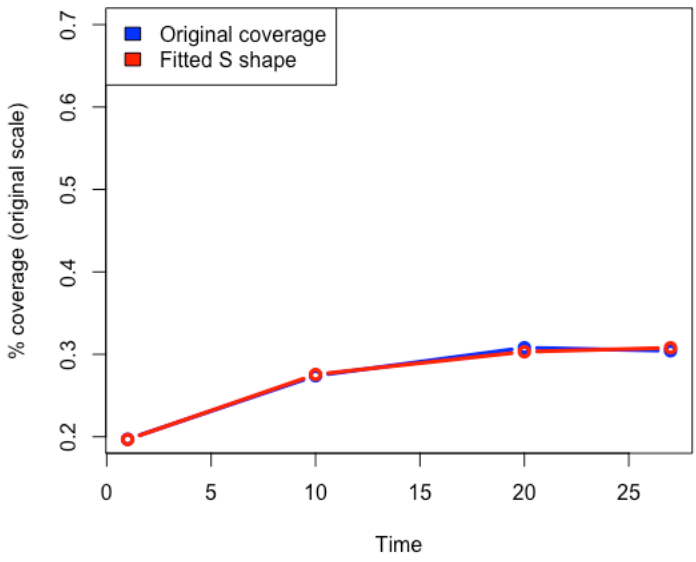

Figure 10 Predicted and observed hypertension prevalence.

Table 11: Observed and predictive prevalence of hypertension in Ghana.

Year	Original prevalence	Predicted prevalence	Absolute percentage error
1990	0.1970	0.1966894	0.157664975
2000	0.2740	0.2755607	0.56959854
2010	0.3080	0.3031108	1.587402597
2017	0.3043	0.3079146	1.187840946

MAPE = 0.88%

Below is a prediction of 34 years, from 1990 – 2030; the dotted line shows prevalence in 2024.

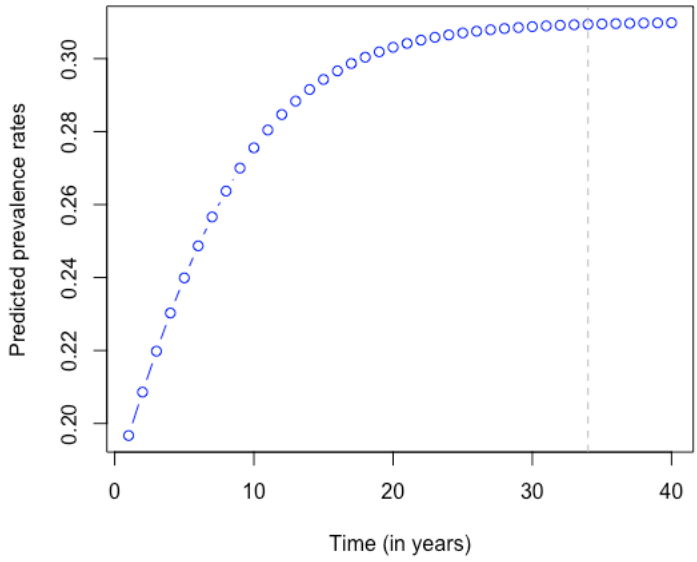

Figure 11: Predicted hypertension prevalence.

estimate-crude-deaths

The model performs this procedure yearly to estimate the number of patients dying/exiting the model for all reasons, including DM and non-DM causes.

We multiply the *female-crude mortality* and *male-crude mortality* by the count of patients in the respective age groups and sex to determine the number of deaths among the age groups. We then select at random the number of patients in the age group and instruct them to die.

We do not represent DM deaths because the condition we modelled, acute DM complications, hardly result in deaths. If we had focused on chronic DM complications and comorbidities (e.g., heart diseases and stroke), then deaths from DM would be an outcome of interest.

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Appendix D: Cases for verifying the programmed ABM model (white-box testing)

Cohort size

1. At any point in the model, the count of inpatients, outpatients and discharged patients must equal the total number of patients. We coded the model to print errors whenever the condition is not met. We ran 100 iterations of the base case model to test, and no error was printed.

Medicine adherence and access

2. In the conceptual model, we expected all outpatients (clinical-state = 2) who missed appointments (appointment > current week) to have no medicines or outstanding prescriptions to buy (prescription = -1). Also, we expected that patients who had no insurance (insurance = 0) and were very poor (wealth <= 1) could not afford medicines and thus did not proceed to check for medicine availability in their community (check-med-in-com). We asked patients checking medicines availability to print an "error" if they didn't meet the conditions.

3. The number of patients who do not have medicines (prescription = -1) should be equal to or less than the number of patients who have missed appointments in a week. Otherwise, there is an erroneous code or bug. Patients who do not have medicines constitute missed appointments and outpatients who cannot afford them. We coded the model to print out an error message if the difference in missed appointments and patients with no meds exceeds zero.

Diet behaviour per clinical-state

4. We expected the prevalence of poor diet behaviour among outpatients, including those discharged, to match the predicted value of PDiet (a global variable in the model). We also expected all inpatients

to have good diet behaviours and be medicine adherent. Consequently, we ran the model 100 times, printing an error message if the condition was unmet.

Hospital services

5. We expected patients who attended health facilities due to emergencies or review appointments to be admitted if they have poorly controlled blood glucose. On the week of discharge, these patients should have a recovery period equal to the time until their next appointment. To verify, we traced, in turn, 50 randomly selected inpatients until their week of discharge and their next appointment, observing their clinical state, recovery period, and appointment. We confirmed that the recovery-period and appointment was equal to the current week (ticks), clinical-state = 2 (outpatient/recovered for the complication leading to admission).

6. Given that diet and medicine adherence influenced blood glucose control in the base case, we expected that if all patients adhered to medication and ate healthily, they would all have good control. Consequently, there should be no admissions. The opposite is expected if all patients ate unhealthily and did not take medicines. We confirmed the expected when we ran the model under these conditions.

Appendix E: Results of Probabilistic Sensitivity Analysis

	Parameters	PRCC	P.value	95%CI - lower	95%CI - upper
Good BGC					
1	MedRural	-0.1229	0.2648	-0.3436	0.1355
2	MedUrban	-0.0029	0.98	-0.2798	0.2151
3	UrbanProp	-0.0397	0.7068	-0.2533	0.1795
4	UrbanProDiet	-0.7105	0	-0.8184	-0.615
5	RuralProDiet	-0.6084	0	-0.7409	-0.4885
6	AttendanceProp	0.3849	0.0001	0.1893	0.5682
7	ReviewInterval	-0.1852	0.0949	-0.3996	0.0221
8	LenStay	0.0111	0.9253	-0.2687	0.204
Moderate BGC					
1	MedRural	0.0778	0.4828	-0.1754	0.2764

2	MedUrban	-0.0132	0.9159	-0.2621	0.2657
3	UrbanProp	-0.107	0.3353	-0.3581	0.1109
4	UrbanProDiet	0.5297	0	0.3623	0.7186
5	RuralProDiet	0.338	0.001	0.1604	0.6057
6	AttendanceProp	0.0764	0.5508	-0.2025	0.3097
7	ReviewInterval	0.0357	0.7429	-0.2171	0.2084
8	LenStay	-0.0465	0.6684	-0.2955	0.1284
Poor BGC					
1	MedRural	-0.0283	0.8041	-0.2744	0.2119
2	MedUrban	0.0437	0.6827	-0.1543	0.2806
3	UrbanProp	-0.0855	0.2972	-0.248	0.0789
4	UrbanProDiet	0.2586	0.0118	0.0595	0.5011
5	RuralProDiet	0.4274	0	0.2448	0.6119
6	AttendanceProp	-0.7841	0	-0.8894	-0.7097
7	ReviewInterval	0.3256	0.001	0.1323	0.5448
8	LenStay	0.0466	0.6808	-0.1428	0.3274
Good medicine adherence					
1	MedRural	0.0707	0.4373	-0.1136	0.2742
2	MedUrban	-0.005	0.9672	-0.2957	0.1917
3	UrbanProp	-0.072	0.5713	-0.3244	0.1716
4	UrbanProDiet	0.0643	0.4996	-0.0875	0.2782
5	RuralProDiet	0.0651	0.5723	-0.1715	0.3078
6	AttendanceProp	0.8335	0	0.7638	0.9147
7	ReviewInterval	0.0587	0.5495	-0.1218	0.2894
8	LenStay	0.0301	0.8204	-0.2228	0.3202
Moderate medicine adherence					
1	MedRural	0.0778	0.4816	-0.1777	0.3014
2	MedUrban	-0.0132	0.9061	-0.2288	0.2411
3	UrbanProp	-0.107	0.46	-0.4271	0.1858
4	UrbanProDiet	0.5297	0	0.3768	0.712
5	RuralProDiet	0.338	0.0012	0.1062	0.5246
6	AttendanceProp	0.0764	0.5046	-0.1281	0.2919
7	ReviewInterval	0.0357	0.7231	-0.1621	0.2239
8	LenStay	-0.0465	0.7122	-0.2886	0.1979
Poor medicine adherence					
1	MedRural	-0.0409	0.6721	-0.2543	0.1596
2	MedUrban	-0.0425	0.6589	-0.2761	0.1283
3	UrbanProp	-0.1143	0.2441	-0.3154	0.0604
4	UrbanProDiet	-0.1109	0.364	-0.4023	0.159
5	RuralProDiet	-0.1945	0.0539	-0.4549	-0.011
6	AttendanceProp	-0.8078	0	-0.8866	-0.7416

7	ReviewInterval	0.3237	0.0038	0.1096	0.5141
8	LenStay	-0.0664	0.5271	-0.2723	0.1218
Incidence of admissions					
1	MedRural	-0.1274	0.2691	-0.3731	0.0913
2	MedUrban	0.0747	0.5183	-0.2027	0.272
3	UrbanProp	0.0291	0.7845	-0.2271	0.2566
4	UrbanProDiet	0.3614	0.0006	0.1391	0.5875
5	RuralProDiet	0.5597	0	0.4068	0.7128
6	AttendanceProp	-0.8225	0	-0.8942	-0.7524
7	ReviewInterval	-0.1497	0.1369	-0.3688	0.0469
8	LenStay	0.0349	0.7531	-0.1672	0.2415
Outpatient Attendance					
1	MedRural	-0.0444	0.6478	-0.2418	0.1885
2	MedUrban	0.0058	0.9616	-0.2974	0.2263
3	UrbanProp	-0.0905	0.4981	-0.3515	0.193
4	UrbanProDiet	0.0744	0.4301	-0.0847	0.2879
5	RuralProDiet	0.1325	0.2403	-0.077	0.3752
6	AttendanceProp	0.732	0	0.6413	0.8535
7	ReviewInterval	-0.4631	0	-0.6455	-0.2852
8	LenStay	0.0115	0.9328	-0.2655	0.2686

Appendix F: Blood glucose outcomes and Medication adherence behaviours by interventions (after 10 years)

Reference	Comparator	Mean of Differences	95%CI lower	95%CI upper
Good BGC				
Inter0	Inter1	0	0	0
Inter0	Inter2	-22	-24	-21
Inter0	Inter3	0	0	0
Inter0	Inter4	-22	-24	-21
Inter2	Inter4	0	0	0
Inter1	Inter3	0	0	0
Poor BGC				
Inter0	Inter1	0	0	0
Inter0	Inter2	24	22	26
Inter0	Inter3	0	0	0
Inter0	Inter4	24	22	26
Inter2	Inter4	0	0	0
Inter1	Inter3	0	0	0

Moderate BGC				
Inter0	Inter1	0	0	0
Inter0	Inter2	-1	-2	-1
Inter0	Inter3	0	0	0
Inter0	Inter4	-1	-2	-1
Inter2	Inter4	0	0	0
Inter1	Inter3	0	0	0
Good Medicine Adherence				
Inter0	Inter1	0	0	1
Inter0	Inter2	-94	-86	-101
Inter0	Inter3	1	0	1
Inter0	Inter4	-93	-85	-102
Inter2	Inter4	0	0	0
Inter1	Inter3	0	0	0
Poor Medicine Adherence				
Inter0	Inter1	0	0	0
Inter0	Inter2	52	48	57
Inter0	Inter3	0	0	0
Inter0	Inter4	52	48	57
Inter2	Inter4	0	0	0
Inter1	Inter3	0	0	0
Moderate Medicine Adherence				
Inter0	Inter1	0	0	0
Inter0	Inter2	38	34	43
Inter0	Inter3	0	0	0
Inter0	Inter4	38	34	43
Inter2	Inter4	0	0	0
Inter1	Inter3	0	0	0
Admissions				
Inter0	Inter1	0	0	0
Inter0	Inter2	14	11	16
Inter0	Inter3	0	0	0
Inter0	Inter4	14	11	16
Inter2	Inter4	0	0	0
Inter1	Inter3	0	0	0
Outpatients Attendance				
Inter0	Inter1	0	0	0
Inter0	Inter2	-23	-27	-20
Inter0	Inter3	0	0	0
Inter0	Inter4	-23	-26	-20
Inter2	Inter4	0	0	0
Inter1	Inter3	0	0	0

Appendix G: Literature review of cost-effectiveness studies on SSB tax implementation

Studies	Perspective	Cost (health)	Cost (non-health)	Outcomes reported
Jones 2018 (Thesis) Canada	Health sector	Direct medical costs	Excluded tax implementation cost	cost-savings or cost-incurred, DALYs
Lal et al, 2017 (Australia)	Societal	Healthcare costs include hospital services, medicines, and health professionals. Out-of-pocket healthcare cost (OOP): medicines, services, practitioners, equipment and hospital cost.	Intervention cost: implementation, administration, compliance for government. Administration cost for industry. Deadweight loss: net loss in total economic welfare attributed to new tax/tax increase. (cost data from the Australian Institute of Health and Welfare)	HALYs gained, healthcare cost saved, out-of-pocket. Healthcare expenditures saved are estimated based on a reduction in morbidity and mortality.
Chisholm et al., 2004 (Global)	Societal	Patient-level cost: clinical services, medicines, salaries, capital cost of equipment.	Program cost: administrative, training and enforcement, salaries, capital cost of equipment. (cost data from WHO CHOICES)	DALYs averted
Veerman et al., 2016 (Australia)	Health system	Healthcare cost	tax implementation cost (cost data from WHO estimate of legislative changes)	DALYs averted, prevalence, incidence and mortality
Wang et al., 2012,	NS	Health and medical care cost	NE	Medical cost savings

Studies	Perspective	Cost (health)	Cost (non-health)	Outcomes reported
Basu et al., 2013 (US)	Government	Medical cost	Tax cost Deadweight loss	Incremental costs, QALYs, body mass index, diabetes per person and
Mekonnen et al., 2013 (California)	NS	Direct medical cost	NE	avoided cases of diabetes and CHD, and associated healthcare cost savings
Long et al., 2015 (US)	societal	Healthcare cost	Tax implementation cost to government and industry Tax compliance cost (assumed to be 1% of total tax revenue, excluding credit card fees and unrecovered tax). Tax revenues were not part of the economic analysis because they are transfer payments with no net impact on societal costs.	ICER, QALYs, cost per life-year (LY) saved, cost per DALY averted
Manyema et al., 2016 (South Africa)	Health sector	Healthcare costs	NE	Deaths averted, DALYs averted
Basto-Abreu et al., 2019 (Mexico)	NS	Direct medical cost	Planning and development Operational/implementation/auditing cost	Diabetes incidence averted, DALYs averted, healthcare cost saving.
Long et al. 2019 (US)	Not specific (stakeholders' perspective)	Healthcare costs	Implementation cost to government and industry	Healthcare cost savings, net costs, and QALYs
Saxena et al., 2019 (South Africa)	NS (societal assumed)	Medical costs, OOP medical costs,	Patient cost: indirect costs due to productivity losses averted)	Healthcare savings, revenue to government, DALYs and deaths averted, direct medical cost savings

Studies	Perspective	Cost (health)	Cost (non-health)	Outcomes reported
Saxena et al., 2019 (Philippines)		Medical costs, OOP medical cost	NE	Deaths averted, healthcare cost savings, catastrophic expenditure averted.
Wilde et al., 2020 (US)	Societal, Health sector, other stakeholder groups	Healthcare cost, OOP healthcare cost (indirect healthcare cost, e.g....., productivity loss, excluded).	Implementation cost to government and industry (included only in societal perspective assumed to be 2% of total tax revenue)	CVD reduction, QALYs, healthcare cost savings,
Lee et al., 2020 (US)	Societal, Government, Healthcare (included tax implementation cost to government and industry as intervention cost).	Direct-medicines and services indirect medical cost travel and waiting time intangible cost – productivity loss	Tax Implementation costs to government and industry compliance costs (assumed to be 2% of total tax revenue).	Fatal and non-fatal CVD averted, QALYs, healthcare cost savings
Kao et al., 2020 (Canada)	Health system	Healthcare cost (direct medical cost)	NE	DALYs, healthcare cost savings

Appendix H: Data Collection tool for Diabetes Medicines Prices in Ghana

Cost of Blood Glucose Lowering Medicines in Type2 Diabetes in Ghana

We seek to explore how physicians prescribe diabetes medicines, including Metformin, Sulphonylurea, Thiazolidinediones, Dipeptidyl-Peptidase IV (DPP-4) Inhibitors, Sodium-Glucose Co-Transporter-2 (SGLT-2) Inhibitors, and various Injectables. The objective is to understand and gather data on the frequency and dosage of each prescribed medication to be incorporated in a costing study.

Kindly try as much as possible to complete this form with the average/frequent/usual prescriptions or dosage. Where possible, provide additional information/considerations for prescription/ dosage.

Medicines	Prescription Information	Average duration on prescription, e.g., 1month/3 months
1. Metformin	Dosage: Frequency:	
2. Sulphonylurea: Glibenclamide:	Dosage: Frequency:	
Glipizide:	Dosage: Frequency:	
Glimepiride:	Dosage: Frequency:	
Thiazolidinediones (Pioglitazone)	Dosage: Frequency:	
DPP-4 Inhibitors	Dosage: Frequency:	
SGLT-2 Inhibitors	Dosage: Frequency:	
Injectables Type of Injectable:	Dosage: Frequency:	
Additional Information:		

Reference

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