12-2-2023

Patient-centric Self-Management: A Systems View of Lifestyle Factors and their Impact on Chronic Diseases

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Full research paper

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Abstract

The COVID-19 pandemic has accelerated the adoption of digital healthcare and highlighted the importance of patient-centred lifestyle management for chronic conditions. However, the current focus primarily concerns health professionals and disease prediction models, neglecting the comprehensive consideration of patients' lifestyle factors. This results in a lack of models for lifestyle management and a scarcity of studies exploring the inter-relationships among different lifestyle factors within patient-centric self-management systems. Consequently, the holistic management of chronic conditions is hindered, as lifestyle factors are not adequately addressed. To address these issues, this study utilises diabetes as a case study to develop interrelated models that encompass both the behavioural aspects of lifestyle factors and the biological impacts on individual health and wellness. Through system dynamics modelling techniques, this research aims to provide a holistic understanding of the complex interactions within a patient's life and enable personalised management and care.

Keywords: chronic disease self-management, diabetes, small data, system dynamics models, lifestyle factors.

1 Introduction

The healthcare landscape has undergone significant changes in recent years, shifting from traditional in-person care to digital health. This transformation has been further accelerated by the global impact of the COVID-19 pandemic, which has prompted the widespread adoption of digital healthcare solutions (Petracca et al., 2020). One area where this adoption is particularly prominent is in the management of chronic conditions. Chronic disease patients, who are increasingly prevalent worldwide, require ongoing management and the formation of healthy lifestyle habits to cope effectively with their conditions (Seixas et al., 2021; Powers et al., 2017). Many studies regularly report that an unhealthy diet, physical inactivity, or tobacco consumption are modifiable, and a healthy lifestyle can effectively prevent critical health conditions (Ng et al., 2020; Centers for Disease Control and Prevention, 2011;). Especially medical experiments and studies report that the reversal of type 2 diabetes was seen after appropriate medical interventions and the adoption of healthy lifestyles (Taheri et al., 2020; Hallberg et al., 2019).

By leveraging digital health technologies, patients can track their health indicators, collect relevant data, and actively participate in their self-management (Jiang & Cameron, 2020). Smart technologies and wearable devices enable convenient tracking, while the Internet of Things has facilitated the integration of diverse management systems. Moreover, advancements in analytics techniques and small data, derived from big data and/or "local" sources, have paved the way for accurate prediction models and personalised recommendations (Marsch, 2021). Health professionals can now actively engage in patient management with digital health tools, and a wide array of commercially available devices support self-management practices (Doyle et al., 2019).

Despite the availability of these technologies and the strong evidence that people with effective self-management skills can significantly improve their quality of life, many patients still face challenges in effectively managing their chronic conditions (Riegel et al., 2021). A UK study concluded that lack of education and one-size-fits-all approaches were the barriers to effective management of type 2 diabetes in primary care (Rushforth et al., 2016). On the technological side, a key issue lies in the siloed development of digital health devices and algorithms. Commercially available solutions often lack interoperability, making integration and data sharing difficult (Gay & Leijdekkers, 2015). Furthermore, the current focus of digital health models primarily revolves around health professionals and dominant model development in disease prediction (Si et al., 2021). However, many studies advocate for a holistic approach to self-management (Vainauskienė & Vaitkienė, 2021). Not many studies consider individual patients' lifestyles and circumstances, and few studies have implemented such comprehensive approaches. Consequently, numerous self-management devices and systems have been developed without a strong research background in lifestyle management or established protocols, hindering their effectiveness and usability in real-world settings (Doyle et al., 2021). To address these limitations, this study proposes an interrelated model that encompasses behavioural aspects, the medical impacts of personal health, and overall wellness.

Models are used to describe a problem, an object, or a situation. Furthermore, models are used to describe the structure, relationships, purposes, and behaviour of a system. This enables us to use models to understand the current state of a system and also predict its future states. (Rouse & Morris, 1986). Hence, modelling holistic interrelationships among lifestyle factors can educate people about which factors and behaviours are essential for adopting sustainable and healthy lifestyles. The education through modelling can be personalised if the patients use their situations and data and observe potential outcomes based on different scenarios (Jeffries, 2022). This can strongly persuade individuals and families to change their behaviours and habits. Using diabetes as a case study, the research aims to develop system dynamics models that enable patients to simulate their health outcomes based on lifestyle changes. Our research adopts the Design Science Research (DSR) methodology. The goal is to provide a foundation for the development of patient-centric self-management systems that consider the complex interplay between lifestyle factors and chronic diseases.

In the following section, we first develop the research rationale by exploring the research background and identifying the objectives that we need to achieve (Section 2). Section 3 explicates our research methodology. In section 4, we develop the lifestyle factors interrelationship models (Causal Loop Diagram and Stock and Flow Diagram) based on various literature on type 2 diabetes mellitus. Section 5 implements the lifestyle factors models through a simulation prototype. Section 6 discusses and concludes our research.

2 Research Background

2.1 Chronic Conditions

Chronic diseases have become a severe problem that causes 40% of premature deaths under the age of 70, and The World Health Organization (Wing & Yang, 2014) estimates that chronic illnesses can cause 52 million deaths by 2030. Common chronic conditions include diabetes, cancers, cardiovascular diseases, respiratory diseases, and dementia. Among those, diabetes often leads to devastating complications that are also chronic – such as kidney failure, myocardial infarction, and stroke. Therefore, the prevalence of diabetes causes significant medical and economic losses. WHO has estimated that the cumulative labour lost from deaths due to diabetes alone to be $32.8 billion for Canada and the UK from 2005 to 2015 (National Advisory Committee on Health and Disability, 2007). Even the current COVID-19 outbreak has proven that people with diabetes show a poor prognosis for the infection (Apicella et al., 2020).

Type 2 diabetes is a complicated chronic disease where glucose regulation is not functioning properly due to the inadequate secretion of insulin, a reduction in insulin sensitivity of the target cells for insulin hormone, or both (Fu et al., 2013; Kahn et al., 2006). Apart from genetic risks, diet, exercise, smoking, and stress are the core causes of diabetes; thus, self-management often focuses on the care of these aspects (American Diabetes Association, 2018). Fortunately, many studies report that unhealthy lifestyles are modifiable, and critical health conditions can be effectively prevented by promoting lifestyle medicine (Johnston et al., 2008; Rippe, 2018). Therefore, lifestyle and self-management research have a vital role in addressing these limitations and supporting the development of more effective evidence-based strategies for people with chronic conditions. In this regard, digital health has emerged as a powerful tool that offers numerous benefits in monitoring and managing chronic conditions.

2.2 Digital Health and Technological Advancement

Digital health technologies have witnessed remarkable advancements, offering a wide range of hardware, software, and analytics solutions to enhance healthcare delivery and support patient self-management (Mathews et al., 2019). Prominent technologies such as the Internet of Things (IoT) and smart homes enable seamless connectivity with various healthcare devices that can collect and transmit vital health data, providing a comprehensive view of a patient's health status (Franco et al., 2021). For example, wearable devices, such as smartwatches and fitness trackers, have gained popularity for their ability to monitor vital signs, track physical activities, and provide personalised health recommendations (Lingg et al., 2014) Furthermore, smart devices, including smart pillboxes (Choi, 2019) and smart inhalers (Reddel et al., 2022), assist patients in medication adherence and disease-specific management.

In the realm of software, various health apps have revolutionised the way individuals engage with their health. These apps offer a wide array of functionalities, including health tracking, medication reminders, and access to educational resources. They empower patients to take a proactive role in managing their health and enable seamless communication with healthcare professionals (Frank, 2000). Health apps also facilitate the integration of data from wearable devices, creating a comprehensive health profile that can inform personalised interventions and treatment plans. The vast amount of health data generated by digital health software and hardware necessitates prompt and appropriate analytics to provide valuable insights to patients.

2.3 Small Data and Decision Analytics

Small data and analytics can play vital roles in digital health, enabling the extraction of meaningful insights from vast amounts of health data. Fidelman and Bonde (2012) proposed that "Small data connects people with timely, meaningful insights (derived from big data and/or "local" sources), organised and packaged – often visually – to be accessible, understandable, and actionable for everyday tasks." Kavis (2015) also described "Small data as the small set of specific attributes produced by the Internet of Things. These are typically a small set of sensor data such as temperature, wind speed, vibration, and status." Small data can help people learn about their lifestyles better and find certain patterns and habits that can be used for self-management (Schwartz et al., 2020). Therefore, by analysing small, targeted datasets, healthcare professionals can gain a deeper understanding of patient's unique characteristics, behaviours, and health conditions (Burford et al., 2019). This granular approach allows for tailored interventions and more precise treatment plans, improving patient outcomes.

Also, artificial intelligence (AI) and machine learning techniques play a pivotal role in digital health. These technologies have the potential to transform healthcare by leveraging large-scale data to drive predictive modelling, pattern recognition, and decision-making (Hsu et al., 2022). These analytics-driven approaches have the power to augment clinical decision-making and enhance patient care across various healthcare settings. By integrating data from various sources, such as electronic health records, wearables, and patient-reported outcomes, decision analytics can provide a comprehensive view of a patient's health status. Moreover, the use of analytics in digital health also enables continuous monitoring and real-time feedback for patients (Marsch, 2021).

As we discussed, the concept of small data has been around since the advent of the web (Small Data Group, 2013), and many scholars try to leverage analytics-driven feedback to empower patients to participate actively in their self-management. However, there are several challenges, including modelling issues, that arise when implementing and utilising these technological advancements within patient-centric self-management systems.

2.4 Research Issues and Objectives

Digital solutions have shown huge potential in transforming healthcare, particularly in the management of chronic conditions (Seixas et al., 2021; Jiang & Cameron, 2020). However, several issues hinder the development and implementation of these solutions. One challenge lies in the modelling approaches employed in digital health solutions. Many of the existing models focus primarily on prediction (Si et al., 2021), often relying on medical testing-based algorithms that support health professionals' decision-making (Yang et al., 2021; Hsu et al., 2020). While these models play a crucial role in diagnosing and managing diseases, they often overlook the holistic management of chronic conditions. The impact of lifestyle factors, which significantly influence the progression and management of chronic diseases, is not adequately addressed (Moody et al., 2022).

Furthermore, the lack of comprehensive lifestyle factor models makes patients use separate applications to collect and manage data pertaining to different aspects of patients' lifestyles. This fragmented approach creates difficulties in integrating and synthesising data, hindering the development of a unified and holistic view of their health (Hughes et al., 2020). Another notable issue lies in the reliance on historical health databases for analytics modelling. However, chronic condition management can be much more beneficial if real-time data collection and monitoring of dynamic relationships between lifestyle factors and health outcomes. Current analytics models often fail to incorporate real-time data collection, limiting their effectiveness in supporting timely interventions and personalised care.

To provide patient-centric self-management in digital health, developing modelling approaches that embrace lifestyle factors and their interrelationships is essential. This is particularly important for diabetes management as the behaviour and activities of the individual throughout the day result in fluctuations in blood glucose levels. Furthermore, the patient's body reacts to blood glucose regulation dissimilarly at different times, even on the same day (Mathew & Tadi, 2020; Bunescu et al., 2013). Due to these reasons, this research identifies and outlines several research objectives as follows.

- Develop a holistic interrelationship model among lifestyle factors in terms of diabetes cases using causal loop and stock and flow diagrams.
- Implement a prototypical simulation application that can be used with small data to deliver customised self-management information and knowledge to patients.

To achieve these objectives, this paper discusses a methodological approach first. After that, the paper will discuss the developed lifestyle factors models and implemented simulation systems.

3 Methodology

Information systems research often stimulates critical thinking by integrating existing research from different disciplines (Taylor et al., 2010). In line with the objective of addressing the current digital health solutions for chronic management, particularly by unpacking their modelling issues and suggesting sustained development of self-management solutions, the research adopts the Design Science Research (DSR) approach. This approach aims to change and improve the world by building original artefacts, such as concepts, processes, models, frameworks, architectures, and systems (Myers & Venable, 2014). Also, given the interdisciplinary nature of the study environment, this study synthesises Nunamaker et al.'s (1991) multimethodological approach. The four key phases of this research are observation, theory building, systems development, and evaluation.

The initial observation phase involved literature review to gather insights into clinically essential facts and factors related to chronic disease management. This journey helps researchers to understand and build theories of the key elements and their interrelationships. Moreover, while working in the faculty of medicine and health sciences at a leading university in New Zealand, one of the researchers received valuable feedback on the model from clinicians across different specialities. This exploration and evaluation allowed for a deeper understanding of the desired status of chronic condition management. In diabetes, "Glucose Homeostasis" is the central component of management that is closely related to our lifestyle factors such as diet, exercise, sleep, and stress. Therefore, in the theory-building phase, various models were developed, starting from an overarching causal loop diagram (CLD) aiming to capture the intricate connections and dependencies. To delve deeper into the interrelationships between the identified factors, detailed stock and flow diagrams (SFD) were developed.

The systems development phase involved the building and implementation of simulation models that provide a visual representation of how different variables influence each other over time, allowing for a deeper understanding of the dynamics between lifestyle factors and health outcomes. In the evaluation phase, researchers applied simulated outcomes to refine the models and update the interrelationships and basic rules used in the SFD. The modelling software Stella© was utilised.

4 Lifestyle Factor Models

McAfee and Brynjolfsson (2012) said, "You can't manage what you don't measure". This comment could be considered a pillar of quantified-self technologies. While quantified-self technologies have emerged to measure various human activities, the retention rates for these devices and solutions are often low (Khalaf, 2014). To ensure sustainable self-management for chronic conditions, lifestyle factors must be considered and understood in relation to each other and their impact on patients' health. Therefore, this paper proposes the addition of another pillar: "You can't transform what you don't model."

In the context of chronic illness management, understanding the interrelationships and causal effects of patients' lifestyle factors is crucial. However, it is hard to find models representing the relationships among these lifestyle factors for system development as they are understudied and underdeveloped. To show these interrelationships and propose an implementable model for systems, the paper utilises CLD and SFD created using Stella®. In the following sub-sections, the paper discusses the steps of CLD and SFD development.

4.1 Overall Lifestyle Factor Model

There is no single cause of type 2 diabetes, but evidence suggests that obesity is highly associated with insulin resistance (Kahn et al., 2006), and there is a range of contributing elements, including genetic and lifestyle risk factors (Farmer et al., 2004). Therefore, the model's focus is to create a clear picture of how lifestyle changes can result in different diabetes health outcomes. For this purpose, the relationship between blood glucose homeostasis and obesity is constructed in the model by using the components of our major lifestyle factors: diet (Lim et al., 2011; Zeevi et al., 2015), exercise (Colberg et al., 2010), rest (sleep) (Mesarwi et al., 2013), and stress (American Diabetes Association, 2013). The model (Figure 1) was constructed step by step, starting with glucose homeostasis.

4.1.1 Glucose Homeostasis

A CLD is given in Figure 1 to demonstrate how an equilibrated blood glucose level is maintained in the human body. The amount of glucose in the blood varies with food intake and glycogen breakdown from the liver, and depending on insulin secretion and glucagon release, the blood glucose can be kept at its baseline level (Dagoberto et al., 2013).

When we consume food, it is converted into glucose and released into the bloodstream. Increased blood glucose levels stimulate beta-cell groups in the pancreas to secrete insulin, which lowers blood glucose levels by converting glucose into glycogen stored in the liver and combining it with glucose absorbed by body cells. Insulin sensitivity and beta-cell insulin response are crucial for this homeostasis mechanism. Conversely, when blood glucose levels drop, alpha cells in the pancreas secrete glucagon, prompting the liver to break down glycogen into glucose and release it into the bloodstream (Levinson et al., 2011). In type 2 diabetes, glucose cannot be used by the body cells due to impaired insulin sensitivity, leading to beta-cell dysfunction and inadequate insulin secretion over time (Fu, Gilbert, & Liu, 2013).

4.1.2 Lifestyle Effects

According to the American Diabetes Association (2018), nutrition therapy (diet), physical activity (exercise), smoking cessation, and psychological care (stress) are the fundamental self-management aspects of diabetes care. This paper expands the model by including sleep, as a growing body of literature shows a link between sleep disorder and type 2 diabetes incidents (Mesarwi et al., 2013).

Unhealthy diets can increase the risk of developing insulin resistance and type 2 diabetes (Kahn et al., 2006). Therefore, the body weight dynamics were included in this model, and it can be explained by the energy balance mechanism. For example, when there is a surplus in energy balance, our body stores the excess energy in the fat depot; thus, it is positively related to obesity and vice versa.

With time, exercise contributes to increasing muscle mass, which reduces the risk of obesity. Also, to capture the individual's eating habits, eating time, food quantity, and food type (GI) are added as variables. Exercise improves insulin action, increases muscle mass, and lowers blood glucose. Therefore, the model represents them by connecting exercise to muscle mass and glucose used by cells. It is also connected to stress levels and sleep quality. Various research has conclusively shown that exercise releases hormones and signalling molecules to improve psychological health and sleep quality (Harvard Medical School, 2011).

Stress reactions are designed to deal with short-term danger; however, if they continue, they can cause long-term high blood glucose levels (American Diabetes Association, 2013). Sleep quality is another lifestyle factor that is determined by sleep duration, time, and continuity. Therefore, these elements were added as variables to the model.

Lastly, Common type 2 diabetes symptoms, such as hunger, fatigue, frequent urination, and pain in the hands and feet, create a cycle affecting lifestyle factors (American Diabetes Association, 2015). These symptoms often make patients create a vicious cycle in their lifestyles. For example, increased food intake leads to frequent urination, reduced sleep quality, increased stress levels, and decreased insulin sensitivity.

Learning the interrelationships between glucose levels and lifestyle effects helps individuals manage their health. Based on these models, the research developed SFDs, as explained in the following section.

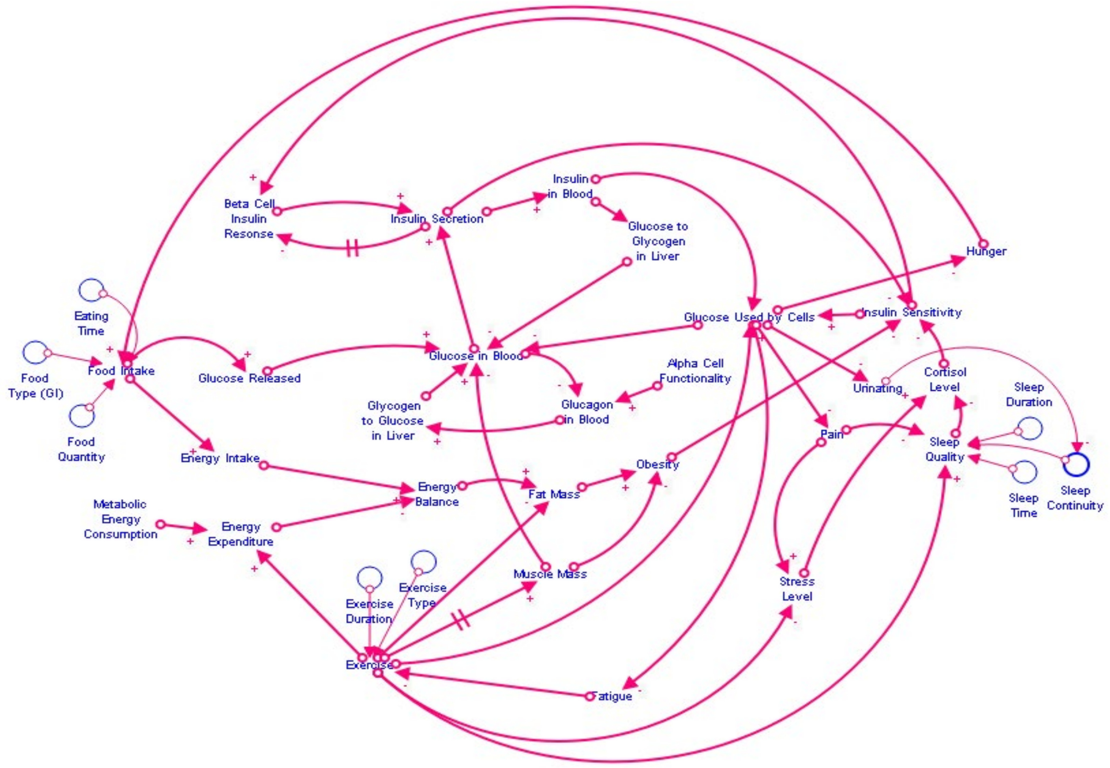

Figure 1 Lifestyle Factors Model.

4.2 Detailed Lifestyle Factor Models

From the CLD, the research findings highlight insulin sensitivity as a crucial factor in managing type 2 diabetes. However, knowing the complex relationship between insulin sensitivity and glucose level can be overwhelming to non-experts. To enhance comprehension, this research has adopted the divide-and-conquer rule. We first develop two simple models (Figure 2 and Figure 3) that show the inflow and outflow of glucose. We then develop a model (Figure 4) that integrates these two simple models and shows the current state of glucose levels. This representation helps patients understand how the inflow and outflow of glucose contribute to the current state of glucose levels in the bloodstream.

4.2.1 Inflow and outflow of glucose

The inflow model is constructed based on food intake, where the carbohydrates consumed in each meal are quantified and represented as glucose levels (Figure 2). As our body utilises glucose as energy for its cells, glucose levels naturally decrease. Glucose absorption varies from one person to another, and it may even be influenced by various lifestyle factors. In addition to this natural phenomenon, lifestyle factors can affect the outflow of glucose.

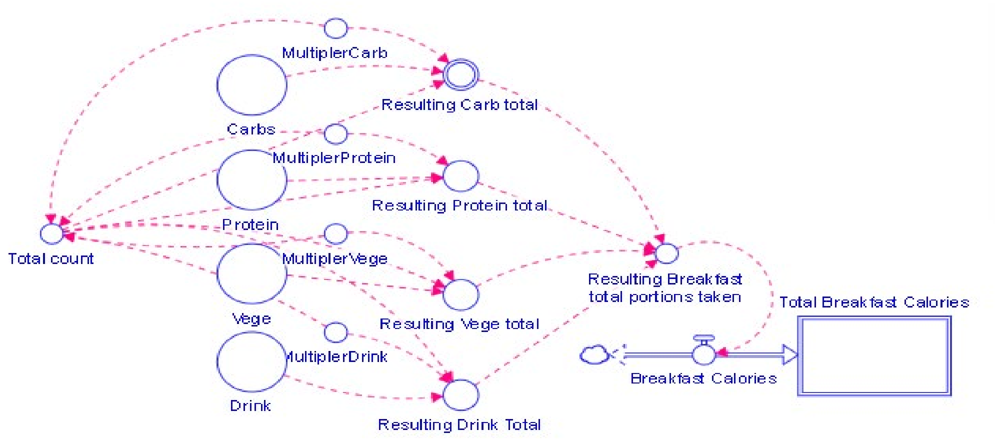

Figure 2 Inflow of Glucose

Insulin sensitivity plays a significant role in balancing glucose levels in the bloodstream and ensuring sufficient energy utilisation by body cells. Therefore, the outflow model (Figure 3) is constructed around insulin sensitivity. When it is at a good rate, glucose in the bloodstream is balanced, and body cells get enough energy by using glucose.

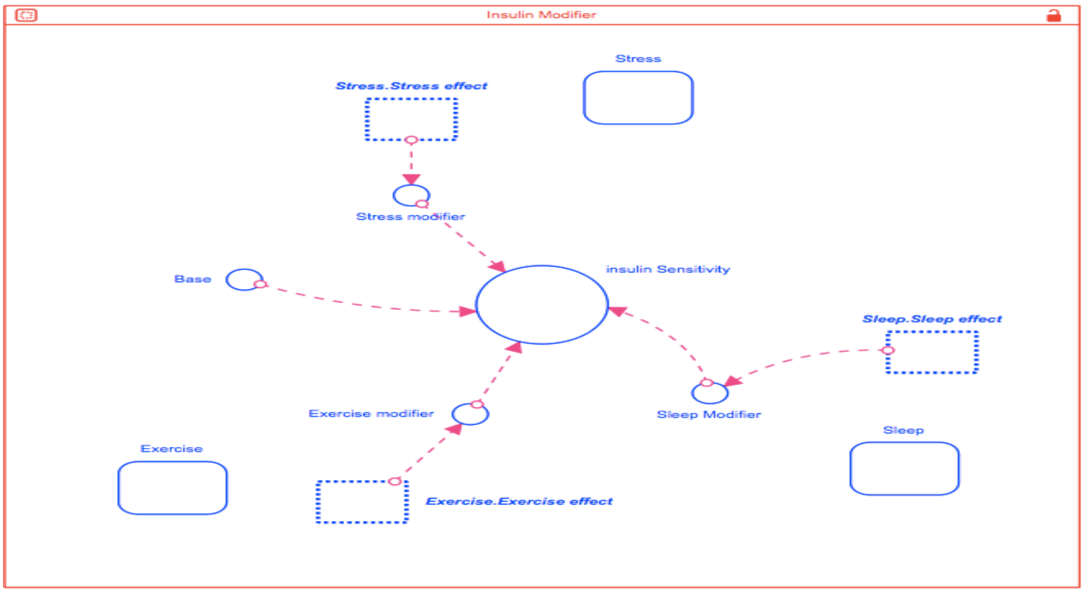

Figure 3 Outflow of Glucose

As highlighted in section 4.1 and Figure 1, lifestyle factors have a direct impact on insulin sensitivity. To simulate the effects of these factors, additive, and subtractive multipliers are employed. When lifestyle factors are within a favourable range, insulin sensitivity increases, resulting in balanced glucose levels. Conversely, if lifestyle factors are unfavourable, insulin sensitivity decreases, leading to elevated glucose levels. For example, when the patient experiences an awful, stressful event, insulin sensitivity decreases, so the glucose level status is high. Or, when the patient has done a reasonable amount and intensity of exercise, the insulin sensitivity increases to reduce the glucose level in the bloodstream.

4.2.2 Current State of Glucose Levels

The current state of glucose levels is a vital aspect of this research, integrating the previously mentioned inflow and outflow models to provide a comprehensive understanding of glucose levels (Figure 4). Monitoring the current state of glucose levels is crucial as persistent high glucose levels can lead to various detrimental health outcomes (Zeevi et al., 2015). To further illustrate the impact, simulated outcomes will be presented in the subsequent section, showcasing different scenarios and their corresponding effects on glucose levels.

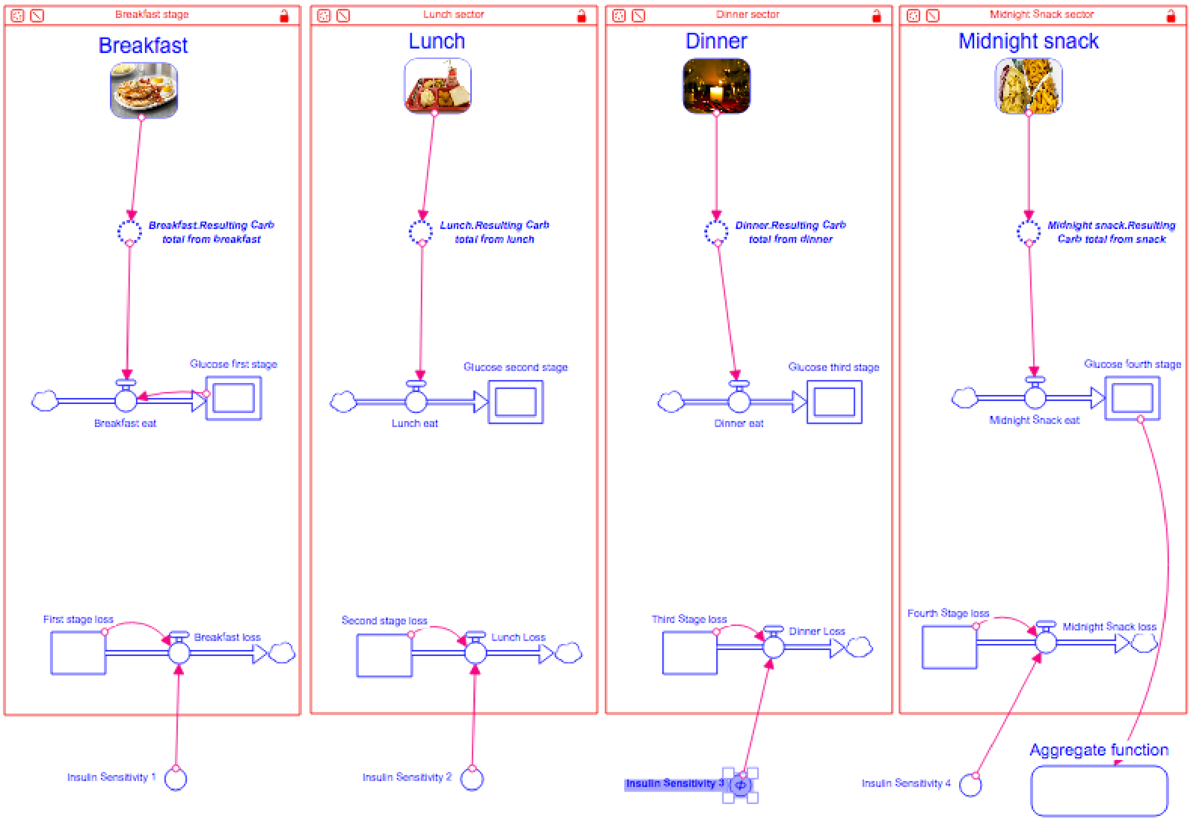

Figure 4 Current State of Glucose Levels

5 Lifestyle Factors Simulation Prototype

The modelling of holistic interrelationships among lifestyle factors serves to enhance our understanding of how specific behaviours and factors impact our lives. However, current information systems often lack comprehensive lifestyle factor models and their individual-level relationships. Additionally, simulations are rare within these systems.

To address these limitations, this research employs system dynamics modelling to delve deeper into the relationships between lifestyle factors. We implemented a lifestyle factor simulations prototype that enables patients to simulate various scenarios. The modelling process in the prototype consists of two simulation phases: the first phase explores the effects of diet, while the second phase examines the impact of sleep, stress, and exercise on insulin sensitivity in type 2 diabetes patients. It is important to note that genetic factors have been excluded from this simulation, as the focus is on comprehending the holistic connections between chronic disease and daily lifestyles.

5.1 Diet Effects

Modelling incorporates collected data and knowledge from various sources (Zeevi et al., 2015 ; American Diabetes Association, 2013; Mesarwi et al., 2013; Lim et al., 2011; Colberg et al., 2010) to enable simulations. In this implementation, data and knowledge are input for simulations. However, future systems could use small data to identify unique lifestyle patterns and individual coefficients for each factor. The data fields in Figure 5 show portion or calorie amounts of nutrients for a meal. The portion of nutrients follows the diabetes plate method that helps control blood glucose levels, the simulation uses 12 dividing portions for calculation. For example, the ideal formula for this simulation can present six dividing portions of non-starchy vegetables, three dividing portions of protein, and three dividing portions of starchy vegetables or carbohydrate-containing food. Then, the patient can input calories for each nutrient. Caloric values for each nutrient can be imported from other devices or easily edited by the patient.

Another factor is "Insulin Sensitivity", which determines the body cells' natural glucose utilisation. Insulin Sensitivity is a critical coefficient that can be discovered and calculated from small data collections. Higher sensitivity means greater glucose usage by body cells, typically observed in healthier people (Kahn et al., 2006). Once all values and variables are entered, the patient can view the amount of glucose in the bloodstream. The simulation result is shown in both graph and table format (Figure 5). The graph depicts the conversion of carbohydrates into glucose over time, illustrating the transformation of dietary carbohydrates into glucose following each meal. This helps the patient to understand 1) how adjusting carbohydrate, protein, fat, and beverage consumption can lower glucose inflow into the bloodstream, and 2) the impact of insulin sensitivity on reducing blood glucose levels.

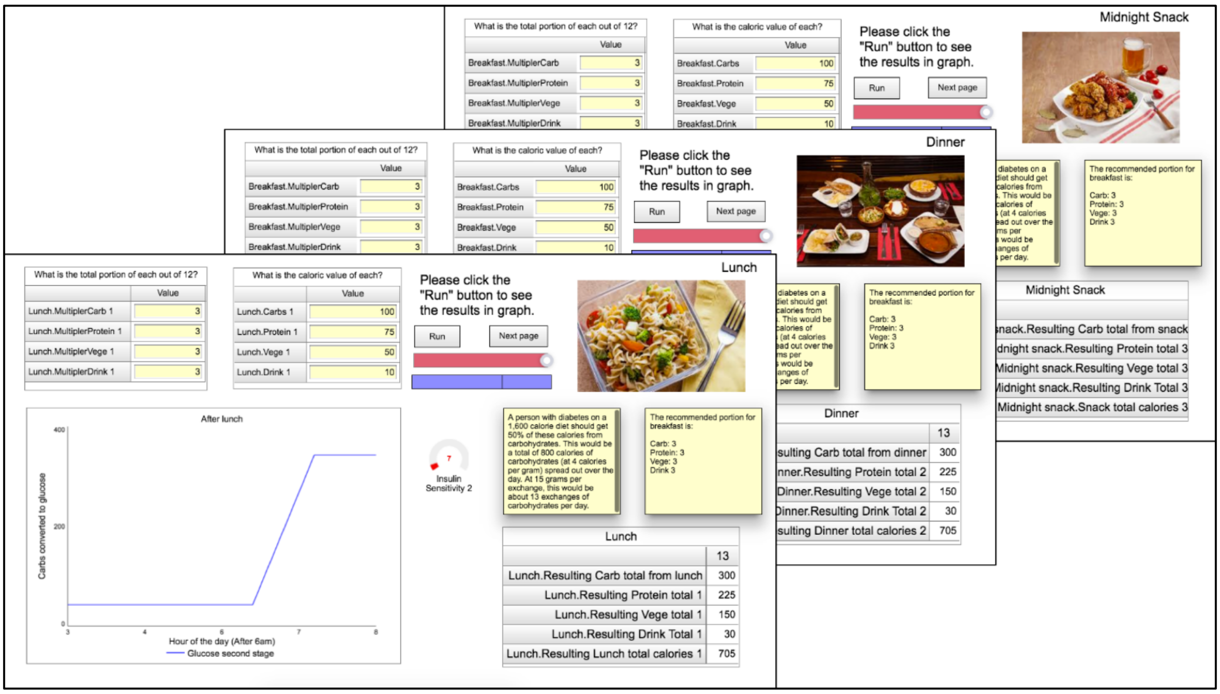

Figure 5 Diet Effects

5.2 Lifestyle Effects

Modelling tries to visualise how daily activities make different health outcomes regarding glucose levels. The chosen activities are exercise, sleep, and stress level. Modelling educates the holistic interrelationships and causal relationships among various activities and factors in people's lifestyles. This simulation is for educating individuals and families, especially diabetic patients, and helping them find out the optimal level of sleep and exercise as well as manage stress. Therefore, based on the patient's sleep, exercise, and stress level input, the simulation shows how the glucose level changes. For example, if the patient's sleep quality and duration are within the suggested optimal range, the glucose level gets lower, and the graph shows its effect on the patient (Figure 6). The patient can simulate the effect of exercise and stress levels similarly. These simulations have been built based on the aforementioned CLDs and SFDs.

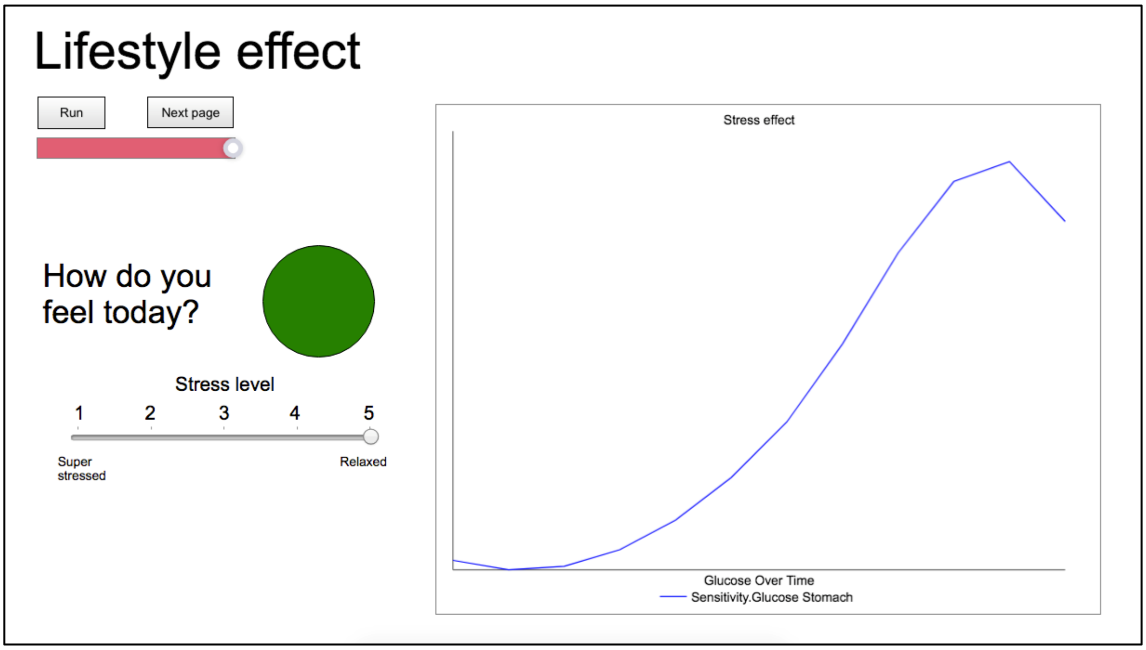

Figure 6 Lifestyle Effects

6 Discussion and Conclusion

The objective of this study was to address the challenge of underdeveloped modelling approaches in chronic health management, particularly in relation to the lack of relationship models between chronic conditions and lifestyle impacts. Therefore, the research has chosen system dynamics and simulations for representing the holistic interrelationships among factors, as system dynamics modelling approaches are suitable for understanding nonlinear problems characterised by interdependence, feedback loops, and causality (Richardson, 2013).

By focusing on type 2 diabetes, this research aimed to build models that would facilitate effective disease management. Broad literature investigation revealed that prior studies primarily focused on the relationship between individual lifestyle factors and the disease, without considering a holistic perspective. This study sought to bridge these gaps by constructing a comprehensive CLD that integrated various lifestyle factors and core health concerns, including diet, exercise, sleep, stress, and glucose homeostasis. To understand the impacts of these lifestyle factors on the disease, specific SFDs were developed.

The simulation based on these models provided patients with an understanding of the effects of their diet and lifestyle. By observing the simulated results, patients could grasp the impact of different lifestyle factors on the disease management process. Although the models and simulations were developed using the diabetic case, the findings suggest that the structure of these models can be applied as a framework to manage other chronic conditions as well.

Moreover, the creation and application of such models establish a basis for crafting patient-centric self-management solutions. Through the utilisation of this framework, personalised interventions and strategies can be devised for individuals dealing with various chronic conditions, enhancing the efficiency of self-management. This is particularly relevant as many chronic conditions are influenced by a combination of lifestyle factors and medications. Also, by utilising small data collected from various devices, the proposed models can analyse individual profiles and comprehend the patient's lifestyle and interrelationships. The patient-centric self-management system based on these models can expand to incorporate prediction, recommendation, and sustainable transformation models to generate insightful information from the measured and collected data. Various solvers, such as data mining, recommendation algorithms, system dynamics, and mathematical equations, are utilised to analyse the data. Additionally, knowledge derived from research findings, heuristics, rules, and collective social knowledge in the systems can relate to the models to enhance patients' understanding of their lifestyles and diseases.

This study uniquely contributes to the field of Chronic Diseases Self-Management. Through these models and modelling systems, real-time and real-world data (small data) can be modelled precisely to show holistic relationships among lifestyle factors (Richardson, 2013). Therefore, people can see the causal effect of relationships in their lives and be able to identify root issues. Furthermore, the links shown in models often persuade people to adopt new lifestyles for their sustainable lifestyles.

Current prototypes are implemented with only core system functionalities to validate concepts, processes, models, and frameworks that the research has proposed. The researchers plan on implementing a fully functioning patient-centric diabetes management system that uses small data. Finally, we hope the research can be an impetus for making human lives well, happy, and sustainable.

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