MOBILE HEALTH APPLICATION FOR PROACTIVE SELF-MANAGEMENT: A CASE STUDY OF HYPERTENSIVE DIABETIC PATIENTS IN THAILAND

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ABSTRACT

This study addresses the global health issues associated with diabetes and hypertension, two widespread chronic conditions. Conducted in Chiang Rai, Thailand, the study investigates the effectiveness of a mobile application designed to support self-management among patients with both hypertension and diabetes. The mobile application enables users to track their personal and clinical data while receiving individualized health recommendations. These recommendations are based on the user's health trend and level of engagement. To identify health condition trends categorized as positive, negative, or neutral, agent-based methods were utilized. Personalized recommendations were generated using association rules that assess each patient’s engagement level. The application was evaluated for both effectiveness and user satisfaction among healthcare professionals and patients in Thailand. Results from the evaluation indicated a moderately high level of effectiveness and satisfaction, with a 78% success rate and an average user rating of 4.18 out of 5.

Keywords: Hypertension, Diabetes, Mobile Application, Patient Modeling, Self-Management, Association Rule

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INTRODUCTION

1.1 Introduction

Non-communicable diseases (NCDs) are prevalent chronic conditions that pose significant health challenges on a global scale. World Health Organization (WHO) reports that NCDs are responsible for nearly 74% of all deaths worldwide, underscoring their immense impact on health systems (1). The increasing incidence of these diseases is strongly linked to modifiable behaviors such as unhealthy eating habits, sedentary lifestyles, tobacco consumption, and excessive alcohol intake. In addition, environmental influences, particularly air pollution, have further intensified the NCD burden (2). Therefore, addressing these risk factors is critical to both the prevention and control of NCDs, promoting better health outcomes for populations (3, 4). Within the broader spectrum of NCDs, diabetes and hypertension are particularly prominent. Type 2 diabetes mellitus (T2DM), for instance, has been on the rise, currently affecting approximately 38.4 million individuals in the United States, which equates to 11.6% of the population (5). Compounding this issue, a significant proportion (73.6%) of adults with diabetes aged 18 and older also suffer from hypertension (6).

Diabetes results from either insufficient insulin production or the body's inability to effectively utilize insulin, causing elevated levels of blood glucose. The condition is closely linked to a higher risk of developing cardiovascular diseases, strokes, retinopathy, and kidney complications. Globally, diabetes is estimated to be responsible for around 1.5 million deaths, nearly half of which occur before the age of 70. It is also implicated in approximately 460,000 deaths related to kidney failure and accounts for about 20% of all deaths caused by cardiovascular conditions (7).

In the context of Thailand, diabetes affects 9.5% of individuals aged 15 years and older. The condition is most prevalent among women aged 70–79 (24.6%) and men aged 60–69 (18.6%). Regionally, the highest prevalence is found in Bangkok (12.5%), followed by central (10.6%), northeastern (9.5%), northern (8.9%), and southern regions (6.5%) of the country. Regarding diagnosis, 30.6% of individuals had not been previously diagnosed, 13.9% were diagnosed but awaiting treatment, 29.3% were undergoing treatment without effective outcomes, and 26.3% had their condition under control (8).

Hypertension is a condition characterized by increased pressure exerted against the walls of blood vessels. When left uncontrolled, it significantly raises the risk of developing serious health issues, including kidney disease, cardiovascular conditions, and stroke (9, 10). In Thailand, 25.4% of individuals aged 15 and above are affected by hypertension. The highest incidence is observed in those aged 80 years and older, with a prevalence rate of 76.8%. Regionally, central Thailand reports the highest rate (27.5%), closely followed by the northern region (27.4%), Bangkok (27.2%), northeastern Thailand (24.3%), and the southern region (21.0%). Regarding diagnostic status, 57.0% of individuals had not been previously diagnosed, 4.1% had been diagnosed but were still awaiting treatment, 22.0% were on medication but had not achieved effective control, and only 16.9% had successfully managed their condition (10).

1.1.1 Problem Identification

Globally, diabetes and hypertension represent a substantial and growing health (11, 13, 14). The prevalence of type 2 diabetes is predicted to rise from 415 million cases to 642 million by 2040 (11). Similarly, hypertension is even more common, with a recent worldwide estimate of 1.39 billion cases (11, 14). In Thailand, noncommunicable diseases (NCDs), including diabetes and cardiovascular diseases (where hypertension is a major risk factor), are the leading cause of mortality, accounting for 74% of all deaths (15). Specifically, the prevalence of diabetes in Thailand among people aged ≥ 15 years was 9.5% in 2021, a significant increase from 6.9% in 2009 (15) While hypertension prevalence in Thailand has remained high, around 25% of adults, over the past 15 years, awareness and control have fluctuated (15 -17). The coexistence of diabetes and hypertension is a particularly concerning clinical scenario due to their intertwined nature and compounded effects on cardiovascular health (12, 14) Hypertension is twice as frequent in patients with diabetes compared to those without (11, 14). Both conditions share similar risk factors such as obesity, endothelial dysfunction, vascular inflammation, and oxidative stress, suggesting a significant interplay (11, 12). The presence of either condition doubles the risk of developing the other (16). For example, insulin resistance and hyperglycemia in diabetes can worsen blood pressure control, while elevated blood pressure exacerbates diabetic complications (12). This synergistic effect accelerates atherosclerosis and significantly increases the risk of cardiovascular events, renal dysfunction, retinopathy, and other micro- and macrovascular complications (12, 14).

Thailand has a strong commitment to universal health coverage, which includes free hypertension treatment at the primary care level (11, 15) This system has contributed to early improvements in hypertension awareness and control (17). The country has also implemented various policies to tackle NCDs, such as increasing taxes on health-harming products and plain packaging for tobacco (15) Furthermore, the Thai government has shown concern about the rising prevalence of diabetes and obesity, implementing tiered excise tax rates on sugar-sweetened beverages and considering similar taxes on salt (15). Despite these efforts and universal health coverage, hypertension awareness has not consistently improved, and blood pressure control has even decreased in recent years (17). There is a recognized need to improve diagnosis and management, potentially through strategies like community-based screening, better adherence to treatment guidelines, and collaboration with the private sector (17). While the sources discuss the burden and healthcare access extensively, specific details on the widespread use and impact of advanced technologies like continuous glucose monitoring for diabetes management in Thailand are less prominent, though mHealth initiatives and their potential are mentioned (18). The focus remains on strengthening primary care, improving screening, and ensuring adherence to existing treatment protocols within the framework of the universal healthcare system (17).

Diabetes and hypertension have long been major contributors to both illness and death across populations. Their frequent co-occurrence is not by chance, but rather a reflection of cardiometabolic syndrome—a condition marked by the presence of multiple cardiovascular disease (CVD) risk factors, including type 2 diabetes mellitus (T2DM), high blood pressure, abnormal lipid levels, abdominal obesity, and chronic kidney disease (6). The complexity of managing these two conditions stems from the serious health complications they can cause, which can severely diminish quality of life. Globally, the increasing prevalence of obesity and physical inactivity has further exacerbated the burden of diabetes and hypertension, resulting in escalating healthcare expenditures and emerging as a critical public health challenge. As such, comprehensive and effective management strategies are essential to reduce the likelihood of adverse outcomes and the associated long-term healthcare costs.

1.1.2 The Conceptual Idea of the Solution

Modern innovations such as mobile applications, artificial intelligence, and widespread internet access, offer substantial opportunities to enhance remote communication and improve accessibility to healthcare services. Particularly, mobile health applications have shown promise in supporting individuals managing non-communicable diseases (NCDs), enabling them to monitor and regulate their health more effectively, ultimately leading to better quality of life. However, despite the growing development of mobile health tools for NCD care, there remains a notable gap in addressing the specific needs of individuals who suffer from both diabetes and hypertension.

With progress in medical treatments, many patients remain vulnerable to complications from NCDs due to inadequate self-management. Empowering individuals to manage their health independently is essential throughout the disease journey. Self-management is widely regarded as a vital component in maintaining quality of life and improving clinical outcomes in NCD care. It requires active participation in activities such as problem-solving, making informed decisions, using available resources, and communicating effectively with healthcare providers—all of which are essential to appropriate disease management (19, 12). This also includes behavior change strategies, ongoing self-monitoring, and evaluating how well those strategies influence desired outcomes. Yet, fostering these capabilities in patients can be difficult, especially due to limitations in health literacy. Nevertheless, mobile health applications have been identified as a practical and cost-efficient approach for encouraging self-management behaviors (21).

With the availability of affordable health monitoring tools, advanced smartphones, and internet connectivity, portable systems to support patient self-care are increasingly feasible. Still, the key lies in designing a model that delivers care efficiently, is user-friendly, and adaptable to mobile platforms. This study centers on developing a personalized model specifically tailored for individuals living with both hypertension and diabetes. By offering such a model through a mobile application offers a practical solution, ensuring timely and accessible health guidance without the need for frequent hospital visits. The subsequent aim of this study is to integrate the model into a mobile platform and assess user satisfaction with its implementation.

1.2 Research Objective

The primary intention of choosing this topic is to assess the effectiveness of a mobile appplication in managing hypertension and diabetes among hypertensive diabetic patients in Chiang Rai, Thailand. Specifically, the study aims to evaluate the impact of the mobile application on blood pressure and blood sugar control, medication adherence, and overall quality of life for the patients. By examining the effectiveness of the mobile application and identifying its beneficial features, the research seeks to contribute to the development of effective digital interventions for managing hypertension and diabetes in Thailand, ultimately improving health outcomes and reducing the burden on the healthcare system.

1.3 Scope of Study

This study aims to evaluate the effectiveness of a mobile application in managing hypertension and diabetes among hypertensive diabetic patients in Chiang Rai, Thailand. The focus will be on assessing the impact of the mobile application on blood pressure and blood sugar control, medication adherence, and quality of life indicators. The study will specifically target a sample population of hypertensive diabetic patients in Chiang Rai and examine the features of the mobile application that are most beneficial for managing these conditions.

1.3.1 Overview of Methodology

The methodology for this study involves several steps. First, a sample population of hypertensive diabetic patients in Chiang Rai will be selected. Then, a mobile application will be developed, which includes features for tracking blood pressure, blood sugar levels, and medication adherence. Participants will be asked to use the mobile application to record their blood pressure readings, blood sugar levels, medication adherence, and self-reported quality of life indicators. The collected data will be analyzed and statistically analyzed to evaluate the effectiveness of the mobile application and identify any relationships between variables.

1.3.2 The Initial Idea of Targeted Data and Collection Method

The targeted data for this study includes blood pressure readings, blood sugar levels, medication adherence, and self-reported quality of life indicators. Participants will be required to record their blood pressure readings and blood sugar levels using the mobile application, either by self-reporting or by integrating the mobile application with compatible devices for accurate measurements. Medication adherence will be tracked through the mobile application's reminder system and participants' self-reported medication usage. Additionally, participants will provide self-reported information on their quality-of-life indicators within the mobile application. Data collection will rely on participants' active engagement with the mobile application and regular follow-ups from the research team to ensure compliance and accurate data entry. Collected data is put into association rule mining software to calculate the patient model that can be utilized within the mobile application.

CHAPTER 2

LITERATURE REVIEW

2.1 Theoretical Background

In this section, all works related to this thesis are presented. The first part brings up the topics that are being utilized within the research. The second part focuses on methods and technologies for implementing the mobile application. The last section discusses the use of technology and potential methods of developing mobile applications.

2.1.1 Association Rule

Association rules are a data mining technique used to discover patterns of items that frequently occur together within a dataset. These relationships are typically expressed as "if-then" rules, making them highly adaptable for integration into mobile applications. In commercial contexts, association rule mining is widely used in market basket analysis to detect common product pairings. For instance, identifying that customers who purchase ice cream often buy chocolate syrup as well (41). Algorithms such as Apriori and FP-Growth are commonly applied for this purpose, each offering different trade-offs in terms of speed, accuracy, and computational efficiency, thereby supporting model optimization (41). In constructing these rules, three key metrics are utilized: support, confidence, and lift.

Support measures the frequency with which a specific combination of items appears in the dataset. A higher support value indicates that the itemset occurs more frequently. This metric is calculated using Equation (2.1).

$$s(\{x\} \rightarrow \{y\}) = \frac{r(\{x\},\{y\})}{t} \qquad (2.1)$$

, x represents the antecedent, an item that appears earlier in the dataset record, while y denotes the consequent—another item that appears subsequently within the same record. The support value (s) indicates how frequently both **x** and **y** occur together in the dataset. The term r({x},{y}) refers to the number of records containing both items, and t is the total number of records in the dataset.

The confidence value reflects the likelihood that item y will appear in a record given the presence of item x. A higher confidence score suggests a stronger association between the antecedent and consequent, implying that the occurrence of x increases the probability of y appearing in the same entry. This measure is calculated using Equation (2.2).

$$c(\{x\} \rightarrow \{y\}) = \frac{r(\{x\},\{y\})}{r\{x\}} \qquad (2.2)$$

, x represents the antecedent, an individual item present in the record—while y is the consequent, another distinct item that follows in the same record. The confidence value (c) measures the probability that y appears when x is present. Here, r({x},{y}) denotes the number of records containing both x and y, and r{x} indicates the number of records that contain only x in the dataset.

The lift value is a ratio that evaluates the strength of the association between x and y. A lift value greater than 1 implies a positive association, meaning the presence of x increases the likelihood of y occurring. Conversely, a lift value less than 1 indicates a negative association, where the occurrence of x reduces the likelihood of y. This metric is computed using Equation (2.3)

$$l(\{x\} \rightarrow \{y\}) = \frac{c(\{x\} \rightarrow \{y\})}{s\{y\}} \qquad (2.3)$$

, x represents the antecedent item, an element that appears in the record and y represents the consequent item, a different element that follows within the same record. The lift value (l) measures the strength of the association between x and y, where c({x}→{y}) is the confidence score indicating the likelihood of y occurring with x, and s{y} refers to the support value for records containing only y.

These metrics, support, confidence, and lift, play a critical role in assessing the strength and relevance of association rules. Rules that exhibit low support or confidence values may be excluded from the final model, as they may not meet the predefined thresholds for statistical significance or practical applicability.

In healthcare, association rules have proven valuable in identifying patterns within medical data. For example, research in (42) demonstrated how this method can be applied to medical records to detect frequently co-occurring diseases. One study applied it to analyze symptom clusters related to COVID-19 (43), while another leveraged protein groupings to identify early indicators of breast cancer (44). Similarly, (45) used association rules to uncover links between specific health issues and treatments, such as the association between diabetes and insulin use, achieving a reasonable level of accuracy. In a separate investigation, (46) applied the technique to numeric data ranges, such as age, blood glucose levels, and body mass index (BMI) to format the data for rule generation. In this study, association rules were instrumental in refining the system for delivering personalized health recommendations.

Association rule mining has emerged as a valuable data mining technique in healthcare, offering the potential to uncover meaningful relationships between diseases and health conditions. This approach can reveal hidden patterns and associations within large datasets of patient information, leading to improved disease prediction, enhanced patient care, and more efficient resource allocation (47). For instance, one study applied the FP-Growth algorithm followed by association rule mining to patient visit data from a hospital coded with ICD-10, successfully identifying association between chronic conditions such as hypertension and diabetes (47). Similarly, another study (48) utilized cluster analysis in combination with association rule mining to explore patterns of multimorbidity and disease associations in hospitalized older patients, demonstrating that disease associations can vary depending on the patients' functional status. These techniques, by leveraging patient data including diagnosis codes, can assist healthcare providers in understanding potential comorbidities, improving diagnostic accuracy, and tailoring treatment effectiveness, thus contributing to the broader goal of personalized patient care (47, 48). The integration of association rule mining with robust classification systems like ICD-10 allows for a data-driven approach to enhance the efficacy and efficiency of healthcare services.

2.1.2 Patient Modeling

Patient modeling, also known as patient classification, involves grouping individuals based on shared characteristics or medical conditions to streamline resource allocation and support treatment planning (22). This approach plays a vital role in aligning healthcare services with the specific needs of each patient. Although it may not directly impact the clinical quality of care, patient classification contributes to the operational efficiency of healthcare systems and can enhance long-term care delivery. Currently, patient modeling is widely used to collect and interpret behavioral data, providing deeper insight into patient preferences and supporting more informed decision-making. One of its key benefits is identifying individuals who may be at risk of deviating from their treatment regimens. This insight allows for the development of targeted strategies to support adherence and improve health outcomes (23, 24). To understand patient behavior and traits, various techniques can be employed, including surveys, interviews, direct observation, or the use of tracking technologies operated by professionals (25). In the healthcare field, patient modeling is frequently applied to generate personalized profiles or simulations of patients' medical attributes, aiding clinicians throughout the diagnostic and treatment planning process (26). Both data-centric and knowledge-based methodologies are commonly adopted, utilizing approaches such as agent-based modeling (27–30) and fuzzy logic systems (31–33).

When modeling patients with hypertension, several approaches, particularly machine learning (ML) techniques, are commonly employed (34). These include decision trees, naive Bayes classifiers, artificial neural networks, and logistic regression models. A notable method is the use of modular agent-based models that incorporate the pharmacodynamic effects of antihypertensive drugs to simulate individualized treatment responses, thus supporting precision medicine efforts (35). These modeling strategies have demonstrated strong potential in forecasting hypertension-related outcomes and informing effective interventions. Similarly, ML techniques are extensively being applied in the modeling of diabetes patients. Algorithms such as logistic regression, random forest, and support vector machines have proven effective in analyzing patient histories and real-time data to guide diagnosis and treatment planning (36). These models not only support clinical decision-making but also offer high predictive accuracy, underscoring their reliability in managing diabetic patient care (37).

Advanced patient-modelling techniques are increasingly leveraging the intersection of medicine and engineering, particularly through artificial intelligence (AI), to enhance chronic disease management and pave the way for precision medicine (38, 39). These techniques involve creating virtual replicas of patients, organs, or biological systems, often referred to as digital twins (DTs) or digital human twins (DHTs), which contain multidimensional and patient-specific information (40). AI algorithms analyze extensive historical datasets from clinical trials, real-world sources, and real-time data from sources like wearable devices. This allows for the generation of comprehensive predictions of future health outcomes, potential diagnoses, disease progression, and treatment responses for individual patients (38). These models integrate various data types, including medical imaging, clinical notes, laboratory results, and wearable device data, to simulate complex interactions between genetic and environmental factors (39, 40). The aim of these advanced modelling techniques is to provide a deeper understanding of disease, personalize treatment plans, predict treatment efficacy, and ultimately improve patient outcomes in a more precise and individualized manner (39).

As modern computing power continues to advance, machine learning (ML)-based approaches have become particularly effective for handling large-scale datasets. On the other hand, knowledge-based systems are more suitable when data availability is limited or computational resources are constrained. In this context, the current study adopts a knowledge-based approach within a mobile health application framework. Specifically, the patient modeling system was constructed using the clinical experience and insights of healthcare professionals, integrating newly introduced elements such as condition progression trends and patient engagement levels to generate individualized health recommendations.

2.1.3 Mobile Health (mHealth)

Current mobile health (mHealth) applications serve a wide range of functions, such as monitoring symptoms (49), tracking daily physical activities, supporting mental health, delivering educational content on various health topics, and facilitating telemedicine services (50). These tools are generally accessible to the public, provided users have regular access to smartphones (50). One of the key benefits of mHealth solutions lies in their affordability and enhanced accessibility, made possible by the portability and computing power of modern smartphones, offering significantly greater functionality than older feature phones with limited capabilities (51). In the context of non-communicable disease (NCD) management, mHealth apps hold considerable promise by empowering patients to engage in self-care and take a more active role in managing their health. This involves helping users establish health goals, maintain regular follow-ups, and participate in decisions concerning treatment and lifestyle adjustments, guided by insights derived from data-informed recommendations (2).

Existing self-management approaches for chronic conditions face several limitations. One key challenge is that many interventions primarily emphasize self-management without direct human involvement (64). While health professional assistance is essential for managing chronic conditions, mHealth can fill gaps between consultations, but its effectiveness, especially when combined with professional interventions, requires investigation (64). Furthermore, socioeconomic issues create significant barriers to self-management of conditions like diabetes, including healthcare costs, the financial costs of healthy eating, and living in deprived areas (65). Low health literacy also hinders the ability of patients to effectively self-manage, impacting their understanding of medical information (65, 66). Moreover, the concept of self-management itself can be poorly understood and applied (67). Several reviews indicate that current approaches to self-management support often suffer from the absence of standardized metrics and reliable tools for assessing outcomes at the individual level. Additionally, the lack of integration of patient-reported outcomes into platforms that provide patients with access to their health data represents a missed opportunity to enhance user engagement and promote broader utilization (68).

Patient engagement with health data and self-management is influenced by a multitude of factors spanning social, personal, technological, and systemic domains. Patient ability factors such as awareness of access tools, education and literacy levels, health literacy, digital skills, and language proficiency significantly impact engagement (66, 69). Patient motivation factors, including their attitude towards using mHealth, perceived usefulness, and desire to maintain good health, also play a crucial role (70). Conversely, having an underlying disease can sometimes decrease the intention to use mHealth, indicating a need for tailored applications (70). Technological factors, such as the usability and accessibility of digital platforms and mobile applications, are critical (66, 70). For instance, the availability of equipment and education on its use can reduce inequity (70). Healthcare professionals' attitudes and skills in supporting patient access and use of their data are also important. Ultimately, policies aimed at improving patient access to health data must be complemented by efforts to equip the public with the skills and knowledge required to effectively engage with this information (66). Involving patients in the design of data access systems is recognized as a key enabler, underscoring the importance of tailoring these environments to align with the diverse needs and preferences of various patient populations (66).

The long-term effectiveness and usability of mHealth interventions are areas of ongoing investigation. While mHealth combined with health professional-led interventions show short- and medium-term benefits, the evidence for long-term sustained effects is less conclusive, potentially due to factors like adherence fatigue (64). The effectiveness of mHealth can vary widely depending on the intervention methods and the level of professional involvement (64). For instance, self-guided mHealth solutions without professional support may have limited impact on outcomes like quality of life and ease of use (64). Usability is a crucial aspect influencing the adoption and continued use of mHealth, particularly among older adults who may have trouble due to unfamiliarity with technology (70). Factors like ease of use and the availability of facilitating conditions are significantly associated with the intention to use mHealth among experienced users (70). Addressing concerns related to data security, privacy, and perceived effectiveness is essential for long-term engagement (70). Future research should explore specific features of mHealth applications that enhance patient engagement, especially in empowering underserved communities (66).

2.2 Related Works

In this section, the problems that were found from other works and the methods used for this thesis are discussed.

2.2.1 Mobile Health Technologies

A growing body of research demonstrates the effectiveness of mHealth applications in supporting patients with diabetes and hypertension. These applications often include features for data tracking (blood glucose, blood pressure), medication reminders, educational content, and feedback mechanisms. A systematic review by Li et al. (21) found that mHealth interventions significantly improved blood pressure control in adults with hypertension. Similarly, studies have shown that apps for diabetes management can lead to better glycemic control and increased patient engagement (18). However, a gap remains in applications designed to simultaneously address the complex needs of patients with co-morbid hypertension and diabetes. Furthermore, many existing applications lack sophisticated personalization, often providing generic advice that may not be relevant to an individual's specific situation or engagement level. Despite the growing adoption of mobile health technologies, their integration into healthcare systems continues to encounter several obstacles. These include technical challenges such as concerns over data security and patient privacy (59), as well as individual-level issues like limited health literacy and lack of user knowledge (60). Structural barriers within healthcare systems, including economic and financial constraints, further complicate adoption efforts (61). Accessibility issues and inconsistencies in medical data formats across different platforms also pose significant challenges to effective implementation (62). The rapid expansion of mHealth solutions has heightened user concerns regarding privacy and security, highlighting the urgent need for standardized system architectures to safeguard sensitive health information (63). Addressing these challenges is essential for the effective and sustainable incorporation of mHealth into healthcare infrastructure, and it calls for a holistic strategy that tackles technical, personal, and organizational limitations.

2.2.2 Association Rule Mining in Healthcare

Association rule mining has emerged as a valuable data mining technique in healthcare, offering the potential to uncover meaningful relationships between diseases and health conditions within large datasets of patient information. This approach can reveal hidden patterns and associations, leading to improved disease prediction, enhanced patient care, and more efficient resource allocation. For example, research has applied this method to medical records to detect frequently co-occurring diseases. One study utilized it to analyze symptom clusters related to COVID-19, while another leveraged protein groupings to identify early indicators of breast cancer. Similarly, association rules have been used to uncover links between specific health issues and treatments, such as the association between diabetes and insulin use, achieving a reasonable level of accuracy.

The technique can also be applied to numeric data ranges, such as age, blood glucose levels, and body mass index (BMI), to format data for rule generation. In one instance, the FP-Growth algorithm combined with association rule mining successfully identified associations between chronic conditions such as hypertension and diabetes from patient visit data coded with ICD-10. Another study utilized cluster analysis in combination with association rule mining to explore patterns of multimorbidity and disease associations in hospitalized older patients. These techniques assist healthcare providers in understanding potential comorbidities, improving diagnostic accuracy, and tailoring treatment effectiveness, contributing to personalized patient care

A variety of mHealth applications have been developed to support the management of hypertension and/or diabetes. Some of these applications integrate additional hardware for automated health data collection, which has demonstrated beneficial outcomes (52), while others depend on users to manually input their information (53, 54). Certain applications focus on delivering educational materials or motivational messages to support patients in understanding and managing their conditions. Others offer personalized recommendations derived from user-provided data, and some include features that facilitate direct communication with healthcare professionals (550. In some cases, these recommendations are powered by machine learning algorithms (56).

Systematic reviews of existing mobile applications targeting diabetes and hypertension management have found that most tools on the market aim to support patient self-management without involving clinicians directly (57, 58). These applications typically help users track essential health indicators such as blood glucose and blood pressure, as well as monitor related behaviors including physical activity, dietary intake, and medication compliance. They often include reminders for critical actions and may also provide condition-specific educational content. While users generally report improved health outcomes from using these tools, several studies also point out usability challenges due to complex application interfaces and designs.

2.3 Summary of Proposed Study

This study proposes the development and evaluation of a mobile health application for the proactive self-management of patients with both hypertension and diabetes. The core of this proposal is the application of Association Rule Mining to create a personalized recommendation engine.

The study uses a knowledge-based approach to create a patient modeling system. This involves categorizing individuals based on two primary components: their engagement amount and their condition trend based on past activities. These classifications are built with insights from healthcare professionals who care for patients with both hypertension and diabetes. Patient modeling is a crucial component for identifying individuals at risk of not following treatment and for personalizing healthcare services with specific patient needs, thereby contributing to operational efficiency and long-term care delivery.

Using this classification system as a foundation, Association Rule Mining will be used to generate a set of "if-then" rules that link patient profiles to a specific, expert-validated recommendation. The final output will be a mobile application that can assess a user's profile and deliver customized, actionable advice, moving beyond the generic feedback common in existing applications. The study will conclude by evaluating the accuracy of the recommendation model and the usability and satisfaction of the mobile application with both healthcare professionals and patient users.

By combining patient modeling, association rule mining, and mHealth technologies, this study aims to bridge existing gaps in personalized healthcare solutions by integrating data-driven insights with expert knowledge. The overarching goal is to improve health outcomes, support patient self-management, and alleviate the burden associated with diabetes and hypertension.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Overview

This study focuses on developing a patient modeling system integrated into a mobile health (mHealth) application to help patients with chronic disease self-management. The study aims to utilize patient modeling techniques to classify patients based on their health characteristics and engagement levels, enabling personalized recommendations and interventions. By leveraging association rule mining, the model identifies correlations between patient behaviors, conditions, and treatments, improving the recommendation.

The application specifically targets the management of hypertension and diabetes, using knowledge gained from the expertise of healthcare professionals to build the model. By using information such as health trends and user engagement, the system aims to improve self-management to treatment plans and overall health outcomes.

Using patient modeling, association rule mining, and mHealth technologies, this study aims at the existing gaps in personalized healthcare solutions. Which highlights the potential of combining data-driven insights with expert knowledge to enhance the accessibility, efficiency, and effectiveness of chronic disease self-management tools available on a mobile phone.

3.2 Methodology

This chapter outlines the various components that went into the development of this study, such as the source data from healthcare experts, the association rule methods and application development. It also provides details on how these elements function and interact with each other.

To ensure the protection, confidentiality, and welfare of all individuals involved, this study has obtained full ethical approval from the Research Ethics Committee of Mae Fah Luang University. The study was cleared to proceed under the project number EC 24105-13 and was issued the Certificate of Approval number COA 189/2024. All data was anonymized, and informed consent was obtained from every participant before their involvement in the study.

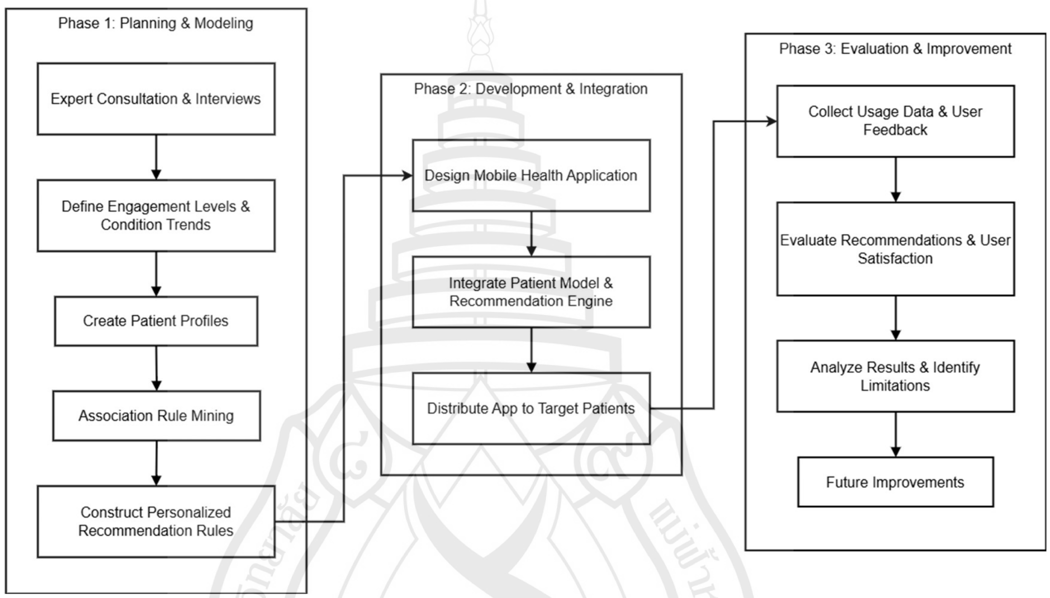


Figure 3.1 Overall methodology

3.2.1 Step-by-step of Research Methods

In this study, patient modeling was developed based on two key components: the patient's level of engagement and the trend in their health condition progression, as illustrated in Figure 3.1. The following section provides a detailed explanation of these components.

3.2.1.1 Phase 1: Planning & Modeling

This initial phase focused on building the theoretical and logical foundation of the personalized recommendation system.

1. Step 1: Expert Consultation & Interviews: The process began with in-depth knowledge acquisition from 10 healthcare professionals with expertise in managing patients with hypertension and diabetes. These consultations and interviews

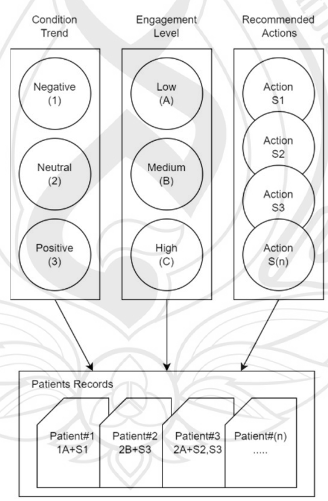
were crucial for understanding how doctors assess patient status, what factors influence their recommendations, and the treatments they typically prescribe.

2. Step 2: Define Engagement Levels & Condition Trends: Based on the qualitative data from the expert interviews, two primary components for patient classification were identified Engagement Level and Condition Progression Trend

3. Step 3: Create Patient Model: By combining the two components, a classification matrix was created to define patient model. Each profile represents a unique patient state requiring a tailored intervention strategy.

4. Step 4: Association Rule Mining: The Association Rule Mining technique was applied to the knowledge base. This step aims to identify and formalize the relationships between the nine patient profiles (the antecedents, or "if" conditions) and the corresponding expert recommendations (the consequents, or "then" actions).

5. Step 5: Construct Personalized Recommendation Rules: The output of the mining process was a finalized set of "if-then" rules. These rules form the core logic of the recommendation engine, capable of linking a specific patient profile to a specific, actionable piece of advice.



Source (71)

Figure 3.2 Proposed patient modeling

According to Figure 3.2, both engagement levels and condition progression trends were derived from insights provided by healthcare professionals who manage patients with comorbid hypertension and diabetes. The specific methodologies used to define and assess each component are discussed in the subsequent section.

3.2.1.2 Phase 2: Development & Integration

This phase involved the technical implementation of the mobile application, and the integration of the model developed in Phase 1.

1. Step 1: Design Mobile Health Application: A user-centered design approach was used to create the mobile application's interface and features. The design prioritized ease of use, clear data visualization, and straightforward data entry for patients.

2. Step 2: Integrate Patient Model & Recommendation Engine: The personalized recommendation rules developed in Phase 1 were coded and integrated into the application's backend. The system was engineered to take user data, classify the user into one of the nine patient profiles, and create the corresponding recommendation.

3. Step 3: Distribute App to Target Patients: The completed application prototype was distributed to a group of patient volunteers from the target demographic (hypertensive diabetic patients) for use over a specified period.

3.2.1.3 Phase 3: Evaluation & Improvement

The final phase focused on assessing the effectiveness and usability of the application and identifying areas for future enhancement.

1. Step 1: Collect Usage Data & User Feedback: Throughout the trial period, anonymous usage data was collected. Following the trial, user satisfaction and feedback were gathered from both the patient volunteers and a group of healthcare professionals using structured surveys and focus groups.

2. Step 2: Evaluate Recommendations & User Satisfaction: The collected data was analyzed to evaluate two key aspects, Model Accuracy (assessed by comparing the association rule recommendations to the original expert dataset). and User Satisfaction (survey given to patient caretaker and professional satisfaction with the application's usability, features, and perceived usefulness).

3. Step 3: Analyze Results & Identify Limitations: The evaluation results were analyzed to draw conclusions about the study's success. This step also

involved a critical reflection on the study's limitations, such as sample size and the reliance on self-reported data.

4. Step 4: Future Improvements: Based on the analysis and identified limitations, a list of potential future improvements was compiled. This includes suggestions for refining the recommendation model, adding new application features, and planning for larger-scale validation studies.

3.2.2 Engagement Levels

As previously mentioned, the engagement levels were established through an analysis of insights provided by healthcare professionals. Interviews were conducted with 10 experts specializing in the relevant medical field to gather their experiences regarding patient classification and treatment approaches. These professionals also completed survey questionnaires designed to identify key factors for use in patient modeling and recommendation generation. The content of both the interview and survey instruments was reviewed by a panel of three experts, two from the healthcare sector and one from the field of mobile application development.

The interview questions focused on aspects of patient care, including treatment planning and strategies for managing cases where patients do not adhere to their prescribed plans. These questions were deliberately open-ended to allow the healthcare experts to provide concise versions of care strategies, which were later incorporated into the recommendation system. Based on the information collected, patient engagement, defined as the degree to which individuals follow medical advice, was categorized into three levels: low, medium, and high. The specific criteria for each category are outlined in Table 3.1.

Table 3.1 Engagement level and explanation

No.	Engagement Levels	Explanation
1	Low	The patient adheres to less than 40% of the recommended activities and medication regimen. For instance, this may include missing half or more of the prescribed medication doses, not following the dietary recommendations for over two days per week, and engaging in physical activity fewer than three days per week.
2	Medium	The patient demonstrates compliance in approximately 40–70% of activities and medication adherence. Examples include having minor medication lapses, equivalent to missing fewer than two days' worth of doses in a week, adhering to dietary guidelines for less than two-thirds of the week, and exercising fewer than four times per week.
3	High	The patient follows more than 70% of the recommended health behaviors and medication schedule. This includes taking medication as prescribed daily, maintaining the recommended diet for more than half of the week, and engaging in at least 30 minutes of physical activity five days a week.

As shown in Table 3.1, engagement levels are determined based on the extent to which patients follow the recommendations provided by healthcare professionals. The specific thresholds for activity frequency were established based on the consensus of the majority of expert opinions.

3.2.3 Condition Progression Trend

This study utilizes a condition progression trend model to assess the directional changes in a patient's symptoms by analyzing key health indicators, including blood pressure, body weight, blood glucose levels, and other relevant metrics, all evaluated against standardized reference ranges. The model classifies these trends into three distinct categories, reflecting the possible variations in health status, as established in prior research [51]. Detailed definitions for each category are presented in Table 3.2.

Table 3.2 Condition progression trends and explanation

No.	Condition Progression Trends	Explanation
1	Positive Condition Progression Trend	The patient's health indicators show improvement, shifting toward the optimal or healthy range. For example, a reduction in body weight from the overweight category toward the healthy range.
2	Negative Condition Progression Trend	The patient's condition is deteriorating, with health metrics deviating further from the ideal range. An example includes weight gain that transitions the patient from the overweight range into the obese category.
3	Neutral Condition Progression Trend	There is minimal or no significant change in the patient's health condition, with metrics remaining relatively stable. For instance, maintaining body weight consistently within the healthy range without notable fluctuation.

From Table 3.2, a positive condition progression trend signifies an improvement in the patient's health, with clinical measurements approaching those typical of healthy, asymptomatic individuals. Conversely, a negative progression trend indicates a decline, where health indicators deviate further from the standard ranges. For patients whose condition remains relatively unchanged, the neutral progression trend is used to monitor stability. These classifications serve as a basis for guiding patients toward appropriate follow-up care and medical recommendations.

3.2.4 Patient Modeling

The patient modeling framework, which incorporates both condition progression trends and engagement levels, is utilized to generate personalized sets of recommendation outcomes for each patient. The various types of patient models applied in this study are presented in Table 3.3.

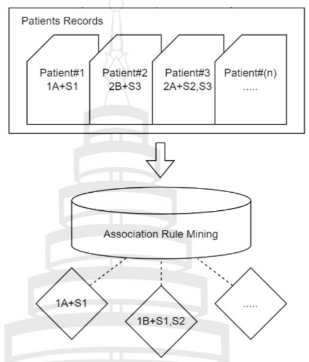
Table 3.3 Types of patient modeling

No.	Tag	Explanation
1	1A	Negative condition trend with low engagement
2	1B	Negative condition trend with moderate engagement
3	1C	Negative condition trend with high engagement
4	2A	Neutral condition trend with low engagement
5	2B	Neutral condition trend with moderate engagement
6	2C	Neutral condition trend with high engagement
7	3A	Positive condition trend with low engagement
8	3B	Positive condition trend with moderate engagement
9	3C	Positive condition trend with high engagement

As shown in Table 3.3, patient profiles are categorized according to their engagement levels and condition progression trends. Each unique profile warrants a corresponding set of tailored recommendations. For instance, patient 1A exhibits a negative progression trend compared to the previous diagnosis and demonstrates low engagement. In contrast, although patient 1C also shows a negative trend, their high engagement level suggests they require a different recommendation strategy. The process for constructing these personalized recommendations is detailed in the following section.

3.3 Personal Recommendation Model

Based on the patient modeling, which incorporates engagement levels (low, medium, and high) and condition progression trends (positive, negative, and neutral), personalized recommendations can be developed for each patient.



Source (71)

Figure 3.3 Personal recommendation construction

As shown in Figure 3.3, general recommendations typically provided by healthcare professionals are systematically aligned with individual patient profiles using association rules, reflecting the clinical judgment and experience of the professionals. These standard recommendations are outlined in Table 3.4.

Table 3.4 Set of general recommendations

No.	Recommendation	Explanation
1	Advise	Provides general guidance to the patient
2	Educate	Delivers detailed educational information to the patient
3	Encourage	Offers motivational support to the patient
4	Solo-session	Conducts a one-on-one consultation with the patient and their caregiver
5	Group-session	Facilitates group sessions involving multiple patients and a professional care team
6	Home-check	Schedules an in-home visit for patient care
7	Monitor	Initiates a health monitoring plan for the patient

Table 3.4 (continued)

No.	Recommendation	Explanation
8	Reconsider	Reviews and potentially revises the existing treatment strategy
9	Follow-up	Arranges a follow-up appointment for continued care

As presented in Table 3.4, general recommendations for managing patients with both hypertension and diabetes should consider key lifestyle factors such as diet, medication adherence, and physical activity. While external influences—such as family dynamics and socioeconomic status—also play a significant role, they are beyond the scope of this study. Patients typically adhere to dietary and treatment guidelines initially, but over time, adherence may decline. This is often attributed to family members either intentionally relaxing the regimen to improve the patient’s emotional well-being or neglecting the plan altogether due to a lack of caregiver support.

For patients who adhere well to their care plans, positive reinforcement is encouraged. Conversely, those who struggle with adherence may require additional attention, including motivational support and further education to reinforce the consequences of non-compliance. Group sessions have also been found effective in providing both professional and peer support, with follow-up through individual counseling or home visits when necessary. Personalized care plans should be aligned with each patient's specific condition. To generate these individualized recommendations, association rule mining was employed to align appropriate interventions with patient profiles, as viewed through the lens of healthcare professionals.

Personal Recommendation Construction

Association rule mining is a data analysis method used to identify meaningful patterns or relationships between variables within large datasets. This technique is particularly effective for detecting frequent co-occurrences, correlations, or associations among different items. It serves as a valuable tool for deriving actionable insights from complex data, thereby supporting data-informed decision-making across various domains, including mobile health applications. In constructing these rules, three key metrics are utilized: support, confidence, and lift.

These metrics, support, confidence, and lift, play a critical role in assessing the strength and relevance of association rules. Rules that exhibit low support or confidence values may be excluded from the final model, as they may not meet the predefined thresholds for statistical significance or practical applicability.

Once the association rules are generated, they are compared against the original expert-provided rules by evaluating whether the generated consequences align with those suggested by the healthcare professionals for each antecedent. The degree of alignment is then measured as a percentage match. A higher percentage indicates stronger agreement between the generated recommendation and the expert responses. Since a single antecedent may correspond to multiple expert-identified consequences, the matching percentage is calculated based on how many of the expert-provided outcomes align with the generated result. The outcomes of this analysis are summarized in Table 3.5.

Table 3.5 Sample of key metrics of association rules

Profile: Antecedents	Consequents	Support	Confidence	Lift
1A: Negative Condition + Low Engagement	Educate	0.097	0.875	2.52
Negative Condition + Medium Engagement	Encourage	0.069	0.625	1.00
Negative Condition + High Engagement	Reconsider	0.111	1.000	2.88
Neutral Condition + Low Engagement	Educate	0.097	0.875	2.52
Neutral Condition + Medium Engagement	Encourage	0.097	0.875	1.40
Neutral Condition + High Engagement	Encourage	0.111	1.000	1.60
Positive Condition + Low Engagement	Educate	0.097	0.875	2.52

Table 3.5 (continued)

Profile: Antecedents	Consequents	Support	Confidence	Lift
Positive Condition + Medium Engagement	Encourage	0.069	0.625	1.00
Positive Condition + High Engagement	Encourage	0.111	1.000	1.60

To illustrate the process of calculating the association rule metrics, the rule ‘Negative Condition + Low Engagement → Educate’ is used as an example.

Among the 72 records analyzed, there were 7 instances where this combination (1A+S2) occurred, representing the negative condition with low engagement alongside the general recommendation to educate. There were 8 instances of the 1A profile (negative condition + low engagement) and 25 instances involving the ‘Educate’ recommendation (S2). This yields a support value of 7/72, or 0.097. The confidence value is obtained by dividing the co-occurrence frequency by the frequency of the antecedent, resulting in (7/72) / (8/72) = 0.875. The lift value is calculated by dividing the confidence value by the relative frequency of the consequent, giving the calculation (7/8) / (25/72) = 2.52, which suggests a strong and meaningful pattern. Rules with high lift and confidence were prioritized for integration into the recommendation system.

In this study, association rules are integrated with patient modeling to generate personalized recommendations tailored to individual patient profiles. Examples of these customized recommendations are presented in Table 3.6.

Table 3.6 Personal recommendation rules

No.	Recorded data
1	3B, follow-up
2	2B, follow-up, reconsider, encourage
3	1B, home-check, encourage, reconsider
4	3A, follow-up, educate
5	2A, follow-up, educate
6	1A, home-check, educate
7	3C, encourage

Table 3.6 (continued)

No.	Recorded data
8	2C, encourage, reconsider
9	1C, reconsider, educate
10	3B, encourage

As illustrated in Table 3.6, if a patient classified as having low engagement experiences weight gain, a condition categorized as a negative progression trend (profile 1A), the personalized recommendation would include a home visit and additional educational support regarding their condition. Once the association rules are generated, they are compared against the original expert-provided rules by evaluating whether the generated consequences align with those suggested by the healthcare professionals for each antecedent. The degree of alignment is then measured as a percentage match. A higher percentage indicates stronger agreement between the generated recommendation and the expert responses.

Since a single antecedent may correspond to multiple expert-identified consequences, the matching percentage is calculated based on how many of the expert-provided outcomes align with the generated result. For instance, if the expert responses for the "Negative Condition + Low Engagement" profile include one vote for "Educate," one for "Reconsider," and three for "Encourage," a generated rule of "Educate" would result in a 20% match, while "Encourage" would yield a 60% match.

3.4 Design and Development of Mobile Application

3.4.1 Application Design Phase

In this phase, the design process centers on the systematic development of a structured framework for building the software application. The framework is specifically customized to address the needs of individuals managing both diabetes and hypertension, with a focus on thoughtfully designing and conceptualizing a user-centric mobile application. This approach aims to improve the effectiveness of chronic disease management among the target population. The mobile application acts as an interface that delivers personalized care recommendations based on the patient model. The model classifies users according to their engagement levels and health condition trends. Once classified, the application retrieves a matching recommendation rule, which guides the user with practical advice based on the generated rules. The roles and interactions of users involved in care management are illustrated in Figure 3.3, while a detailed explanation of these use cases is provided in Table 3.7

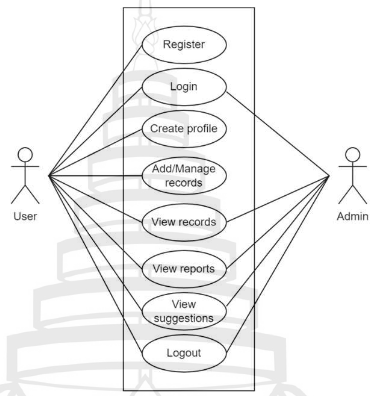


Figure 3.4 Use case for patient and administrator

Table 3.7 Use case description

Actor	Use case	Use case description
Patient	Registration	Users are required to create a profile prior to accessing the application.
	Login	Users must be authenticated to gain access to the application.
	Records	Users can record their activities and physical health data.
	Report	Users are able to view and review their historical data and generated reports.
	Suggestions	Users can see recommendations generated by the prediction system.
	Logout	Users have the option to delete their account from the application.

Table 3.7 (continued)

Actor	Use case	Use case description
Admin	Login	Administrators must log in before performing any actions within the system.
	Records	Administrators are permitted to modify data within the application.
	Report	Administrators can access and review reports stored in the system.
	Logout	Administrators can log out after completing their tasks.

3.4.2 Mobile Application Development Phase

The goal of this phase is to design and implement a mobile application that can collect user input, analyze the data, and deliver appropriate recommendations, with a particular focus on accommodating elderly users. As such, creating a user-friendly interface is essential. The application is developed to operate on the Android platform, ensuring straightforward installation and accessibility. The development process of the mobile application is illustrated in Figure 3.5.

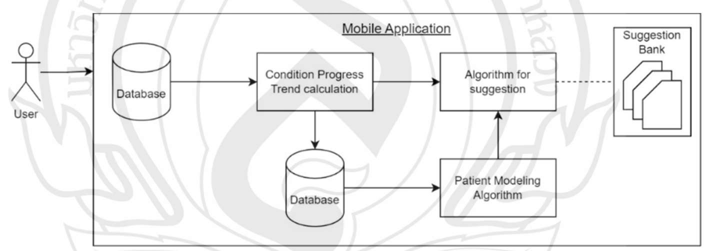


Figure 3.5 Mobile application development diagram

As depicted in Figure 3.5, the mobile application is integrated with a private server that securely stores user data. All user inputs are transmitted to and retained on this server, enabling efficient data access and processing. Core features of the application include managing personal information, tracking disease-related data, monitoring dietary intake and physical activity, and delivering health-related guidance. To ensure rapid data handling, both the database and computational services are hosted on the same private web server, optimizing performance and response time. Patient modeling is embedded into the application's backend, allowing for seamless mapping from user input to a personalized recommendation. The application calculates the user's engagement level and condition trend, then queries the appropriate rule.

If there are no strong rules available, the system defaults to general recommendations such as "Follow-up" or "Monitor." to push the user to directly consult with the experts in the meantime. In future versions, weak recommendations may be flagged for review or enhanced using reinforcement learning from user interactions.

3.5 Evaluation of Mobile Application

The evaluation of the developed mobile application was carried out to assess user satisfaction. A structured survey questionnaire, combined with a 5-point Likert scale, was employed to capture users' perceptions of the application's usability and effectiveness. The specific survey items and corresponding results are detailed in the following section. To summarize user feedback, the average score for each question was calculated, reflecting overall user sentiment on a scale from 1 to 5. The interpretation of these numerical ranges is provided in Table 3.8 below.

Table 3.8 Likert scale average score explanation

Averaged value	Meaning
4.50 to 5.00	Strongly agree / Very satisfied
3.50 to 4.49	Agree / Somewhat satisfied
2.50 to 3.49	Neither agree nor disagree / Neither satisfied nor dissatisfied
1.50 to 2.49	Disagree / Somewhat dissatisfied
1.00 to 1.49	Strongly disagree / Very dissatisfied

3.5.1 Details of Targeted Group of Participants

The target population for this study comprised of hypertensive diabetic patients aged 60 years or older residing in the Chiang Rai region. Participants were required to have been receiving concurrent medical treatment for both hypertension and diabetes. Additionally, each participant needed to have at least one caregiver who was actively involved in their care and capable of operating a smartphone device.

3.5.2 Data Collection Method

The collected data are divided into two main components: source information for constructing the patient model and user satisfaction survey responses. The source data were obtained through interviews with healthcare professionals, focusing on how they manage patient care, monitor adherence to treatment plans, and provide motivation to patients. The satisfaction survey data were gathered from patients and focused on various aspects of the application's usability, including its graphical interface and design, the accuracy of its predictions, and overall user satisfaction following application use.

3.5.3 Type of Survey

To assess the application's usage and performance, a satisfaction survey was administered using a five-point Likert scale, ranging from least satisfied to most satisfied. The survey was distributed alongside the mobile application to ensure that all participants in the testing group received it. Participants were instructed to complete the survey after using the application for the designated testing period. Survey responses were collected electronically and subsequently processed by the researcher for analysis.

3.5.4 Ethical Issues

Several ethical considerations arose during the data collection process for this study. Firstly, when gathering data for the development of patient models, it was essential to ensure anonymity, no identifying information could be linked to the healthcare experts who contributed to the dataset. Secondly, recruiting participants from the patient group posed additional challenges. Individuals with hypertension and diabetes are classified as requiring more intensive care compared to those with non-chronic conditions, making it more difficult to assemble a sufficiently large group of participants willing to engage in the research program.

3.6 Evaluation Methods

The developed mobile application was evaluated to assess user satisfaction. This assessment employed a survey questionnaire using a five-point Likert scale to gauge users' perceptions of the application's usability and effectiveness. The specific survey items and corresponding results are detailed in the following section. To represent the overall user sentiment, the mean score of responses for each question was calculated on a scale from 1 to 5. The interpretation of these numerical ranges is provided in Table 3.9 below.

Table 3.9 Likert scale average score explanation

Averaged value	Meaning
4.50 to 5.00	Strongly agree / Very satisfied
3.50 to 4.49	Agree / Somewhat satisfied
2.50 to 3.49	Neither agree nor disagree / Neither satisfied nor dissatisfied
1.50 to 2.49	Disagree / Somewhat dissatisfied
1.00 to 1.49	Strongly disagree / Very dissatisfied

The satisfaction survey was administered to the target group, consisting of medical professionals and caregivers responsible for supporting patients with both hypertension and diabetes. A total of 33 participants completed the survey after using the application over a two-week period. Each response was evaluated by calculating the average score for each question, which was then interpreted using predefined scale descriptions. For instance, an average score of 4.59 indicates that respondents generally expressed strong agreement with the corresponding statement.

CHAPTER 4

RESULTS AND DISCUSSION

This section presents the evaluation metrics and comparison of the results, which are also discussed in detail.

4.1 Professional Opinion Guidelines

After consultations with 12 medical professionals and nutritionists regarding general healthcare guidelines for hypertensive diabetic patients, as referenced in Table 3.1, the key questions and their consolidated responses are summarized in Table 4.1.

Table 4.1 Questions and answers from the consultation

Question	Answer
Guidelines for offering personalized health care plan options for patients with diabetes and high blood pressure. What matters must be considered, such as treatment principles? food consumption, exercise, etc.	Food consumption, drug prescriptions, exercise, and additional factors such as family, economy, and society.
After the patients have received advice on diet control and health care. According to your experience, how does the patient respond to the advice?	Most are willing to follow instructions, may ask some questions, but when they go home, they may forget and don't really follow along. Some will only do it close to the time of the appointment. Those who don't follow through are usually due to family factors. For example, family members buy food/cook food for patients and then eat without consulting the menu with doctors, or the lack of a caretaker leading to self-care without someone to help with medicine or exercise.

Table 4.1 (continued)

Question	Answer
Can patients be grouped according to their response to the advice given? If so, what groups are there?	- Good Control group, good test results - Uncontrolled, poor test results, but does not have health complications - Uncontrolled, extremely poor test results, and having health complications.
What to do when the patient is able to strictly follow the instructions.	General positive reinforcement. Praise, encouragement, and advice on maintaining good behavior.
What to do when the patient is not following the instructions.	Consult with the patient about the reasons that prevent them from following the instructions. Give an example of the consequences if the patient doesn't take care of themself. Arrange proactive monitoring. Use societal factors to help encourage.
How much importance do the patients place on diet and exercise?	Patients do prioritize food more than exercise. Food: Food is often bought from outside or cooked by the family. This makes changing diet difficult due to patients preferring their old diet, but it has some working results. Exercise: Limitations due to age make it difficult to exercise. For patients who do work on labor tasks, they think that working for the day already counts as exercise.
What is the format for giving advice that is likely to make patients follow it?	Using group advice sessions with open discussion amongst patients, with guidance by medical professionals. Provide in-depth individual counseling. May arrange a home visit to directly listen to problems or to provide direct care periodically.

Table 4.1 (continued)

Question	Answer
Preparation of the patient's self-care plan, should it be personalized or not?	Personalized planning is recommended. Plan according to the patient's behavior, family conditions, the economy, and a person's willingness to learn.
Is the promotion of mental health necessary for maintaining the treatment?	It is highly necessary due to the aging society era causing more depression in the patients. Which may lead to complications caused by mental conditions.
How should the patient's care plan be modified if needed?	Adjust according to health conditions, caring behavior and check for complications. The frequency of visits may be adjusted accordingly.

In summary, the general approach to managing hypertensive diabetic patients through personalized healthcare plans should consider key lifestyle factors such as diet, medication adherence, and physical activity. Additionally, external influences, including family dynamics and socioeconomic status, play a crucial role in shaping patient behavior and should be considered in the care strategy. Although patients often begin by following dietary and medical recommendations, adherence may decline over time, often due to family members relaxing guidelines to maintain the patient's emotional well-being or a lack of consistent caregiver support.

Positive reinforcement is recommended for patients who comply with their treatment plans, while those who struggle with adherence may benefit from targeted interventions, including social support and enhanced education about the risks of non-compliance. Group sessions can also serve as a valuable support mechanism, offering both peer interaction and professional guidance, followed by individualized consultations or home visits when appropriate. Ultimately, care plans should be tailored to each patient’s unique circumstances, considering their behavior, family environment, socioeconomic background, and mental health status, with flexibility to adapt as conditions or complications arise.

Furthermore, the valuable insights and data gathered from these healthcare professionals during these consultations were instrumental in the development of the patient recommendation model and the generation of association rules, which are detailed in the subsequent section on the next section. The specific data from these expert interviews, along with their reviews, are used to create the dataset that will be deriving personalized recommendations.

Once the association rules were generated, they were evaluated by comparing the consequents of the generated rules to those originally provided by experts for each antecedent. The degree of agreement is presented as a percentage match. A higher percentage indicates greater alignment between the generated rule and expert input. Since multiple expert recommendations may exist for a single antecedent, the percentage is calculated based on how many expert-provided outcomes align with the generated one. For instance, if the expert responses for the “Negative Condition + Low Engagement” profile include one vote for “Educate,” one for “Reconsider,” and three for “Encourage,” then a generated rule of “Educate” would yield a 20% match, while “Encourage” would result in a 60% match. The highest match observed was 72.73% for “Positive Condition + High Engagement,” suggesting that the model closely aligns with expert judgment in certain cases.

Table 4.2 Percentage of rules matched with original dataset

No.	Antecedent Condition Trend	Matched Percentage
1	Negative Condition + Low Engagement	28%
2	Negative Condition + Medium Engagement	15%
3	Negative Condition + High Engagement	5.88%
4	Neutral Condition + Low Engagement	8%
5	Neutral Condition + Medium Engagement	38.89%
6	Neutral Condition + High Engagement	41.67%
7	Positive Condition + Low Engagement	5%
8	Positive Condition + Medium Engagement	50%
9	Positive Condition + High Engagement	72.73%

4.2 Patient Recommendation Model

Based on data gathered from interviews with eight healthcare experts and subsequently reviewed by two additional professionals, a total of 72 records were used to generate the initial set of association rules. These results are presented in Table 3.8. For clarity, the antecedents and consequents listed in the table have been translated from coded tags into human-readable labels.

Table 4.3 Sample of association rules calculated from the dataset

Antecedents	Consequents	Support	Confidence	Lift
Negative Condition + Low Engagement	Educate	0.097	0.875	2.52
Negative Condition + Medium Engagement	Encourage	0.069	0.625	1
Negative Condition + High Engagement	Reconsider	0.111	1	2.880
Neutral Condition + Low Engagement	Educate	0.097	0.875	2.52
Neutral Condition + Medium Engagement	Encourage	0.097	0.875	1.4
Neutral Condition + High Engagement	Encourage	0.111	1	1.6
Positive Condition + Low Engagement	Educate	0.097	0.875	2.52
Positive Condition + Medium Engagement	Encourage	0.069	0.625	1
Positive Condition + High Engagement	Encourage	0.111	1	1.6

To illustrate the calculation of metric values, the association rule 'Negative Condition + Low Engagement → Educate' is used as an example. Within the dataset of 72 records, there are 7 instances where this specific combination (coded as 1A+S2) occurs, representing patients with a negative condition trend and low engagement who received the 'Educate' recommendation. There are 8 total occurrences of the 1A profile and 25 instances involving the 'Educate' action. This results in a support value of 7/72, or 0.097. The confidence value is calculated by dividing the support value of the rule by the support value of the antecedent: (7/72) / (8/72) = 0.875. To determine the lift value, the confidence score is divided by the relative frequency of the consequent, yielding (7/8) / (25/72) = 2.52.

To validate the robustness of the recommendation engine, an accuracy analysis was conducted to ensure that the Association Rule Mining process consistently produced similar results. The model was executed 100 times, and on each run, the generated rules were compared against the baseline rules provided by the clinical experts. The average accuracy and standard deviation across these 100 generations were calculated for each of the nine patient profiles. This process helps to demonstrate that the model is not overly sensitive to minor variations and that the resulting rules are relatively stable and not the product of a random statistical anomaly. The results of this accuracy analysis are presented in the table below.

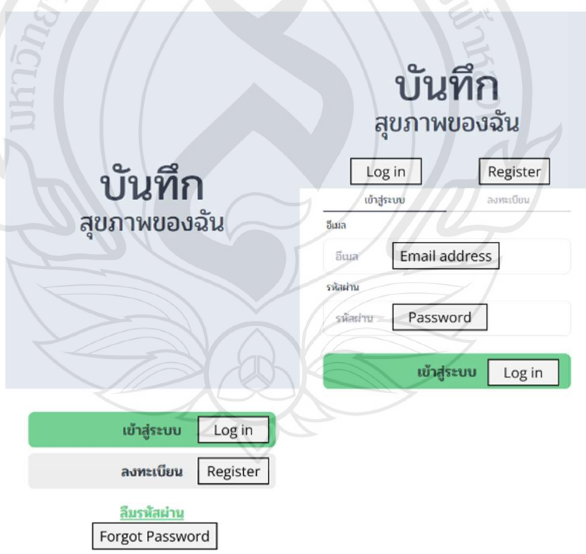
Table 4.4 Average accuracy and standard deviation from 100 generations

Patient Profile Type (Antecedents)	Average Accuracy (%)	Standard Deviation
Negative Trend + Low Engagement	78.52	3.1
Negative Trend + Medium Engagement	65.27	4.5
Negative Trend + High Engagement	71.83	3.9
Neutral Trend + Low Engagement	62.19	5.2
Neutral Trend + Medium Engagement	58.47	6.1
Neutral Trend + High Engagement	66.71	4.8
Positive Trend + Low Engagement	74.35	3.5
Positive Trend + Medium Engagement	70.94	4.2
Positive Trend + High Engagement	80.11	2.8

The average accuracy for all patient profiles falls within the range of 58.4% to 80.1%, showing a consistent and meaningful alignment with expert opinion across multiple iterations. Furthermore, the low standard deviation value suggests that the model reliably produces a similar set of rules on each run. This low variance suggests that the model reliably produces a similar set of high-quality rules on each run, reinforcing the conclusion that the underlying patterns it identifies are genuine and not coincidental. This accuracy analysis is a crucial attribute, as it provides confidence that the recommendation engine is robust and can be trusted to provide consistent, logical guidance to users of the mobile application.

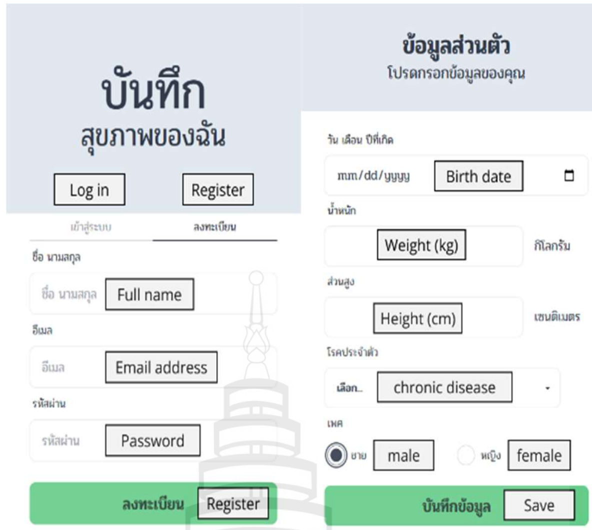
4.3 Mobile Application

The development of the mobile application prioritized core functionality in data collection, while ensuring ease of use through a straightforward and intuitive interface. The menu navigation was designed to align with common patterns found in other widely used mobile applications, thereby minimizing the learning curve for new users. Sample screenshots of the user interface, including translated labels, are presented below.



Note Landing page (left), log-in form (right)

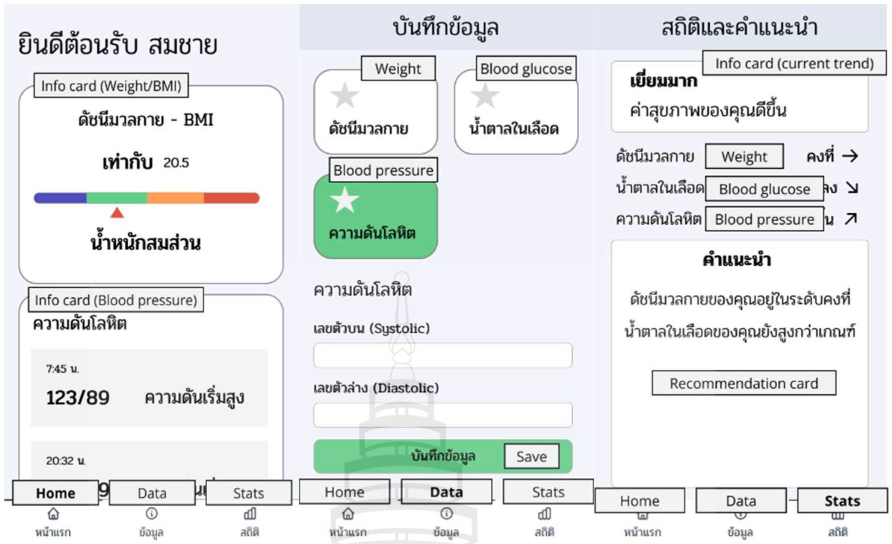
Figure 4.1 Examples of mobile applications (1)



Note Registration form (left), user information form (right)

Figure 4.2 Examples of mobile applications (2)

To begin using the application, users are required to register an account and create a personal profile. The application collects basic information, including date of birth (used to calculate age), body weight (in kilograms), and height (in centimeters), which are used to compute the user's Body Mass Index (BMI). Users must also indicate the type of chronic condition they have, diabetes, hypertension, or both, and specify their gender. The user's full name is used solely for display purposes within the application, while the email address and password are used for authentication and to enable secure access to personal data.



Note Home page displaying user's information (left), data collection form (middle), recommendation page (right)

Figure 4.3 Examples of mobile applications (3)

The home screen of the application presents users with a visual summary of their most recent health data using easy-to-read graphics and large text for clarity. Key health indicators, including BMI, blood pressure, and blood glucose levels, are displayed prominently. Each metric is shown on a separate card, which users can tap to view a full history sorted by the most recent entries at the top.

The data entry page allows users to input their health information. The interface dynamically adjusts based on the type of data selected. For instance, if a user chooses to enter BMI, only the weight and height input fields will appear. Similarly, selecting blood glucose prompts a form tailored specifically for that data type.

The stats page offers a comprehensive summary of changes over time, integrating the Patient Recommendation model to interpret the user's current health status. Each metric card includes a brief explanation of the user's trend direction, whether improving, stable, or declining, and provides actionable guidance tailored to their current condition.

When significant changes in health status are detected, whether related to diabetes, hypertension, or both, the application issues tailored suggestions on areas such as exercise or dietary adjustments. These recommendations are intended to guide daily decisions but should not be considered a replacement for professional medical advice. Healthcare professionals may reference this data when determining appropriate clinical interventions.

Users are encouraged to log their health data daily, ideally at the same time each day, to ensure consistency and reduce variability influenced by lifestyle factors. The application includes a customizable notification feature that reminds users to record their health information at their preferred time.

4.4 Satisfaction Survey

The satisfaction survey was administered to a target group consisting of medical professionals and caregivers responsible for assisting hypertensive diabetic patients. A total of 33 participants, patients' caretakers and healthcare professionals, completed the survey after using the application over a two-week period. The survey employed a five-point Likert scale to assess user satisfaction, with response options ranging from "very unsatisfied" to "very satisfied." Each response was assigned a numerical value: 1 for very unsatisfied, 2 for unsatisfied, 3 for neutral, 4 for satisfied, and 5 for very satisfied. The average score for each question was then calculated to evaluate overall user perception. The complete list of survey questions and corresponding response scores is presented in Table 4.5 below.

Table 4.5 Survey questions and responses

Questions	AVG	SD
Recommendation is easy to understand	4.18	6.43
Recommendation is appropriately personalized	3.94	5.77
Recommendation is complete with information	3.91	7.16
Recommendation can be used on daily basis	4.21	6.62
Function is useful for daily lifestyle improvements	4.27	7.57
Function has variety in recommendation	4.00	5.59
Application is easy to understand	4.15	6.31
Application is well-designed	4.30	7.30
Application feels fast and responsive	4.30	7.23
Application feels secure in storing information	4.39	7.96
Basic functions are easy to use	4.27	7.02
Texts in application are easy to read	4.21	6.91
Color usages are clear to read	4.33	7.64
Overall satisfaction of using application	4.09	6.31

Note Abbreviations: AVG = Average Likert Scale score of the questions, SD = Standard Deviation of the Likert Scale

The survey results indicate a generally high level of user satisfaction, with average scores falling within the “satisfied” range. Participants expressed positive feedback regarding the application's user-friendly interface and the perceived security of personal data stored within the application. However, some concerns were noted, particularly regarding the accuracy of the recommendation system, which in certain cases produced incorrect suggestions due to limited personal data. Additionally, a few users reported that some features lacked clear instructions, affecting ease of use in specific areas.

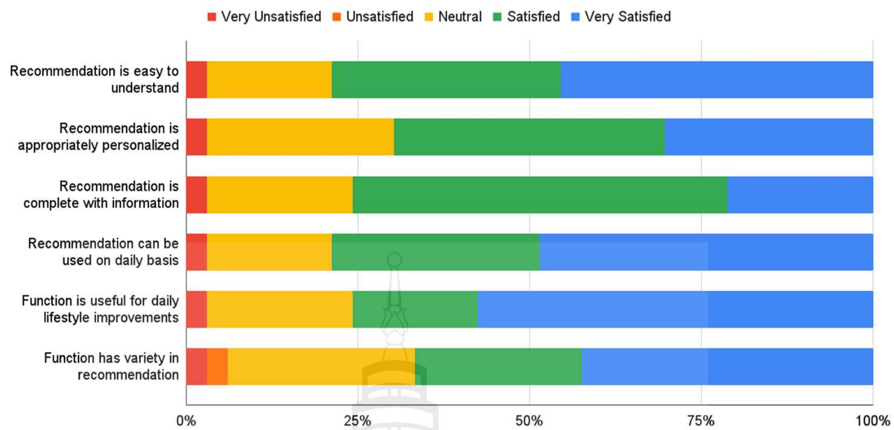


Figure 4.4 Bar graph of survey questions and responses of the recommendation system

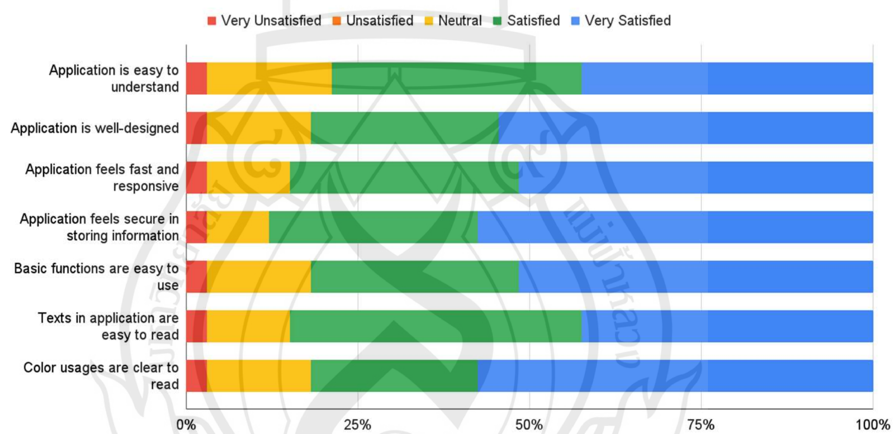


Figure 4.5 Bar graph of survey questions and responses of the application design

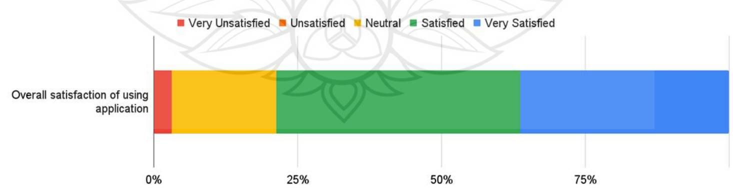


Figure 4.6 Bar graph of survey question and responses of the overall satisfaction

4.5 Limitation

One of the primary limitations of this study is the small dataset used for generating the association rules, only 72 records were collected from the ten experts. While sufficient for a small-scale pilot study, this size may not fully capture the diversity and complexity of real-world patient behaviors. As a result, some generated rules may be weak, overly generalized, or not applicable to all patients. Particularly on the rules with extremely high lift and confidence values. This could limit the accuracy and effectiveness of recommendations provided through the application, especially in cases not represented in the dataset.

4.6 Discussion

This study investigated the use of personalized healthcare plans for hypertensive diabetic patients through the application of association rule mining, aiming to develop general self-care guidelines with support from medical professionals. Despite being based on a limited dataset from healthcare experts, the association rule mining technique effectively identified relevant care patterns.

4.6.1 Association Rule Assessment

The biggest point to consider is the over-training that can occur when a model is built on a very small dataset, in this case 72 records gathered from interviews with eight healthcare professionals and subsequently reviewed by two additional experts. Although the resulting association-rule model displayed high accuracy and confidence values, the degree of alignment between the rules that the model generated and the expert-provided rules was measured as a percentage of matched rules. To address this and to evaluate the model's consistency, an accuracy analysis was performed by running the rule-generation process 100 times. This analysis revealed that the model is remarkably stable, with the average accuracy of the generated rules consistently falling within a strong range of 58.4% to 80.1% when compared against the expert-provided baseline. The low standard deviations across all profiles further underscore this stability, demonstrating that the alignment with clinical logic is not random but a reliable output of the model. The content of these consistently generated rules often emphasizes the value of patient encouragement and direct education on risk management to promote behavioral change, thereby motivating individuals to adopt healthier habits. These generated rules often emphasize the value of encouragement and direct education on risk management to promote behavioral change, motivating patients to adopt healthier habits.

However, certain limitations emerged, such as occasional mismatches between recommendations and patient expectations, possibly due to the narrow training dataset. Notably, several generated rules emphasized the value of patient encouragement, suggesting that positive reinforcement can play a significant role in motivating individuals to maintain healthier habits. In other cases, clear and direct education on potential health risks proved more impactful in promoting behavioral change. Building upon prior research, this study also introduced a user-friendly mobile application designed to deliver practical, personalized guidance to help improve patient lifestyles.

The model validation from healthcare professionals is crucial. Their consensus that the application's core function, Condition Progression Trend and Patient Engagement Level, are relevant to the study's foundation. Their agreement that the nine patient profiles capture most conditions of the patients gives credibility to the model's structure. This feedback indicates that the model is not just a theoretical construct but is grounded in the realities of patient modeling, which is a critical factor for the potential adoption of such technologies as a decision-support tool for patients.

4.6.2 Mobile Application Assessment

The patient evaluation was overwhelmingly positive, with a high satisfaction score of 4.18 out of 5. This is the most important finding for this study. The high ratings for ease of use and perceived usefulness indicate that the user-centered design was successful. Most importantly, users found the application motivational. This suggests that the personalized recommendations were effective in engaging patients and encouraging them to take a more active role in their health. This result is consistent with literature that identifies personalization as a key driver of engagement in mHealth interventions and confirms that the application successfully meets the primary needs of its target users.

This finding confirms the application's potential to fill a gap in chronic care management. However, there are concerns regarding data reliability due to self-reporting and the lack of integration into clinical workflows. This reveals a fundamental challenge in digital health: for a tool to transition from a patient-facing wellness app to an integrated clinical instrument, it must meet strict requirements for data integrity and interoperability. This provides a clear goal for future work required to bridge this gap.

CHAPTER 5

CONCLUSION

This study project set out to examine the effectiveness of a mobile application developed for hypertensive diabetic patients. The application provided a user-friendly platform for tracking blood glucose and blood pressure levels, while also offering personalized health recommendations. Evaluation results indicated that 78% of users were satisfied with the application and expressed interest in its continued development, highlighting its potential to enhance quality of life for this patient group.

The findings support the potential of mobile health technology to improve health outcomes, support self-management, and reduce the burden associated with diabetes and hypertension. The application encourages early detection of symptom changes, fosters patient satisfaction, and promotes active engagement in care.

However, certain accessibility challenges were identified, particularly related to the use of smartphones among specific populations. For some, the cost of purchasing and maintaining mobile devices, including cellular services and electricity, poses a barrier. Additionally, elderly users may experience difficulty navigating touch-based interfaces due to reduced dexterity, making such devices less suitable for them. The application was thus designed primarily for middle-aged users, either living with chronic conditions themselves or caring for elderly family members. As such, a moderate to high level of digital literacy is required, including the ability to read and navigate smartphone technology safely.

The patient recommendation model was developed using 72 records gathered from interviews with 8 healthcare professionals and reviewed by two additional experts. This data was used to generate association rules, which effectively identify relevant care patterns despite the small dataset being used. The degree of alignment between the rules generated by the model and the expert-provided rules were measured as percentage of matched rules. The highest matched percentage observed was from the "Positive Condition + High Engagement" type with 72.73% percentage, while most of the rules matched ranged from 5% to 50%. These generated rules often emphasize the value of encouragement and direct education on managing risks to promote the behavioral change of the patients.

The satisfaction survey which had been given to 33 caregivers and healthcare professionals over a two-week period showed generally high user satisfaction, with average scores falling within the "satisfied" range (average scores above 4.0 out of 5 for most criteria) in which a total of 78% of all responses are within the "satisfied" range. Participants provided positive feedback on the application's user-friendly interface and the perceived security of personal data storage. However, some concerns were noted, particularly regarding the accuracy of the recommendation system, which occasionally produced incorrect suggestions due to the limited personal data used for model training. Despite these limitations, the high user satisfaction scores suggest that the application's approach of integrating patient modeling and association rule mining to provide personalized guidance was well-received.

Future research should aim to evaluate the long-term impact of the application and explore continuous enhancements informed by user feedback and emerging technologies. Planned improvements include expanding the application's capabilities to collect additional health data, such as sleep patterns and physical activity levels, to enhance the accuracy of its predictive features. Additionally, integrating real-time health monitoring devices such as smart watches could improve recommendation accuracy. There is also potential for adaptive rule refinement using patient feedback loops to continuously improve the system's performance. Further development may also introduce direct communication channels between patients and healthcare providers for more personalized guidance. Localizing the application into multiple languages could broaden its reach beyond Thai-speaking users in Thailand.

By integrating emerging technologies with patient-centered care principles, this application has the potential to significantly improve the lives of hypertensive diabetic patients, both in Thailand and in broader global contexts.

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