Context-aware Based Personalized Recommendation on Mobile for Monitoring Excessive Sugar Consumption of Thai Adolescents

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Abstract

Given the harmful effects of excessive sugar consumption, everyone should be aware of the amount of sugar they consume in daily life. Generally, managing nutrition and preventing negative effects from sugar intake requires a nutritional specialist or specialized knowledge, which may not always be readily accessible or understandable. Therefore, there is a need for a mobile application that can track excessive sugar consumption. This study proposes a context-aware personalized recommendation mobile application for monitoring excessive sugar consumption and providing individual recommendations (based on a predefined set of 144 rules) to Thai adolescents. The application is user friendly and can be used to provide recommendations to users for sugar consumption and proper exercise each day. Personal, health, and lifestyle data are collected and analyzed to provide individualized recommendations

to each user. Experiments were conducted with 140 Thai adolescents aged 15 to 25 years old. Users' preferences regarding degree of awareness in presentation style were also investigated. Users rated their satisfaction with the proposed mobile application as very high in terms of both function and personalization. In addition, fully automated recommendations were found to be the preferred degree of awareness among the test group.

1 Introduction

Thailand is currently experiencing a health crisis resulting from high rates of sugar consumption among the Thai population, an issue that should be receiving more attention [1]. A majority of the Thai population is at risk of health problems caused by excessive sugar intake, such as diabetes, obesity, hypertension, and vascular diseases [2]. Recent statistics show that Thailand is experiencing an increase in primary chronic diseases that can be prevented by dietary and lifestyle adjustments, such as type 2 diabetes mellitus, type 3 diabetes, cardiovascular and heart diseases, and cancer [3]. The main risk factor related to improper dietary habits is neglecting to consider nutrition profile and consumption amount at each meal. Observations from the Ministry of Public Health [4] indicate that most Thai teenagers consume more than 20 tablespoons of sugar each day—three times more than the recommended amount. The Ministry found that most Thai people consume sugar in the form of sweetened beverages and condiments in excess of the standards [5] established by the Ministry of Public Health [4]. As a result, Thai teenagers tend to have a high body mass index (BMI). In 2017, teenagers from 27,960 households in Thailand consumed excessive amounts of sugar in their daily meals [5]. Therefore, Thai teenagers need to be aware of their daily sugar consumption and strictly control their dietary habits to prevent the onset of related chronic diseases.

Lack of knowledge about nutritional information makes healthy consumption choices more challenging. However, technology can be used to facilitate the work of doctors and patients. For instance, mobile applications have been developed with which patients can record personal information, consumption data, personal activity, and bloodwork results, allowing experts to verify patients' personal information and behavioral data and make patients feel as though a doctor is always there to advise and monitor

them. The system was created to help predict the occurrence of various abnormalities that may surface, allowing doctors to promptly treat those abnormalities [6]. Other applications have been developed to monitor, control, and make consumption recommendations for diabetic patients [7–9]. However, patient adherence must be strict for these applications to be effective, and they are often not tailored for adolescent users. Moreover, some are designed for the general public [10, 11] or do not make specific recommendations regarding sugar and carbohydrate intake.

Consequently, this study proposes a mobile application designed to monitor excessive sugar consumption and provide personalized recommendations to guide users in controlling their excess sugar and carbohydrate intake before they suffer negative health effects. This study employs a multi-nutritional criteria decision model [12] consisting of a predefined set of 144 rules based on the analysis of personal, health, and lifestyle data under a nutritionist's supervision. Recommendations, including suggestions regarding sugar consumption and exercise, are provided to the user based on the context-awareness principle. The efficiency and user satisfaction of the proposed mobile application was evaluated in testing with 140 Thai adolescents aged between 15 and 25 years old. Users' preferences regarding degree of awareness in terms of the presentation style of the mobile application were also investigated.

2 Literature Review

This section summarizes some existing work related to this study in the areas of mobile applications, context-aware recommendations, and personalized recommendations in healthcare.

2.1 Mobile Applications in Healthcare

As people are now carrying their mobile phones for almost the entire day, portable devices have become an extraordinary source of information, including in the healthcare domain [13]. The utilization of smartphones and tablets has empowered consumers and entrepreneurs and transformed how people access information and consume services. Nowadays, these technologies are poised to alter the healthcare field in terms of service delivery and patient experience [14]. Many healthcare providers use mobile applications to provide quality healthcare services and collect user data for further utilization. Recently, mobile applications designed to facilitate the treatment and diagnosis processes have been widely developed and employed. For example,

a mobile application framework called SleepCare has been proposed for screening and managing the sleep cycle [15]. Many mobile applications have been developed for self-management purposes, especially for chronic conditions such as diabetes [9, 16, 17] and cardiovascular disease [18]. For diabetes, mHealth [9] is an important example. This mobile application focuses on self-management of medical care for diabetes patients and provides necessary related functions, such as heart rate monitoring and vaccination scheduling. In the area of cardiovascular disease, the Cardiac app [18] was developed to detect and record a person's heart rate. Cardiac can be used with a smart wearable device to monitor body temperature and heart rate and send data to a server to prevent emergencies [18]. Mobile applications are also widely used for mental health services. For example, the WHAAM application [19] aims to monitor the behaviors of patients with attention deficit hyperactivity disorder. The application provides tools for evaluating the efficacy of interventions as well as data collection. Gamification in mobile applications also typically increases users' engagement during the treatment process [20].

Mobile applications are also widely employed for general health promotion. Many applications have been developed with the aim of promoting users' well-being [21], especially with regard to diet. Within this category of mobile applications, tools that can monitor eating behavior and provide users with nutrition information are very popular. For example, eDietary Portal [22], iFood [11], and WellCo [23] can be used to manage daily calorie consumption and provide suggestions regarding diet and exercise. The mobile application proposed in this study also aims to promote users' well-being. Rather than monitoring calorie consumption, however, the proposed mobile application monitors sugar and carbohydrate consumption. It is specifically designed and developed for Thai adolescents, who tend to consume excessive amounts of sugar in their daily lives.

2.2 Context-Aware Recommendations in Healthcare

Context-aware computing has been widely introduced in many application areas, especially in the healthcare domain. These applications are very sensitive to the context (i.e., any information that can be used to characterize the users and the situation) [24]. Context awareness relates directly to a system's adaptability [25], which can be demonstrated in various ways, such as its functionality, delivered data and services, or user interface. Context-aware systems and applications change their behaviors based on the context

of the user and the situation. Recently, recommendation systems, a type of context-aware application, have received extensive attention. Context-aware recommendation systems combine contexts and user statuses to execute systems or applications [26, 27].

Generally, a recommendation system is used to tailor products and services to individual users. In the realm of healthcare applications, recommendation systems are widely used in various health-related processes. For example, a system called DIETOS provides individualized nutritional advice to enhance the quality of life of patients with diet-related chronic diseases during the treatment process [28]; E-CARE was introduced to promote remote e-healthcare services, classified into three divisions (primary, secondary, and emergency) [29]; and a system called ADAPT provides context-aware solutions for personalized asthma management [30].

With regard to prevention, the provision of context-aware recommendations for monitoring patients with multiple health conditions is highly prevalent. For example, a self-configuring mobile application using a context-aware architecture [31] was developed for monitoring health and cardiac arrhythmias, including tachycardia and bradycardia, in different situations [32]. The recommended systems in actual situations use clinical data as important contextual information to predict heart failure [33] and monitor hypertensive heart disease [32]. Among the variety of application types, mobile applications can introduce live monitoring tools, which have many advantages, such as coping with dynamic changes and promoting mobility [34]. Many context-aware recommendation systems target older populations and patients and provide monitoring and other services based on the guidance of health experts [36–38]. However, context-aware recommendation systems for healthcare applications have not yet widely been developed for young people, which is the main objective of this study.

2.3 Personalized Recommendations in Healthcare

Context-aware recommendation systems that are designed to provide any response to an individual user can be called personalized recommendation systems [38]. Nowadays, many products and services are delivered to customers in a manner that utilizes recommendation systems to provide greater individualization. These systems rely on the analysis of personal historical data, among other datasets, to identify suitable products, courses, or services [23]. Recommendation systems can reduce the time required to explore the needed data [23, 39]. In healthcare services, many healthcare

providers have applied personalized recommendation systems to understand patients' health conditions and suggest personalized healthcare services to each person [41–44]. Personalized recommendation systems can empower patients' self-monitoring by notifying them of and suggesting appropriate individual healthcare programs, such as medical services and treatment plans [41–43]. In addition, recommendation systems use factors related to users that are collected from applications or smart devices.

In the healthcare domain, three different types of data are normally used in recommendation systems: personal, health, and lifestyle. Personal data are those that represent an individual in general. Health data include measurements related to health conditions, such as BMI, heart rate, and blood pressure. Lifestyle data typically include habits, hobbies, and consumption and exercise behaviors [41–44]. For exercise applications, personalized recommendation systems provide individual programs to help users properly manage their daily life activities [44]. These applications normally require personal, health, and lifestyle data to provide these individualized programs [10, 45–49]. Recently, some mobile applications have employed the context-awareness principle to provide personalized programs to individual users [45]. However, it is still challenging for any mobile application to succeed in engaging users.

Although dietary-related mobile applications have also recently been widely used, few exist that are specifically designed for monitoring excessive sugar consumption among adolescents. The World Health Organization (WHO) and the Food and Agricultural Organization have stated that sugar and other carbohydrate-containing foods play an indispensable role in balancing dietary health [49]. Although there is no evidence that sugar consumption directly causes lifestyle-related health problems such as obesity, heart disease, diabetes, and cancer [49], an improper lifestyle, along with personal health status, can result in a greater impact on the consumption of sugar on personal health.

Therefore, this study proposes a mobile application that is specifically designed for monitoring Thai adolescents' excessive sugar consumption and providing individualized suggestions. Following the principle of context awareness, personal, health, and lifestyle data are used as the main contexts for providing the personalized recommendations in this study. The multi-criteria decision model [12], presented as a predefined set of rules, is used together with the context-awareness principle to provide personalized recommendations. The proposed mobile application was evaluated in terms of user satisfaction with functions and personalization support. The study

also evaluated users' preferred degree of awareness in presentation style to determine the appropriate presentation for engaging Thai adolescents.

3 Methodology

Three processes were involved in the methodology of this study: algorithm design, mobile application development, and mobile application evaluation (Figure 1).

More detail regarding each process is presented below.

3.1 Algorithm Design

The proposed recommendation model consists of two elements: content and presentation style (Figure 2). The content is analyzed based on the multi-nutritional criteria decision model [12] and expert advice. The presentation style is proposed based on the context-awareness principle. Details are provided in this section.

3.1.1 Multi-nutritional criteria decision model

The multi-nutritional criteria decision model [12], shown in Figure 2, is used to determine whether individuals require recommendations regarding their sugar consumption. This model collects nutrition facts and nutritionists' recommendations to create a recommendation that best matches the individual. The model considers each criterion when making a decision. The data used to construct the model include personal, health, and lifestyle data (see Table 1). Personal data include gender and age; health data include BMI and any
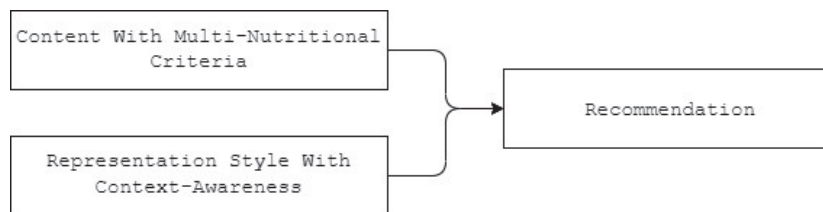

Figure 1   Research methodology.

Figure 2   Conceptual diagram of context-aware recommendation system.

Table 1   Collected data and values

Collected Data	Values
Gender	Male; female
Age (years)	15–18; 19–22; 23–25; 25+
BMI	Weight (kg); height (cm)
Personal diseases	High obesity; heart disease; depression; type 2 diabetes; no disease; other
Limiting daily sugar (Q1)	Scored on five-point Likert scales
Looking for nutrient content on product labels (Q2)	
Limiting high-cholesterol food (Q3)	
Eating at least five different types of fruits per day (Q4)	
Avoiding alcoholic drinks (Q5)	
Avoiding smoking (Q6)	
Avoiding fast food (Q7)	
Avoiding soft drinks (Q8)	
Avoiding desserts (Q9)	
Engaging in hobbies in free time (Q10)	
Engaging in frequent exercise (Q11)	
Being healthy (Q12)	
Getting enough sleep (Q13)	
Preferring to eat fermented foods (Q14)	
Adding sugar every time (Q15)	
Loving food consumption (Q16)	
Having meals on time (Q17)	
Adding sugar to tea or coffee (Q18)	
Preferring online food delivery (Q19)	
Being inspired in food selection (Q20)	

diseases; and lifestyle data were collected through questionnaires (Q1–Q20). The model, presented as a predefined set of 144 rules using a decision tree, was constructed based on data collected from 349 Thai adolescents aged between 15 and 25 years [12]. The collected data are randomly selected from an online questionnaire. The included study received an ethical approval certificate from the university. The details of the collected data and their values are presented in Table 1.

Lifestyle data (Q1–Q20; see Table 1) can be classified into six groups according to the categories of the various criteria [50]: healthy choices (Q1–Q4, Q14, Q18); harm avoidance (Q5–Q9); daily routine (Q15–Q17); physical exercise (Q10–Q12); psychological health (Q13); and common

Table 2   Example classification rules

Rule No.	Definition
1	If Q14 value > 2.5 points and BMI value > 23.8 kg/m^2 and Q3 value > 3.5 points, then Recommendation = Yes
2	If Q14 value > 2.5 points and BMI value > 23.8 kg/m^2 and Q3 value $\leq$ 3.5 points and Q17 value > 2.5 points, then Recommendation = No
3	If Q14 value > 2.5 points and BMI value > 23.8 kg/m^2 and Q3 value $\leq$ 3.5 points and Q17 value $\leq$ 2.5 points and Q7 value $\leq$ 4.5 points, then Recommendation = Yes
4	If Q14 value > 2.5 points and BMI value > 23.8 kg/m^2 and Q3 value $\leq$ 3.5 points and Q17 value $\leq$ 2.5 points and Q7 value > 4.5 points, then Recommendation = No
5	If Q14 value > 2.5 points and BMI value $\leq$ 23.8 kg/m^2 and Q18 value > 4.5 points and Q4 value $\leq$ 3.5 points, then Recommendation = Yes
44	If Q14 value $\leq$ 2.5 points and Q6 value $\leq$ 1.5 points and Q15 value $\leq$ 1.5 points and Q18 value $\leq$ 4 points and Q16 value $\leq$ 2.5 points and BMI value $\leq$ 23.4 kg/m^2 and Q3 value $\leq$ 4.5 points and Q18 $\leq$ 2.5 points and BMI $\leq$ 17.2 kg/m^2, then Recommendation = No

behaviors (Q19–Q20). In this study, five-point Likert scales were used to assess both satisfaction and frequency. This study adopted the classification rules from previous work [12]. Example rules used in this study are shown in Table 2. The output decision comprises two classes: "Yes" and "No." The "Yes" class means that the user needs recommendations regarding sugar consumption, whereas the "No" class means that the user does not need such recommendations.

For example, Rule 1 (see Table 2) declares that users require recommendations from the system to control their sugar consumption if they have an agreement value of more than 2.5 points for the statement that they prefer to eat fermented food (Q14), a BMI over 23.8 kg/m^2, and an agreement value of more than 3.5 points for the statement that they limit high-cholesterol foods (Q3). Rule 2 declares that users do not require recommendations from the system to control their sugar consumption if they have an agreement value of more than 2.5 points for the statement that they prefer to eat fermented food (Q14), a BMI over 23.8 kg/m^2, an agreement value less than or equal to 3.5 points for the statement that they limit high-cholesterol foods (Q3), and an agreement value of more than 2.5 points for the statement that they have their meals on time (Q17).

Individuals who require recommendations will be provided with individualized content in different presentation styles. The details of these two processes are shown as follows.

3.1.2 Context awareness for mobile applications

Context awareness refers to a system's ability to consider an entity's situation by using context [51, 52]. Contextual information may include data obtained from the user or a smart device regarding the specific circumstances. In this study, context awareness is used to design an appropriate degree of awareness and provide different types of recommendation presentation styles to users that best match their preferences. The degree of awareness is evaluated in this study to determine the most suitable presentation style for the target group of Thai adolescents. Three types of recommendation systems are investigated in this study, described below.

Fully Automatic Recommendations

A fully automatic recommendation system is self-adaptive, adjusting its behavior in accordance with its perception of the environment. Such systems require little or no effort from users, and no special knowledge is necessary to use them [53, 54]. In this study, fully automatic recommendations are automatically provided recommendations for sugar and carbohydrate consumption based on the system's calculation of the user's consumption given the information that the user enters into the application (see Table 1), without any intervention from the user.

Partially Automatic Recommendations

Partially automatic recommendation systems require involvement from the user to specify how the application should change or behave in some situations. The system can provide all possible information or actions to the user so that the user can select which actions are appropriate [55]. Such systems are designed such that users can choose a word from the system. For partially automatic recommendations, the system provides automatic carbohydrate intake recommendations based on its calculations. However, it also allows users themselves to calculate and enter the amount of added sugar that they want to consume per day, thereby enabling the system to be flexible in adjusting to the needs of users and allowing them to participate in some decisions.

Zero Automatic Recommendations

For systems that provide zero automatic recommendations, recommendations are provided only based on what the user has set and entered into the system. Such systems allow users to decide all of their consumption goals and recommendations based only on user input. Thus, users are empowered

to determine their own consumption and to decide what is best suited to their needs. However, users' predefined goals will be based on specific guidelines set by nutritionists.

3.1.3 Recommendation design

After the individual is classified as the person requiring the recommendation, the recommendation is constructed based on various factors to suit that user's specific personal health conditions and lifestyle. The associated variables for each factor are presented in Table 3.

The specific details of the recommendations provided in this study are shown in Table 4.

All recommendation rules shown in Tables 3 and 4 were approved by two nutrition specialists. The condition of referral in this study refers to the

Table 3 Descriptions of all factors: body mass index, physical activity, consumption and lifestyle, and diabetes risk

No.	Factor	Variable	Description
1	Body Mass Index (BMI)	BMI1	Being underweight (less than 18.50 kg/m^2)
2		BMI2	Being a healthy weight (greater than or equal to 18.50 kg/m^2 and less than 23.00 kg/m^2)
3		BMI3	Being overweight (greater than or equal to 23.00 kg/m^2)
4		BMI4	Being obese (greater than or equal to 25.00 kg/m^2)
5	Physical Activity(ACT)	ACT1	Engaging in normal activities and some exercise
6		ACT2	Exercising three to five times per week
7		ACT3	Exercising every day
8		ACT4	Engaging in hard exercise every day
9	Consumption and Lifestyle(LIF)	LIF1	Consuming fewer carbohydrates than required (less than 24 g)
10		LIF2	Consuming prescribed amount of carbohydrates (less than or equal to 24 g)
11		LIF3	Consuming excessive amounts of carbohydrates (greater than 24 g)
12	Diabetes Risk (DIA)	DIA1	No diabetes
13		DIA2	At risk of becoming diabetic
14		DIA3	Diabetic

Table 4   Descriptions of recommendations for body mass index, physical activity, consumption and lifestyle, and diabetes risk

No.	Recommendation	Variable	Description
1	Recommendations for Body Mass Index(RBMI)	RBMI1	– Eating good-quality food from adequate range of food groups, focusing on meat, milk, eggs, vegetables, and fruits, getting enough rest
2		RBMI2	– Maintaining health and controlling weight at a healthy level, maintaining the same weight
3		RBMI3	– Limiting foods such as flour, sugar, and fat – Exercising for at least 30 minutes at least three times per week
4		RBMI4	– Avoiding starchy foods such as sugar and fats – Being active while performing daily tasks such as housework, work, and occupation – Exercising for at least 30 minutes every day
5	Recommendations for Physical Activity(RACT)	RACT1	– Exercising at least 30 minutes three times per week
6		RACT2	– Maintaining exercise regimen – Getting enough rest
7		RACT3	– Maintaining exercise regimen – Eating good-quality food from adequate range of food groups, focusing on meat, milk, eggs, vegetables, and fruits – Getting enough rest
8		RACT4	– Maintaining exercise regimen – Eating good-quality food from adequate range of food groups, focusing on meat, milk, eggs, vegetables, and fruits – Getting enough rest
9	Recommendations for Consumption and Lifestyle(RLIF)	RLIF1	– Maintaining level of food consumption
10		RLIF2	– Maintaining level of food consumption
11		RLIF3	– Reducing sugar consumption – Checking blood sugar levels every year

(*Continued*)

Table 4 Continued

No.	Recommendation	Variable	Description
12	Recommendations for Diabetes Risk (RDIA)	RDIA1	– Maintaining level of food consumption
13		RDIA2	– Moderating level of daily food consumption
14		RDIA3	– Limiting foods such as flour, sugar, and fat

related guidelines in food supplements, and each condition is presented as a factor linked with features related to personal health and lifestyle status.

As shown in the Tables 1 and 3, BMI indicates different balances of body weight and height, based on age and gender, that can be used to control daily energy consumption [56, 57]. BMI, measured in kg/m^2, is divided into the following categories: underweight (BMI $<$ 18.50), healthy weight (18.50 $\leq$ BMI $<$ 23.00), overweight (23.00 $\leq$ BMI $<$ 25.00), and obese (BMI $\geq$ 25.00). Since blood glucose is one of the primary energy sources for muscle construction during activity, limiting sugar consumption can balance and improve physical performance [58]. Furthermore, the WHO suggests that daily sugar consumption be limited to 24 grams due to the adverse effects of increased prevalence of dental cavities, micronutrient deficiencies, obesity, and diabetes [49]. Excessive sugar consumption increases the risk of high levels of triglycerides, which can heighten cholesterol levels [59]. Thus, these two factors are linked. Soft drink consumption is also associated with undesirable side effects [60]. However, consuming added sugar may be inevitable due to an individual's personal lifestyle. Personal lifestyle is relevant with regard to sugar consumption among adults insofar as it affects food consumption frequency and schedule [61]. To realize cooperative sugar consumption behavior, the U.S. Food and Drug Administration states that food labeling enables better consideration of health and nutrition contents, even if it does not fit an individual's personal preferences [62]. As all of these are relevant to user behavior, this study applies the mentioned factors with different classes to cover personal information and create 144 recommendation rules based on a predefined ruleset to match as many users as possible (examples presented in Table 5).

Rule 1 (see Table 5) is assigned to a user who is underweight (BMI $<$ 18.50 kg/m^2), engaging in normal activity and some exercise, consuming fewer carbohydrates than required, and not diabetic. The given recommendation for such a user is to consume quality foods from a range of food groups, with a focus on meat, milk, eggs, vegetables, and fruits, and to get enough

Table 5   Sample recommendation rules

Rule	Factor Set	Recommendation Set
1	BMI1 & ACT1 & LIF1 & DIA1	RBMI1 & RACT1 & RLIF1 & RDIA1
2	BMI1 & ACT1 & LIF1 & DIA2	RBMI1 & RACT1 & RLIF1 & RDIA2
3	BMI1 & ACT4 & LIF3 & DIA3	RBMI1 & RACT4 & RLIF3 & RDIA3
4	BMI2 & ACT1 & LIF1 & DIA1	RBMI2 & RACT1 & RLIF1 & RDIA1
5	BMI2 & ACT1 & LIF1 & DIA2	RBMI2 & RACT1 & RLIF1 & RDIA2
6	BMI3 & ACT4 & LIF2 & DIA1	RBMI3 & RACT4 & RLIF2 & RDIA1
7	BMI3& ACT4 & LIF3 & DIA1	RBMI3 & RACT4 & RLIF3 & RDIA1
8	BMI3& ACT4 & LIF2 & DIA2	RBMI3 & RACT4 & RLIF2 & RDIA2
9	BMI4& ACT3 & LIF2 & DIA3	RBMI4 & RACT3 & RLIF2 & RDIA3
10	BMI4& ACT2 & LIF2 & DIA3	RBMI4 & RACT2 & RLIF2 & RDIA3
144	BMI4& ACT4 & LIF3 & DIA3	RBMI4 & RACT4 & RLIF3 & RDIA3

rest. The user should also exercise for 30 minutes at least three times per week and maintain adequate levels of food consumption. Rule 144 is given to a person who is obese (BMI > 25.00 kg/m^2), engaging in hard exercise every day, consuming excessive amounts of carbohydrates, and diabetic. The given recommendation for this user is to avoid starchy foods such as sugar and fats; perform active daily tasks such as housework, work, and occupation; and exercise for at least 30 minutes every day. The user should also eat quality foods from each of the required food groups, focusing on meat, milk, eggs, vegetables, and fruits, and get enough rest. This person should also reduce their sugar consumption, check their blood sugar levels every year, and limit foods such as flour, sugar, and fat.

3.2 Mobile Application Development

The system is a mobile application that the users can access via the internet. The application uses a PHP server (version 7.3 or higher) connected to a MySQL database. The application allows users to save their personal data through the Android platform. It subsequently sends these data to be stored and processed on the server and can then access the information to provide recommendations to users in Android applications. The system's data structure consists of three main parts: personal data, health status, and lifestyle data. These are further divided into personal information, personal disease information, activity information, sugar and carbohydrate consumption information, recommendation information, and daily consumption statistics, all of which were used to create various functions in the algorithm design by linking various processes and data (see Appendix).

Table 6 Descriptive characteristics of user testing group

Factor	Range	Measurement	
		Mean	Standard Deviation
Age	15–25 years	20.81	2.2
Gender	Male, female	—	—
Weight	40–90 kg	57.64	12.97
Height	150–181 cm	164.25	7.72
Body Mass Index	14.88–31.99 kg/m^2	21.25	3.93

3.3 Mobile Application Evaluation

The developed mobile application was evaluated by a group of Thai adolescents aged between 15 and 25 years, including both males and females whose BMIs ranged from 14.88 to 31.99 kg/m^2 and who were accustomed to using technology in daily life. The characteristics of the test group are shown in Table 6.

The evaluation addressed two aspects: user satisfaction and preferred degree of awareness. Within the category of user satisfaction, two aspects were evaluated: satisfaction with functions and satisfaction with personalization support. Five-point Likert scales were used for these measures. Satisfaction with each criterion was assessed using five levels, where 1 indicated the lowest satisfaction and 5 the highest. The possible satisfaction levels were categorized as "very high" (4.21–5.00), "high" (3.41–4.20), "medium" (2.61–3.40), "low" (1.81–2.60), and "very low" (1–1.8).

With regard to preferred degree of awareness, users were asked for their preferences regarding content presentation style at three different phases (over the course of seven days). In each phase, the user was required to indicate their preferred content presentation style from three possible levels of degree of awareness: fully automatic recommendations, partially automatic recommendations, and zero automatic recommendations.

4 Experimental Results and Discussion

4.1 User Interface

The proposed mobile application was designed for the Android platform. Example results are presented for each page of the application interface, as follows.

The homepage and login page, shown in Figure 3, allow users to choose to either register a new account or log into the system with a preexisting
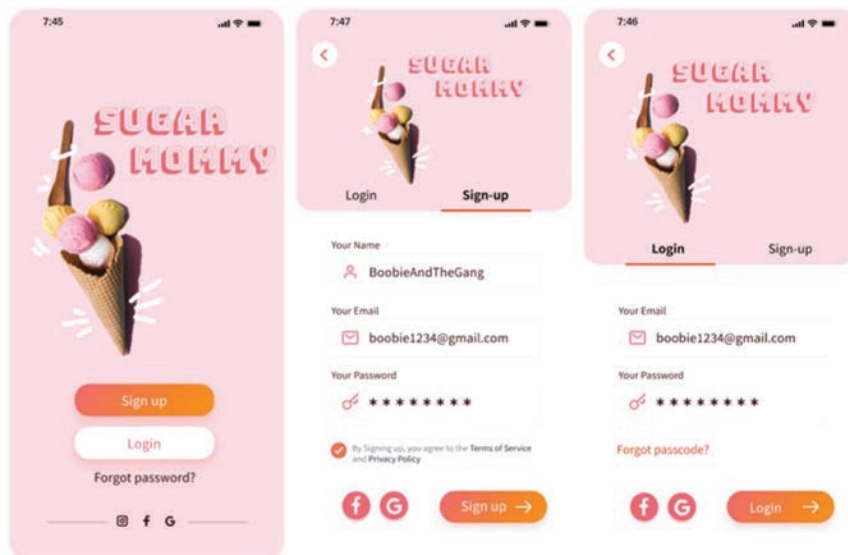
Figure 3   Homepage and login page.

account. The registration page is used to prove the identity of the user as an authentication requirement.

The personal information page, shown in Figure 4, includes all factors relevant to the multi-nutritional criteria. Users do not need to calculate BMI themselves; the system automatically calculates it based on weight and height. Users are also required to provide authorization for users or administrators to observe the stored information. The activity page allows users to choose the activities that suit them so that the system can evaluate whether the user should be provided recommendations to engage in the selected activity. The personal preference page allows users to design the automation level of the recommendation system based on what kind of recommendations suits their lifestyle. If users select Item 1 (fully automatic recommendations), the system will automatically calculate their carbohydrate intake and direct them to the main page, shown in Figure 5. If users select Item 2 (partially automatic recommendations), the system will allow them to enter their daily consumption of sugar (how many grams they would like to set as their daily consumption limit), as shown in Figure 6(a). The system will then make recommendations according to users' requirements. If users choose Item 3 (zero automatic recommendations), the system will ask them to enter their daily limit for sugar consumption by themselves and
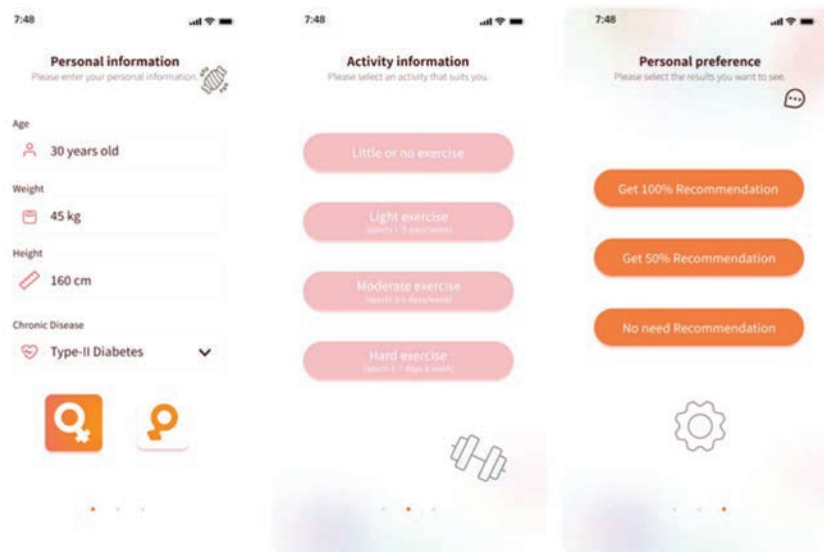
Figure 4 Personal information page.

will calculate the amount of carbohydrate intake as required by the user, as shown in Figure 6(b). The system will then make recommendations according to the user's specifications.

The summary page for daily sugar consumption is displayed in Figure 5. Two separate circles are used to indicate added sugars and carbohydrate consumption. Users can press the + icon to increase their sugar consumption and can click on the added sugars circle to view or edit their sugar consumption information. When the user presses the + icon to increase their sugar consumption level, a page will appear that enables them to fill in the amount of sugar they have consumed, after which they can press the save button to return to the main page. If the user presses the search icon, they are taken to the next page, where they can press the + icon if they have consumed any of the items displayed. After users press the + icon, they are returned to the main page, and their consumption amount is calculated.

As shown in Figure 7, when it is time for dinner, the system shows a summary of users' consumption so that they can see whether they have achieved their target for the day. When users press the sugar consumption circle, the sugar consumption details page appears. Users can delete sugar consumption information by pressing the – button if they have entered their consumption incorrectly. When users press the carbohydrate intake circle, the
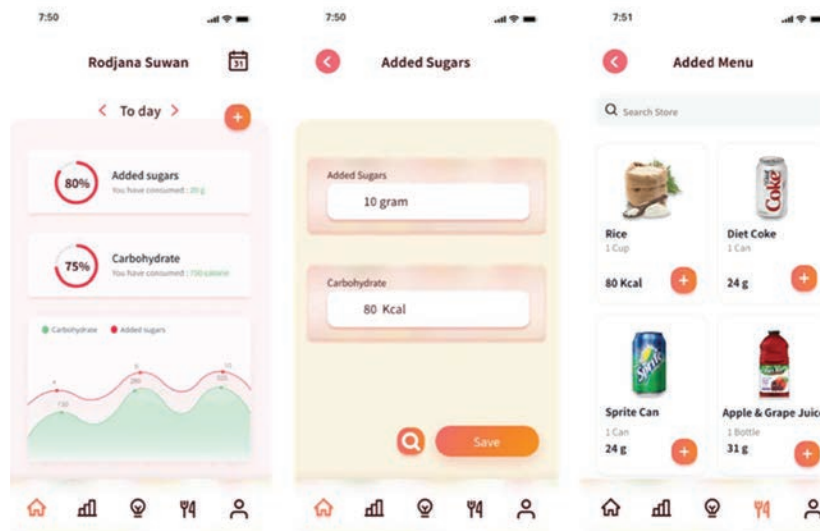
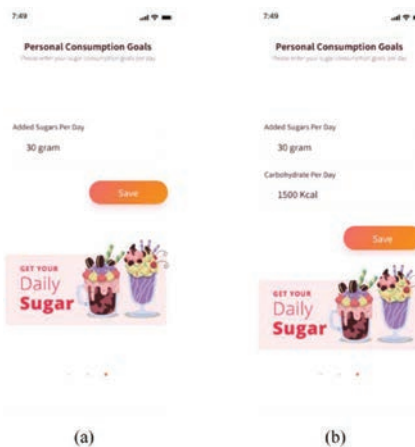**Figure 5**   Personal consumption goals page.

Figure 6   Personal consumption goals page: (a) partially automatic recommendations and (b) zero automatic recommendations.

carbohydrate intake details page appears. Users can delete their carbohydrate consumption information by pressing the – button to delete an entry if they have entered their information incorrectly.

Users' weekly statistics for sugar and carbohydrate consumption can be visualized as a graph presented on the statistics page, as shown in Figure 8.
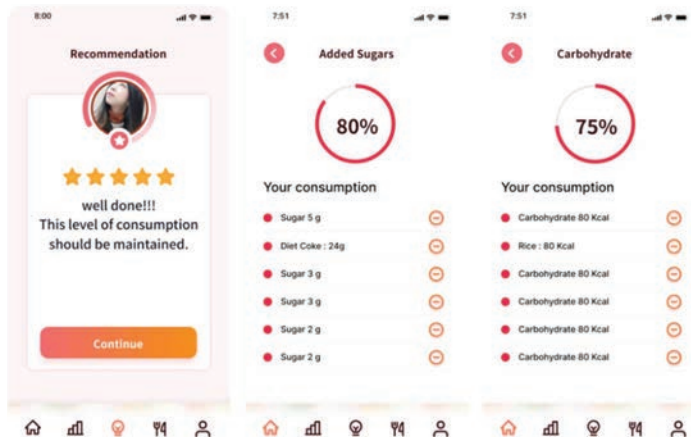
Figure 7 Recommendation level page.

Figure 8 Statistics page.

User profile pages, shown in Figure 9, allow users to edit their profiles. If a user has made an incorrect entry or their weight has changed, the system will make calculations based on the various user data recorded in a log to identify the consumption behavior that has affected the user's weight.

When users press the menu icon, a guide will pop up in the form of an individual recommendation window, as shown in Figure 10. The calendar
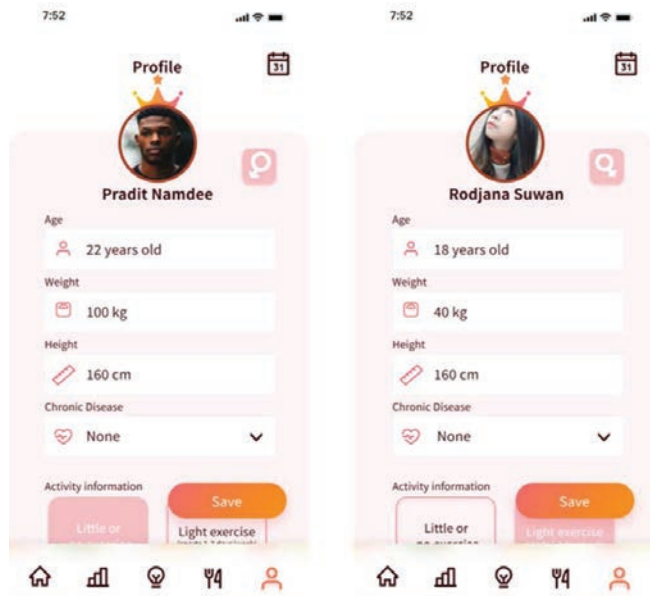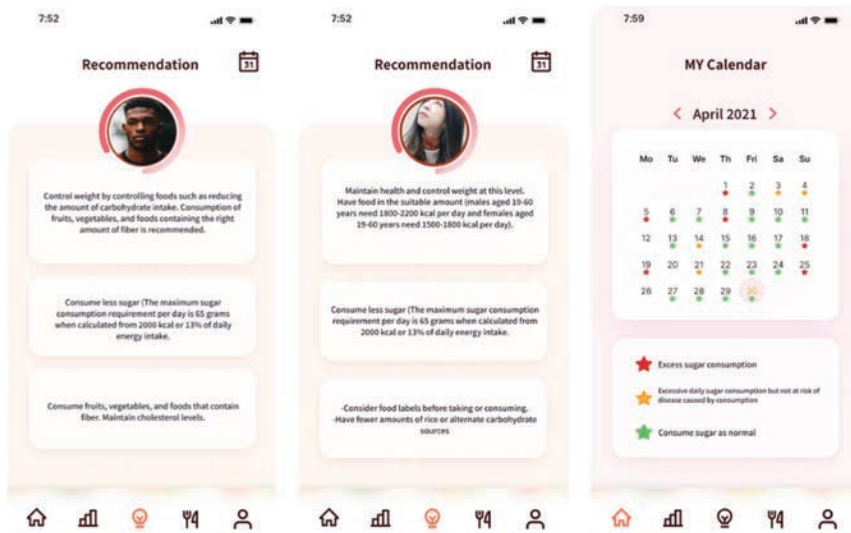
Figure 9   Profile page.

Figure 10   Recommendation results page.

Table 7   User satisfaction results for function and personalization

No.	Item	Mean	Assessment Criteria Level
Satisfaction: Function			
1	The application overall has functions that can be easily used	4.31	Very High
2	The application is useful in daily life	4.27	Very High
3	The classification of the content is clear and appropriate	4.24	Very High
4	The application has a background and menus that are appealing to use	4.10	High
5	The format of the information presented in the application is easy to read and use	4.25	Very High
6	The basic functions of the application are easy to use	4.32	Very High
	Average	4.25	Very High
Satisfaction: Personalization			
7	Information and advice are presented according to users' needs	4.39	Very High
8	Using the application's personal recommendation function is easy and convenient	4.33	Very High
9	The personalized content presented by the application is easy to understand	4.23	Very High
10	This module is essential to maintaining your health	4.26	Very High
	Average	4.30	Very High

page shows users' total monthly consumption results. A star icon appears in different colors to indicate on which days the user's consumption was or not successful.

4.2 Mobile Application Evaluation

An assessment of user satisfaction was designed to prove the usability of the proposed application. Assessment criteria were measured using the aforementioned Likert scale. The user satisfaction results for all samples are presented in Table 7. Furthermore, The evaluation results for efficiency and user satisfaction among a sample of 140 Thai adolescents are reported in Table 7.

Table 8   Evaluation results for degree of awareness

No.	Item	Percentage of Respondents Automatic Recommendation Level		
		Zero	Partial	Full
1	If you want to go on a diet or control your sugar and carbohydrate consumption in the first three days, what kind of recommendations do you prefer?	2	13	85
2	If you want to go on a diet or control your sugar and carbohydrate consumption for a while (days four and five), what kind of recommendations do you prefer?	7	7	86
3	If you want to go on a diet or control your sugar and carbohydrate consumption for a while (days six and seven), what kind of recommendations do you prefer?	4	11	86

4.2.1 User satisfaction with function and personalization

Table 7 shows that user satisfaction with both function and personalization was very high. Users were more satisfied by the personalization than the function of the mobile application. With regard to function-related satisfaction, the item measuring whether users thought the application's basic functions were easy to use obtained the highest satisfaction score. With regard to personalization-related satisfaction, the presentation of information and advice achieved the highest satisfaction score.

4.2.2 Evaluation of degree of awareness

With regard to degree of awareness, users' preferences regarding the three degrees of awareness described previously were investigated. The satisfaction results for these three degrees of awareness at different testing periods are shown in Table 8.

As shown in Table 8, most users are satisfied with fully automatic recommendations for all three phases. In the first phase, 85% of users were satisfied with fully automatic recommendations, indicating that they were interested in receiving the appropriate recommendations as provided by the system without self-calculating. This evidence indicates that users may prefer to try using the appropriate recommendations as provided by the system, rather than working on recommendation creation themselves (whether partial

or full participation). Fully automatic recommendations were also preferred in the other phases by 86% of all users. It can thus be concluded that the application can successfully engage users to follow the recommendations provided by the system. Consequently, the proposed mobile application is deemed suitable for the target group (Thai adolescents). In future work, we aim to apply the personalized recommendation application with other target groups.

4.3 Discussion and Future Work

In this study, 144 pre-referral rules were created, which may not be enough for users of various age groups. Therefore, in future work, we plan to use machine learning and context awareness to apply users' data to precisely categorize people and lifestyles to create automatic recommendations. We will avoid having the user prepare the rules, as here, and will be as flexible as possible in responding to the user's individual characteristics. The background and menus of the application require improvement to increase user satisfaction—a worthwhile endeavor for future work. However, improving the personalized content to be more understandable could be considered in future work. In addition, future studies should focus on expanding the use of the application to different age groups.

5 Conclusion

This study proposes a context-aware personalized recommendation mobile application for Thai adolescents to monitor their excessive sugar consumption and provide them with proper individualized recommendations. The proposed mobile application applies a multi-nutritional criteria decision model together with the context-awareness principle to provide individual recommendations based on the user's personal, health, and lifestyle data. Experiments were conducted with 140 Thai adolescents aged between 15 to 25 years old. The mobile application was evaluated in terms of efficiency, user satisfaction, and degree of awareness. The results showed that the developed mobile application obtained very high user satisfaction with regard to both function and personalization. Fully automatic recommendations were the most preferred presentation style by the evaluation group of young users. In future work, testing should be extended to include other generation groups.

Appendix
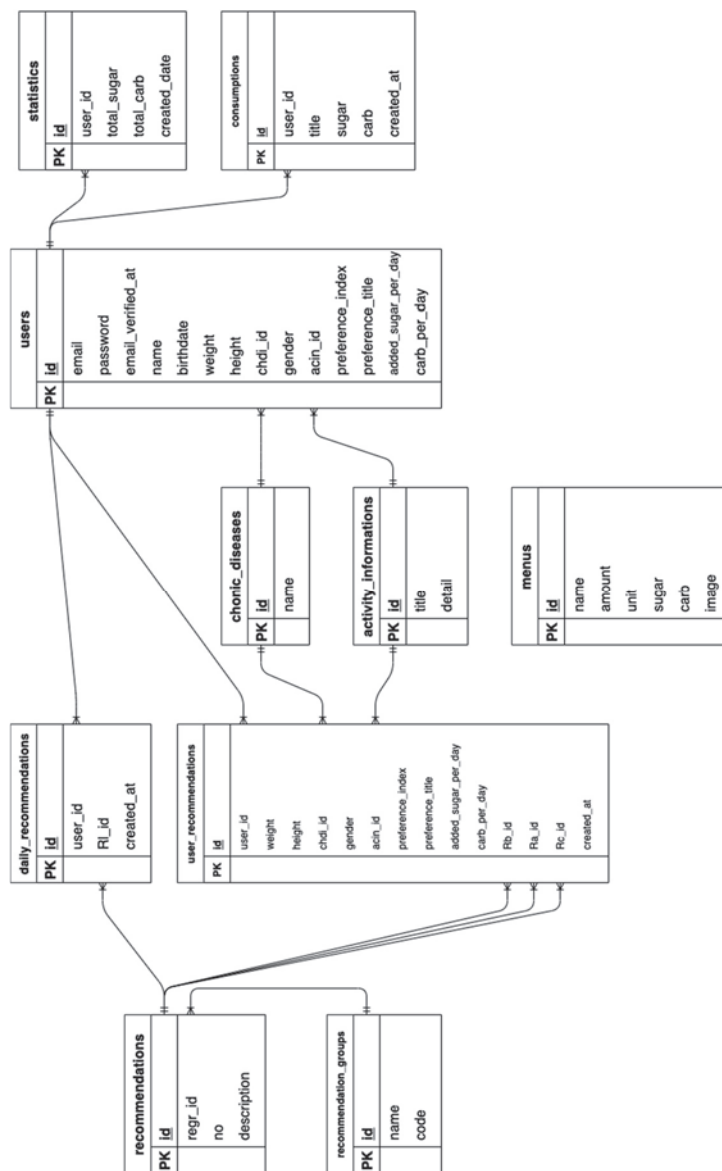
Figure 11   Entity relationship diagram for mobile application development representing all dataset links and data relationships in proposed application.

Acknowledgments

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