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Glucofit: Evaluating Daily Sugar Consumption in Preventing Diabetes using SUS Method

Muhammad Harel[1], Sri Mulyati[2]

Abstract
Diabetes Mellitus (DM) is a growing global health issue, particularly in Indonesia, with excessive sugar consumption identified as a major contributing factor. However, public awareness regarding daily sugar intake remains low, partly due to the complexity of interpreting nutritional information. To address this problem, this study proposes the development of an Android-based application aimed at monitoring daily sugar consumption and supporting diabetes prevention efforts. The application integrates both manual input and automated food detection to estimate sugar intake, along with a barcode scanner for retrieving product nutritional data. A calorie-based calculation method is applied to adjust individual sugar intake recommendations based on personal energy needs. The development follows the AGILE methodology. System functionality was evaluated through black-box testing, while usability was assessed using the System Usability Scale (SUS). The results demonstrated that the application functions reliably, with an average SUS score of 81.43, classified as “Excellent” and within the “Acceptable” range. These findings suggest that the application has a high level of usability and user acceptance, offering a promising tool for promoting healthy sugar consumption behavior and supporting preventive healthcare through digital monitoring.

Keywords:
Evaluation, Diabetes, AGILE, SUS Method

1. Introduction

Health is an important factor in human life, especially in the era of globalization. In the health sector, the quality of life of a country is highly dependent on the ability of the community to maintain its health, especially through the prevention and management of chronic diseases. Diabetes mellitus, which is characterized by hyperglycemia due to impaired insulin production by the pancreas or low cellular sensitivity to insulin, is one of the global health problems [1][2][3]. Diabetes mellitus has become one of the biggest health problems in Indonesia and the world. Based on data provided by the International Diabetes Federation (IDF), the number of diabetics in the world every year is increasing and is even projected to continue to increase until 2045. As of 2021, the number of people with diabetes has reached 537 million. This figure is predicted to continue to increase to 643 million in 2030 and 783 million in 2045. Indonesia is ranked as the fifth country with the highest number of diabetes patients, with 19.5 million patients in 2021, and is predicted to become 28.6 million by 2045 [2]. This increase is influenced by a variety of factors, including genetics, sedentary lifestyles, obesity, and consumption of foods with a high sugar and fat

Corresponding Author: Muhammad Harel (muhammad.harel@students.uii.ac.id)
1 Muhammad Harel, Universitas Islam Indonesia, muhammad.harel@students.uii.ac.id
2 Sri Mulyati, Universitas Islam Indonesia, mulya@uii.ac.id

content [4].

High sugar consumption can increase insulin resistance and lead to various other health complications, such as heart disease, obesity, and hypertension. According to data from the World Health Organization (WHO), excessive sugar consumption is one of the main contributors to the increasing prevalence of non-communicable diseases in the world, including in Indonesia [5].To overcome this problem, the Indonesian government, through the Ministry of Health, has issued Regulation of the Minister of Health Number 30 of 2013 concerning the Inclusion of Information on the Content of Sugar, Salt, and Fat as well as Health Messages on Processed Foods and Ready-to-Eat Foods. The regulation aims to enable the public to find out information on the nutritional value contained in food and beverages written on food labels [6]. However, even though this regulation has been implemented, the level of public understanding of nutrition information is still low. Research conducted by Mauludyani shows that only 37.5% of consumers really pay attention to nutritional information before buying food [6].

This gap shows the need for solutions that are more accessible and used by people in controlling their daily sugar intake. Mobile application-based digital technology is one potential approach to overcome this problem. Along with the increasing smartphone penetration in Indonesia, which has reached 209.3 million active users in 2023 [7]. The development of Android-based applications to monitor daily sugar consumption is an appropriate solution.

This research aims to develop an Android-based application that functions to record and analyze users' daily sugar consumption. This application integrates two methods of recording sugar consumption data, namely (1) manual input based on user knowledge of the number of grams of sugar in the food consumed, and (2) food object detection to estimate the sugar content in the identified food. In addition, this application is equipped with a barcode scanning feature that functions to obtain information on the nutritional content and nutritional level of a product, but this feature is not used as a direct input in recording sugar consumption. To increase user awareness of healthier sugar consumption patterns, the application also provides data visualization in the form of interactive graphs, a notification system that provides reminders of sugar consumption, and educational content regarding recommended sugar consumption limits based on health standards.

The novelty of this study lies in its integration of adaptive behavioral interventions within a mobile application to monitor and manage sugar consumption. Unlike previous works that focus solely on tracking or gamification, this application emphasizes real-time personalized education and automated data capture, combining image detection and barcode input. By focusing on actionable behavior change, this approach provides a comprehensive tool for diabetes prevention tailored to user habits and preferences.

2. Related Works

Several previous studies have developed mobile apps to help monitor sugar consumption. A paper developed a mobile-based app with context-based personalization recommendation features for teens in Thailand. The app leverages users' personal and lifestyle data to provide relevant automated suggestions regarding reducing sugar consumption [8]. Another work designed an e-coaching application with a gamification approach to reduce the consumption of sugar-sweetened beverages in adolescents. The app comes with avatar features, challenges, reward systems, and statistical reports. The results of the study show that gamification elements are able to increase user engagement [9]. An article developed an iOS-based TrackSugAR application with augmented reality

(AR) technology to visualize the sugar content in food in the form of 3D cubes. The app also includes barcode scanning and tracking of sugar consumption data through interactive visual graphs [10].

An article reported that the *Smart Tracking for Healthier Lifestyle* application effectively improved user awareness and control over sugar consumption. The integration of a barcode scanner, consumption reminders, and visual feedback through graphs significantly enhanced users' ability to monitor their dietary habits. The evaluation demonstrated that users became more conscious of their nutritional choices, indicating the application's success in encouraging healthier lifestyles [11]. Another paper found that the daily calorie monitoring application received a strong positive response from users during usability testing. The application, which included features such as login access, educational materials, calorie calculation, and food intake records, was evaluated for its user interface and functionality. Results showed that users appreciated its ease of use and found it beneficial for maintaining dietary discipline, particularly in the context of diabetes prevention [12].

Recent papers concluded that their blood sugar monitoring application contributed positively to diabetes self-management. Users benefited from features such as graphical monitoring, logging activities, alarms, and personalized educational content. The application was particularly well-received for its ability to provide real-time health insights and guidance based on expert recommendations, supporting better glycemic control and personalized user engagement [13]. Another paper evaluated the implementation of electronic medical records using the Agile development method for inpatient mortality reporting. The study reported that the system successfully streamlined the reporting process, enhanced data accuracy, and improved access to patient mortality records. The results indicate that Agile-based development was effective in aligning system functionality with healthcare operational needs, contributing to more efficient health data management [13].

3. Proposed Method

1.1 System Development Flow

The development process of the application adopts the Agile methodology, including Analysis, Planning, Design, Development, and Testing, which facilitates continuous iterations and refinements based on user feedback [14], [15]. To represent the AGILE software development model mathematically, we abstract the iterative and incremental nature of AGILE into a cycle-based formula, emphasizing sprints, features, and feedback loops as follows:

Mathematical Description of the AGILE Development Model

Let:

- P = Total software product
- S_i = The i Sprint (iteration), where $i = 1,2,\ldots,n$
- F_i = Set of features implemented in S_i
- T_i = Time duration of Sprint i
- V_i = Value or functionality delivered in Sprint i
- R_i = User or stakeholder feedback collected after Sprint i
- ΔF_i = Adjustments or new features added based on R_i

Then, the AGILE development process can be described as:

$$P = \bigcup_{i=1}^{n} (F_i + \Delta F_{i-1}) \qquad \text{Eq.1}$$

Subject to:

$$F_i = \text{Develop}(R_{i-1}, T_i), \text{for } > 1; F_1 = \text{Initial backlog features}$$
$$\Delta F_i = \text{Refine}(R_i), R_i = \text{Evaluate}(V_i)$$
$$V_i = \text{Deploy}(F_i), \text{where each } V_i \subseteq P$$

Interpretation:

- Each sprint S_i contributes a set of features F_i, developed based on prior feedback R_{i-1}.
- Feedback R_i obtained from each sprint influences the subsequent sprint by modifying or adding features ΔF_i
- The full product $P$is the union of all features developed and adjusted across n sprints.
- This formulation highlights the iterative, feedback-driven enhancement of the product characteristic of AGILE methodologies.

The analysis stage plays a critical role in identifying user and system requirements. We conducted this stage through surveys, interviews, and comparative studies of existing applications to gather comprehensive insights into user behavior and expectations. This process allowed us to formulate evidence-based feature requirements and design considerations tailored to the end user's needs. By leveraging these insights, we ensured the system's relevance, usability, and alignment with real-world health management scenarios that particularly in the context of monitoring sugar consumption and lifestyle-related conditions such as diabetes.

Afterward, we executed the planning stage to establish a structured workflow for development. The development team created a detailed timeline, defined required resources, and set iteration goals and deliverables. This phase enabled the team to allocate tasks efficiently and monitor progress through each sprint or iteration. In the design phase, we developed system models including use case diagrams, activity diagrams, and database schema to capture functional workflows and data relationships. We also built wireframes to design intuitive user interfaces, ensuring clarity in navigation and interaction. These design artifacts served as blueprints for the development team, minimizing ambiguity during coding and accelerating the transition from conceptual design to working features.

In the development phase, we implemented the application using the Kotlin programming language with support from the Android SDK framework, translating all design outputs into functional code. After development, we conducted the testing phase to validate system reliability and usability. We applied black-box testing to assess whether application features performed as expected without examining internal code. Furthermore, we employed the System Usability Scale (SUS) to quantify the application's usability from the user's perspective. This two-pronged evaluation approach ensured that the application not only met technical specifications but also delivered a positive user experience, reinforcing its readiness for real-world deployment.

1.2 Personalized Sugar Intake Model

Developing a model to monitor sugar intake is essential to drive behavioral changes through continuous feedback and personalized insight. Traditional health campaigns are often one-way and lack contextual relevance. Therefore, by integrating manual input, machine learning-based food detection, and tailored notifications, this application offers a dynamic and adaptive experience aligned with user behavior. To support sugar intake monitoring, the application uses a calculation model based on each user's energy needs. This begins with estimating the Basal Metabolic Rate (BMR**)** using the Harris-Benedict equation [16], [17], [18]:

- Male: BMR = 66 + (13.7 × weight [kg]) + (5 × height [cm]) – (6.8 × age [years])
- Female: BMR = 655 + (9.6 × weight [kg]) + (1.8 × height [cm]) – (4.7 × age [years])

To calculate Total Daily Energy Expenditure (TDEE), the BMR is multiplied by an activity factor as Table 1:

Table 1: Activity factor to calculate Total Daily Energy Expenditure (TDEE)

Activity Level	Multiplier
Sedentary	× 1.2
Light (1–3 days/week)	× 1.375
Moderate (3–5 days/week)	× 1.55
Very Active (6–7 days/week)	× 1.725
Extra Active (twice/day)	× 1.9

According to WHO recommendations, added sugar should not exceed 10% of total daily calories. Since each gram of sugar provides 4 kcal, the formula to calculate the personalized daily sugar limit (in grams) is:

$$\text{Sugar Consumption Limit (grams)} = (10\% \times \text{Total calories})/4$$

This calculated limit becomes a personalized benchmark used by the app to track intake and generate real-time feedback. The system also triggers warning notifications when consumption approaches or exceeds this limit.

4. Experimental Setup

To collect a dataset, the researcher conducted an initial survey of 58 respondents to understand user behaviors, preferences, and challenges related to monitoring daily sugar consumption. The survey results show that although awareness of sugar consumption is quite high, the use of digital health monitoring apps is still low. Respondents showed interest in automatic recording features, consumption history, warning notifications, and educational content about healthy eating. These findings are used as the basis for designing the system of needs and prioritizing the features developed. Fig.1 depicts a use case diagram that represents the user's interaction with the system.

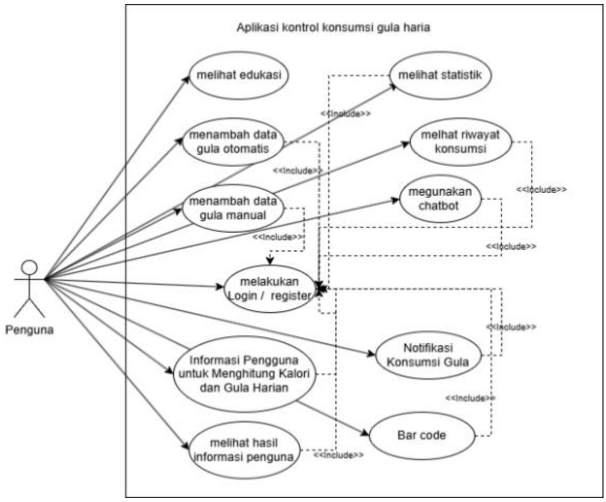

Fig. 1. Use Case Diagram

5. Results and Analysis

Based on the survey results of 58 respondents, the majority of respondents (48.3%) have never used a health monitoring application, while 39.7% use it occasionally, and only 12.1% use it often. However, awareness of daily sugar consumption is quite high, with 53.4% of respondents wanting to be more conscious of their diet, 24.1% for health reasons, and 13.8% for energy and fitness. Most (43.1%) monitor sugar consumption daily, while 29.3% only a few times a week. In terms of record-keeping, 53.4% prefer automatic record-keeping, 22.4% manually, and 24.1% want both. In addition, 82.8% of respondents thought sugar consumption notifications were very important, while 17.2% felt it might be useful.

As many as 93.2% of respondents were interested in the sugar consumption history feature, while 82.8% wanted a suggestion or warning feature when sugar consumption exceeded safe limits. The way to find out the amount of sugar consumption also varies, with 39.7% relying on product labels, 34.5% using personal estimates, and 34.5% wanting a sugar content scanner feature. In addition, 72.4% of respondents rated healthy eating articles and tips as an important feature.

A. Feature system

The following features are the main needs that must be met in the development of this application because they are directly related to the purpose of the application to monitor daily sugar consumption and improve the health of the user. Table 2 describes the features of the application.

Table 2: Features of Daily Sugar Consumption Application

No	Feature	Description
1	User Information for Calculating Daily Calories and Sugar	The User Information page displays the results of daily sugar and calorie consumption calculations based on BMR (basal metabolic rate). Maximum sugar consumption is calculated using 10% of total daily calories, which is then divided by 4. This page also includes the user's personal information, such as name, date of birth, weight, height, and activity, which are used to adjust sugar consumption recommendations
2	Manual Logging Page	The manual recording page allows users to manually add food by uploading images, as well as inputting food names and sugar levels based on user knowledge. This feature cannot detect food composition through label scanning or automatic analysis, so users must fill in the information manually
3	Auto Logging Page	On the Auto Calculate page, users can take pictures of food to be analyzed using a machine learning model. This model, developed by fellow researchers, provides output in the form of food names and the amount of sugar contained. However, this model can only count food in whole portions. If the food photographed is only part of a portion, the model will still count it as a whole portion, and this model can only detect food alone. Users can add images via the camera or gallery
4	Chat Bot Page	On the Auto Calculate page, users can take pictures of food to be analyzed using a machine learning model. This model, developed by fellow researchers, provides output in the form of food names and the amount of sugar contained. However, this model can only count food in whole portions. If the food photographed is only part of a portion, the model will still count

		it as a whole portion, and this model can only detect food alone. Users can add images via the camera or gallery
5	Statistic Page	The Statistics page displays information related to sugar consumption at various times, namely 24 hours, 7 days, 30 days, or custom. Each graph shows the total amount of sugar consumption, with color indicators for easy understanding: green indicates sugar consumption within healthy limits, yellow indicates sugar consumption that needs attention, and red indicates excessive sugar consumption. In each period, the graph also includes data such as average sugar consumption, the highest value, and the lowest value. Below the graph, there is additional information about the total sugar consumption in that period. This statistics page helps users to track and monitor their sugar consumption more clearly and in a structured way
6	Report Page	The report page displays the user's daily sugar consumption in graphs and percentages, as well as a list of foods that have been scanned on the selected day. Each food is displayed along with its sugar content, helping users evaluate their eating habits and increase nutritional awareness. Thus, users can choose foods wisely to avoid excessive sugar consumption. This page also allows users to view reports based on a specific date
7	Education Page	This educational page is part of the main page of the GlucoFit application, which provides articles in four categories: Healthy Eating Patterns, Facts and Education about Sugar, Motivation and Healthy Habits, and Scientific and Health Information. These articles provide important information about sugar management and a healthy lifestyle
8	Information Detail	This detail page is a feature that allows users to monitor and change their daily sugar consumption limit. At the top, there is information about WHO recommendations and Indonesian regulations that suggest a maximum sugar consumption limit of 50 grams per day, but users can adjust the amount as needed. Users can enter a new amount of sugar in the "New sugar" column and click the "Update" button to update the settings. Below, there are three emoticons with descriptions that describe the status of sugar consumption, namely, "Happy" (for sugar consumption up to 60%), "Good" (for sugar consumption 60%-90%), and "Sad" (for sugar consumption exceeding 100%).
9	Barcode Page	The barcode page is a page where users can scan food or beverage barcodes and also get results in the form of the name, weight, nutritional level, and nutritional content of the food or beverage product whose barcode is scanned.

Based on the feature descriptions, the following displays screenshots of the application features on its user interface as depicted by Fig. 2.

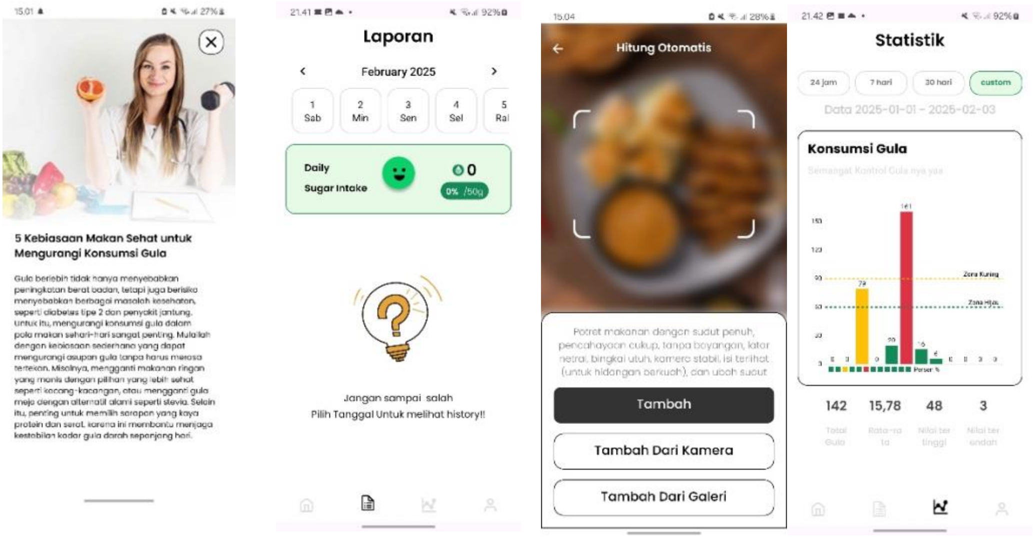

Fig. 2 Application panel of daily sugar consumption dashboard.

B. Evaluation Application

To ensure that the Daily Sugar Consumption Monitoring (Glucofit) application performs effectively for users, we conducted a series of comprehensive evaluations. These included functional testing using Black Box Testing and usability assessment using the System Usability Scale (SUS). The goal of these tests was to evaluate the system's stability, accuracy of core features, ease of use, and overall user satisfaction with the interface and navigation flow. The results from both testing methods provide a holistic view of the application's technical performance and user experience.

Specifically, the System Usability Scale (SUS) was chosen to assess the application's usability. This method uses a set of standardized questions, each rated on a scale of 1 to 5, to evaluate aspects such as ease of use, efficiency, and user satisfaction with the mobile application [19]. SUS is widely recognized for its simplicity, speed, and reliability, offering a quantitative measure across five key dimensions: learnability, efficiency, error rate, user satisfaction, and complexity. It is particularly suitable for identifying user acceptance and comfort during real-world use.

In the Black Box Testing of the Glucofit application, various usage scenarios were tested to ensure the system operates according to user expectations. This included testing login and registration functionalities, daily sugar intake recording (both manually and automatically through image recognition), as well as features for monitoring and visualizing sugar consumption statistics. Furthermore, tests were conducted on interactive chatbot functions that provide healthy eating guidance, display educational articles, and calculate calorie and sugar intake. The application was also tested for its notification system to remind users to log their sugar consumption, and for profile management capabilities such as editing usernames, email addresses, and passwords. Table 3 indicates that all tested features functioned as expected, with satisfactory outcomes across all evaluation scenarios.

Table 3: Status of Tested Features of Daily Sugar Consumption Application

Tested Features	Status	Additional Details
Login and Registration	Succeed	All scenarios went according to expectations
Sugar logging (manual and automatic)	Succeed	Data stored accurately
Food detection from the camera	Succeed	Challenges to complex or local foods
Barcode scanner	Succeed	Works well, not yet used as the main input
Daily notifications	Succeed	Consistent and on time
Chart visualization	Succeed	Provides an understanding of daily sugar consumption patterns
Chatbot interaction & educational articles	Succeed	Provide additional information related to healthy eating

The System Usability Scale (SUS) was applied to 14 users of the Glucofit application. Based on the results of the SUS test, this application obtained an average score of 81.43, which places the application in the "B" grade category, with an "Excellent" assessment on the adjective rating and "Acceptable" on the acceptability range. These results indicate a very good level of usability, with the application being easy to use and efficient, and providing a satisfying user experience. Taking a deeper look at the 5 usability variables tested, learnability and efficiency each obtained a high average score of 4.39, indicating that this application is very easy to learn and allows users to complete tasks quickly and effectively.

The Errors variable, with an average value of 1.57, indicates that the application has a very low error rate, indicating a stable design and freedom from confusion for users. Although the satisfaction variable obtained an average score of 3.48, indicating good satisfaction, there is still room for We are making improvements to enhance the overall user experience. Meanwhile, the complexity variable, with an average value of 1.76, indicates that this application is very simple and not confusing, so it can be easily accessed by various user groups. Overall, the Glucofit application shows very good effectiveness in terms of usability, although there are some areas that can be improved to increase user satisfaction levels. Table 4 describes usability aspects of the Glucofit application with average score and interpretation.

Table 4: Usability aspects of the Glucofit application with average score and interpretation.

Usability Aspects	Average Score	Interpretation
Learnability	4.39	Easy for new users to learn
Efficiency	4.39	Effective and efficient in completing tasks
Errors	1.57	Low error rate
Satisfaction	3.48	User satisfaction is quite high
Complexity	1.76	Simple interface, not confusing
Total SUS Score	**81.43**	**Very Good, in the acceptable category**

The test results show that the developed application is able to help users in monitoring daily sugar consumption more accurately and interactively. The integration of manual and automatic features in sugar consumption recording allows for flexibility of use, as well as supporting different levels of digital literacy of users. The accuracy of food object detection systems is still a challenge, especially in the case of complex or regional foods. Therefore, improved accuracy of image recognition algorithms and training of more representative local datasets is recommended as further development.

The barcode scanner feature provides added value, although it is not currently used as the main input. In the long term, this feature can be used to build a more complete nutrition database and be integrated with official institutions such as BPOM or the Indonesian Ministry of Health. The success of the application in providing notifications and recommendations based on calorie needs also shows great potential in the context of personalizing nutrition education. The interactive visualizations provided successfully improve user engagement and understanding of their consumption patterns. These findings are in line with a study by Suwan et al. [8], which showed that mobile-based apps with a personalized approach are able to increase awareness of healthy lifestyles among adolescents in Thailand. The study extends the approach to a wider segment of the population with a modular and adaptive approach.

6. Conclusion

This study develops a mobile application model using the AGILE methodology for iterative development and employs the System Usability Scale (SUS) to evaluate its usability. Unlike previous approaches that primarily focus on tracking sugar intake, this system offers a more comprehensive solution by incorporating behavioral interventions, such as personalized daily consumption targets and challenge-based engagement. The SUS evaluation resulted in a score of 81.43, which corresponds to a “Very Good” usability level, indicating strong user satisfaction and effective interface design.

These findings suggest that the application can serve as a practical and sustainable digital health tool for promoting healthier lifestyle choices and reducing the risk of chronic diseases such as diabetes. The inclusion of behavior-oriented features strengthens the system’s potential impact beyond simple monitoring. For future work, we plan to enhance the system's intelligence by integrating a machine learning module trained on localized food data to improve recognition accuracy. Additionally, we aim to develop a personalized dietary recommendation engine based on user profiles, health objectives, and consumption history, which will provide more targeted and effective support for diabetic risk prevention.

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