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Development and Application of a Risk Assessment System in Determining Individuals' Susceptibility to Developing Type II Diabetes Mellitus: A Quantitative Study in a Selected Community in Angeles City

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Abstract

Introduction: The incidence of type 2 diabetes mellitus (T2DM) continues to rise worldwide, with many individuals remaining undiagnosed until complications develop. Standard diagnostic procedures are effective but often costly and inaccessible in community settings, causing delays in early detection and management. Objective: This study aimed to develop and apply a digital risk assessment system to identify individuals at risk of developing T2DM in a selected community in Angeles City. The system was designed as a cost-effective, non-invasive, and nurse-led screening tool to support early prevention and promote proactive health initiatives within the community. Methods: A cross-sectional descriptive design was conducted in two phases following approval from the Ethics Review Committee. Phase 1 involved system development and evaluation by community health nurses using a 16-item questionnaire. Phase 2 involved applying the system to 372 community residents using another 16-item questionnaire to generate individual risk profiles. Data were analyzed using percentage, frequency, mean, and standard deviation. Results: The system achieved “best imaginable” ratings in usability, information quality, and interface design, demonstrating its appropriateness for community application. Risk distribution showed that 42.74% of respondents were at low risk, 37.37% slightly elevated, 10.48% moderate, 8.60% high, and 0.81% very high risk for T2DM. Conclusion: The developed system offers a non-invasive, low-cost tool for identifying T2DM susceptibility and empowering early preventive action. Integrating such tools into nursing practice can enhance community screening programs, guide tailored health education, and strengthen primary health care. Raising awareness of personal susceptibility is vital to fostering proactive health behaviors, reducing disease burden, and advancing community-based nursing interventions.

Keywords:
Community Health Nurses, Health Behavior, Risk Assessment, Type 2 Diabetes Mellitus

INTRODUCTION

Diabetes Mellitus (DM) is a chronic metabolic disorder characterized by the inability of the body to produce or effectively utilize insulin, resulting in persistent hyperglycemia. Despite advances in clinical practice, early detection remains a significant challenge, particularly in communities where diagnostic resources are limited. More than 38.4 million individuals in the United States currently live with diabetes (Centers for Disease Control and Prevention [CDC], 2024a). In the Philippines, approximately 4.3 million individuals have been diagnosed, while an estimated 2.8 million remain undiagnosed (Cando et al., 2024). Globally, 8.7 million individuals also remain unaware of their condition (CDC, 2024a). Type 2 Diabetes Mellitus (T2DM) is especially difficult to identify early because its onset is gradual and symptoms are often unnoticed, reducing the likelihood of timely diagnostic testing (American Diabetes Association Professional Practice Committee [ADA PPC], 2024).

Traditional diagnostic procedures such as glycated hemoglobin, fasting plasma glucose, and the oral glucose tolerance test remain essential, yet they are often costly and inaccessible in many communities, especially those with limited laboratory infrastructure (Hakami et al., 2024). These constraints highlight the importance of primary prevention and community focused approaches that enable early identification before complications arise. Community based interventions play an important role in this effort by promoting empowerment, health education, and risk reduction at the population level. According to Nowrin et al. (2023), community-based interventions strengthen prevention efforts by mobilizing local stakeholders, delivering culturally relevant health education, and engaging individuals in lifestyle modification to reduce NCD risk factors. These approaches shift health care from being solely facility dependent to being community driven, thereby increasing access and sustainability.

Community Health Nurses (CHNs) hold central responsibility in these preventive strategies. Their roles in assessment, planning, implementation, evaluation, advocacy, and coordination allow them to identify emerging health needs and initiate timely screening and disease prevention activities (Dar, 2023). They lead community wide assessments, detect risk conditions early, and organize screening programs that connect individuals to appropriate care. CHNs therefore serve as catalysts for early identification of chronic diseases, including T2DM, and their active engagement strengthens the capacity of communities to prevent disease before complications develop.

In the Philippines, national policies also emphasize the importance of early risk detection. The Department of Health (DOH) Administrative Order 2011-0003 highlights the need for community-based prevention and control of chronic lifestyle related noncommunicable diseases through strengthened health promotion and early identification. Complementing this policy, Administrative Order 2012-0029 institutionalizes the Philippine Package of Essential NCD Interventions, which includes structured risk factor assessment for hypertension and diabetes among individuals aged twenty-five years and above. This protocol requires evaluating lifestyle behaviors, family history, obesity indicators, blood pressure, and blood glucose levels to identify individuals who may need referral for confirmatory testing and early management (DOH, 2012). These policies demonstrate the national commitment to proactive NCD prevention, yet manual documentation and paper-based processes remain common in many communities and limit efficiency, timeliness, and the scalability of screening programs.

The integration of digital risk assessment systems presents an opportunity to strengthen these national efforts by supporting more efficient data collection, minimizing errors, and enabling faster identification of individuals at risk for T2DM. Digital systems also complement the work of CHNs by enhancing community screening activities, expanding access to risk evaluation, and enabling evidence based planning at the local level. Early identification made possible through digital tools allows nurses to deliver health education tailored to individual needs and encourages community members to adopt preventive behaviors before disease progression.

Given the rising prevalence of undiagnosed T2DM, this study aims to address an important gap by developing and applying a digital risk assessment system in a selected community in Angeles City. The study also examines the usability of the system among CHNs and evaluates how individual risk results influence awareness and preventive health behaviors. Specifically, this study answered the following questions:

1. How can the risk assessment tool be developed into a system?
2. How can the community health nurses evaluate the system in terms of overall usability?
3. How can the respondents' total risk score for developing type 2 diabetes mellitus be described?
4. How can the respondents' risk factors be described?
5. How can the respondents describe the effect of their risk score to their health behavior?
6. How can the newly proposed risk assessment system be presented?

METHODS

1. Design

The researchers utilized a quantitative descriptive cross-sectional design to assess the development and application of a risk assessment system. Data collection was divided into two phases. The development phase involved CHNs who evaluated the prototype system in terms of system usability, interface quality, and information quality. The application phase involved community residents who described the risk assessment system based on their perceived susceptibility, perceived severity, perceived self-efficacy, and behavioral intention.

2. Sample Size and Sampling Technique

Purposive sampling was used in the development phase, which included three CHNs from a selected university in Angeles City. Inclusion criteria were (1) at least two years of CHN experience and (2) ability to use information and communication technology.

For the application phase, 372 residents were chosen through cluster sampling. Clusters were defined by local streets, and random selection was performed using a random number generator. Residents were included if they were (1) eighteen years or older and (2) living in the community. Exclusion criteria were (1) current pregnancy and (2) prior diagnosis of diabetes mellitus or gestational diabetes. Sample size calculation using the Raosoft Sample Size Calculator indicated that for a population of 11,337 (Philippine Statistical Authority, 2020), a minimum of 372 respondents was required.

3. Instruments

The researchers employed three standardized questionnaires: (1) the Finnish Diabetes Risk Score (FINDRISC), (2) the Computer System Usability Questionnaire (CSUQ), and (3) the Diabetes-related Instrument to Assess Beliefs of Adolescents (DIABA).

To begin with, the FINDRISC is a simple, cost-effective, and noninvasive tool originally developed by Lindström and Tuomilehto in 1998. It is designed to identify individuals at elevated risk for developing T2DM by evaluating eight key variables: age, BMI, waist circumference, physical activity, dietary habits, antihypertensive medication use, history of high blood sugar, and family history of diabetes (Nnamudi et al., 2020). Each factor is assigned a specific point value, resulting in a cumulative score ranging from 0 to over 20. This total score is then classified into five risk categories: low risk, slightly elevated risk, moderate risk, high risk, and very high risk, which collectively estimate the individual's likelihood of developing T2DM within the next ten years.

In addition, the study utilized the CSUQ, a widely adopted tool created by James Lewis in 1995 and revised in 2002. This instrument is intended to measure users' perceived satisfaction and the overall usability of computer-based systems. The CSUQ consists of 16 items, each rated on a 7-point Likert scale, where lower scores indicate higher satisfaction. It yields one overall satisfaction score and three specific subscale scores: system usability (items 1–6), information quality (items 7–12), and interface quality (items 13–15) (Lewis, 2018). This tool is particularly useful for evaluating user experience in various digital environments, including software applications and electronic systems.

Lastly, the DIABA, developed in 2023 by Dorosteh, Ghaffari, Rakshanderou, and Merabi, was incorporated to assess health-related beliefs about T2DM. The final version of the instrument comprises 16 items grouped into four core dimensions: perceived self-efficacy, behavioral beliefs, perceived severity, and perceived susceptibility. Responses are rated using a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5). Notably, two items under perceived susceptibility are reverse-scored to account for misconceptions. Higher scores on the DIABA indicate stronger health beliefs and a greater likelihood of adopting preventive behaviors related to diabetes management and lifestyle modification.

4. Data Collection Process

Phase 1: Development

The researchers collaborated with the developer of the preexisting Electronic Medical Record (EMR) system used in the selected community to design a prototype risk assessment system. The system incorporated features that allowed respondent data to be inputted, scored, calculated, and stored based on the components of the FINDRISC questionnaire. Once the prototype was developed, its functionalities were tested and feedback was provided. Following this, three CHNs were asked to use the system. Afterwards, they completed the CSUQ to assess its overall usability. The collected data from the CSUQ was analyzed, and additional modifications were made to refine the system.

Phase 2: Application

At the start of data collection, the researchers introduced the finalized system to the Barangay Health Workers (BHWs) and oriented them on its usage. During the actual data collection, community respondents visiting the BHC were briefed and asked to provide informed consent. Respondents were interviewed using the system to record their T2DM risk factors. After scores were generated, they answered the DIABA questionnaire. The responses were analyzed and interpreted by the researchers. Lastly, the final output included the presentation of the system's design, algorithm, and effectiveness. A total of 379 individuals were initially interviewed, with 372 included in the final analysis, resulting in an attrition rate of 1.85%.

5. Data Analysis

Descriptive statistics, including frequencies, percentages, means, and standard deviations, were used to analyze the data.

For the FINDRISC, scores below 7 suggested low risk (1 in 100), while scores from 7 to 11 indicated slightly elevated risk (1 in 25). Moderate risk (1 in 6) corresponded to scores between 12 and 14, high risk (1 in 3) to scores between 15 and 20, and very high risk (1 in 2) to scores above 20.

Moving onto the CSUQ, scores were interpreted using a range-based scale from "strongly agree" (1.00 – 1.85) to "strongly disagree" (6.16 – 7.00). For further analysis, scores were converted to a 0 – 100 scale based on the System Usability Scale (SUS), and interpreted using a letter-grade framework from A+ (best imaginable usability) to F (unacceptable usability), based on corresponding percentiles and descriptive labels.

Lastly, for DIABA mean scores were interpreted as follows: 4.50 – 5.00 for strong agreement, 3.50 – 4.49 for agreement, 2.50 – 3.49 indicating uncertainty ("no idea"), 1.50 – 2.49 for disagreement, and 1.00 – 1.49 for strong disagreement. The reversed items followed an inverted interpretation to properly reflect respondents' understanding and beliefs.

6. Research Ethics

Ethical standards were strictly observed to protect participants' rights and privacy. The study received approval from the Angeles University Foundation Ethics Review Committee. Informed consent forms were provided, outlining the study purpose, procedures, possible risks and benefits, and voluntary participation, including the right to withdraw at any time. In accordance with the Data Privacy Act of 2012, all personal information was kept confidential, and participant identities remained anonymous (Pettengill, 2025).

Data stored within the system were transferred to a USB drive, while paper-based documents and consent forms were securely kept and accessible only to the researchers. Following study completion, data destruction occurred one year later following Deakin University guidelines (2023). Paper documents were shredded and incinerated, while digital files were permanently deleted.

RESULTS

Phase 1: Development of the Risk Assessment Module

Subphase 1: Planning

In creating the risk assessment system, the researchers first began with careful planning. This phase started with defining the system, which was conceptualized as a software application designed to automate the risk stratification process using non-invasive and routine clinical data (Bille et al., 2024; De Mesa et al., 2024; Duke University School of Medicine, 2025). In particular, it aimed to assist individuals in understanding their risk and support CHNs in implementing preventive strategies at the primary care level (Dar, 2023; Manawis, 2024; Wee et al., 2023).

Following this, the researchers focused on identifying the necessary resources, including a validated risk assessment questionnaire to serve as the system's foundation, a qualified team of system developers to encode and build the platform, the use of appropriate hardware such as a desktop or laptop, and an ample time frame to allow for proper development, testing, and evaluation.

Subphase 2: Execution

The development of the risk assessment system commenced with a formal partnership between the researchers and the College of Computer Studies (CCS). A letter of intent was sent on August 8, 2024, which led to the initial meeting on August 15, 2024. During this meeting, the researchers presented the objectives of integrating a T2DM risk assessment system within the selected community. Although the original timeline was delayed, development began later, and a prototype was delivered for testing. The first version of the system was then finalized with only minor revisions.

The technical framework of the system was designed as a web-based application that functions as an extension of the pre-existing EMR system. It employed a layered architecture using a Clean Application structure, including the Domain, Application, Persistence, and MVC layers. These handled core entities, business logic, database interactions, and user interface functionalities, respectively.

Several features were incorporated into the system, such as a Create/Update Page for real-time BMI and risk score calculations using JavaScript, an Index Page for managing records, and a Detail Page for displaying complete assessment results. The system also included printing capabilities, a soft delete mechanism, secured authentication, role-based access control and a database backup function.

Table 1. Summary of the Subscales of the Computer System Usability Questionnaire

Subscales	*M* (SD)	SUS. score range	Description	Acceptability
System Usability	1.06 (.14)	99.07	Best Imaginable	Acceptable
Information Quality	1.56 (.54)	90.74	Best Imaginable	Acceptable
Interface Quality	1.33 (.33)	94.44	Best Imaginable	Acceptable
Overall Usability	1.29 (.20)	95.4	Best Imaginable	Acceptable

Note. N = 3. Maximum for M = 1.00. SUS = system usability scale.

Subphase 3: Evaluation

As illustrated in Table 1, it presents the summary of the subscales from CSUQ, indicating the system's overall usability. Based on the results, it showed that the system's usability garnered the highest score among the three (M = 1.06, SD = 0.14, SUS = 99.07). This indicated that the system was easy to use. This was followed by the interface quality (M = 1.33, SD = 0.33, SUS = 94.44). Finally, information quality was last (M = 1.56, SD = 0.54, SUS = 90.74). While small variations existed between the three subscales, all usability factors were still described as acceptable according to its SUS score range equivalent. Thus, the overall usability of the system scored a SUS score range of 95.4 (M = 1.29, SD = 0.20), indicating that the risk assessment system was evaluated as best imaginable. Hence, it was deemed acceptable and ready for deployment.

Phase 2: Application of the Risk Assessment System

Subphase 1: Deployment

Risk Scores

Table 2 presents the summary of the total risk scores among respondents assessed using FINDRISC. Among 372 respondents, 42.74% (n = 159) were classified as low-risk, where only one in 100 is expected to develop diabetes. Meanwhile, 37.37% (n = 139) of the respondents had a slightly elevated-risk, where one in 25 may develop the disease. On the other hand, 10.48% (n = 39) of the respondents were categorized to have a moderate-risk, reflecting that one in six will develop diabetes. Meanwhile, 8.60% (n = 32) were considered to have a high-risk, with the likelihood that one in three will develop diabetes. Lastly, 0.81% (n = 3) belonged in the very high-risk group, where one in two is expected to have diabetes.

Table 2. Summary of the Total Risk Scores Among Respondents Based on the Finnish Diabetes Risk Score

Total Risk Score	Frequency	Percentage	Description	Interpretation
< 7	159	42.74%	Low	One in 100 will develop the disease
7–11	139	37.37%	Slightly elevated	One in 25 will develop the disease
12–14	39	10.48%	Moderate	One in six will develop the disease
15–20	32	8.60%	High	One in three will develop the disease
> 20	3	0.81%	Very high	One in two will develop the disease

Note. N = 372

Risk Factors

Table 3 presents the risk factors of the respondents based on age, body mass index, waist circumference, physical activity, frequency of vegetable, fruit/berries intake, antihypertensive medication usage, history of high blood glucose, and family history of type 1 or type 2 diabetes.

Age

Age is a significant non-modifiable risk factor, as different life stages influence the likelihood of developing diabetes due to lifestyle and metabolic changes. Among the 372 respondents, 60.48% (n = 225) were under 45 years old, 17.74% (n = 66) were 45–54 years, 11.56% (n = 43) were 55–64 years, and 10.22% (n = 38) were over 64 years. These findings highlight the importance of age-stratified screening.

Body Mass Index

BMI indicates whether an individual falls within a healthy height-to-weight range. Of the respondents, 51.08% (n = 190) had a BMI under 25 kg/m², 30.65% (n = 114) were overweight (25–30 kg/m²), and 18.28% (n = 68) were obese (>30 kg/m²). Nearly half of the population being overweight or obese underscores the need for targeted health education and weight management initiatives.

Waist Circumference

Waist circumference measures abdominal fat distribution, a key diabetes risk factor. In the sample, 46.77% (n = 174) were low risk (<94 cm for men, <80 cm for women), 23.66% (n = 88) were moderate risk (94–102 cm for men, 80–88 cm for women), and

29.57% (n = 110) were high risk (>102 cm for men, >88 cm for women), showing significant differences in risk distribution.

Physical Activity

Physical activity was defined as at least 30 minutes per day. Among respondents, 57.53% (n = 214) met this criterion, while 42.47% (n = 158) did not, indicating a substantial modifiable risk factor within the community.

Frequency of Vegetable, Fruit/Berries Intake

Daily consumption of fruits, vegetables, or berries was considered adequate dietary intake. Among respondents, 45.97% (n = 171) consumed these foods daily, whereas 54.03% (n = 201) did not, highlighting a prevalent dietary deficit linked to increased diabetes risk (Karomo, 2020).

Antihypertensive Medication Usage

Use of antihypertensive medications includes drugs such as ACE inhibitors, beta-blockers, calcium channel blockers, diuretics, and ARBs, which help manage blood pressure. Among respondents, 83.06% (n = 309) reported not using these medications, while 16.94% (n = 63) indicated usage.

History of High Blood Glucose

History of high blood glucose refers to previous elevated blood sugar measurements during health examinations, illness, or pregnancy. In this study, 88.44% (n = 329) reported no history, while 11.56% (n = 43) indicated previous elevated levels.

Family History of Type 1 or Type 2 Diabetes

Family history reflects genetic predisposition, increasing susceptibility to T2DM. Among respondents, 63.71% (n = 237) had no family history, 12.10% (n = 45) had a second-degree relative with diabetes, and 24.19% (n = 90) had a first-degree relative affected, indicating significant genetic risk in over a third of participants.

Table 3. Summary of the Total Risk Factors Among Respondents Based on the Finnish Diabetes Risk Score

Risk Factors		Frequency	Percentage
Age:			
< 45 years		225	60.48%
45–54 years		66	17.74%
55–64 years		43	11.56%
> 64 years		38	10.22%
Body Mass Index:			
< 25 kg/m2		190	51.08%
25–30 kg/m2		114	30.65%
> 30 kg/m2		68	18.28%
Waist Circumference:			
< 94 cm	< 80 cm	174	46.77%
94–102 cm	80–88 cm	88	23.66%
> 102 cm	> 88 cm	110	29.57%
Physical Activity ≥ 30 menutes:			
Yes		214	57.53%
No		158	42.47%
Frequency of vegetable, fruit/berries intake:			
Every day		171	45.97%
Not every day		201	54.03%
Antihypertensive medication usage:			
No		309	83.06%
Yes		63	16.94%
History of high blood glucose:			
No		329	88.44%
Yes		43	11.56%
Family history of type 1 or type 2 diabetes:			
No		237	63.71%
Yes; grandparent, aunt, uncle, or first cousin		45	12.10%
Yes; parent, brother, sister, or own child		90	24.19%

Note. N = 372

Health Behaviors

Table 4 presents the health behaviors of respondents based on the DIABA. These constructs were analyzed across the FINDRISC risk categories to understand behavioral and psychosocial factors influencing preventive actions.

Low Risk

Respondents in the low-risk group showed high perceived self-efficacy ($\bar{x}$ = 4.46, SD = 0.22) and perceived severity ($\bar{x}$ = 4.67, SD = 0.14). Behavioral beliefs were moderately high ($\bar{x}$ = 4.18, SD = 0.65), while perceived susceptibility was slightly above average ($\bar{x}$ = 3.66, SD = 0.18), reflecting emerging awareness of personal risk.

Slightly Elevated Risk

Slightly elevated-risk respondents had the highest score in perceived severity ($\bar{x}$ = 4.69, SD = 0.16) and high perceived self-efficacy ($\bar{x}$ = 4.63, SD = 0.15). Behavioral beliefs were moderately high ($\bar{x}$ = 4.21, SD = 0.65), while perceived susceptibility was lower ($\bar{x}$ = 3.83, SD = 0.28), showing acknowledgment of severity but lower personal risk perception.

Moderate Risk

Respondents at moderate risk strongly agreed on their ability to engage in preventive behaviors ($\bar{x}$ = 4.70, SD = 0.25) and recognized the seriousness of diabetes ($\bar{x}$ = 4.69, SD = 0.18). Behavioral beliefs were positively rated ($\bar{x}$ = 4.26, SD = 0.63), while perceived susceptibility was lower ($\bar{x}$ = 3.65, SD = 0.31), highlighting variation in personal risk awareness.

High Risk

High-risk respondents scored highest in perceived severity ($\bar{x}$ = 4.69, SD = 0.09), followed by self-efficacy ($\bar{x}$ = 4.61, SD = 0.07) and behavioral beliefs ($\bar{x}$ = 4.24, SD = 0.52). Perceived susceptibility was lowest ($\bar{x}$ = 3.50, SD = 0.27), indicating a gap between objective risk and personal perception. Overall mean across subscales remained above average ($\bar{x}$ = 4.53, SD = 0.18).

Very High Risk

Very high-risk respondents reported strong self-efficacy ($\bar{x}$ = 4.53, SD = 0.18) and high perceived severity ($\bar{x}$ = 4.58, SD = 0.50). Behavioral beliefs were moderately high ($\bar{x}$ = 3.67, SD = 0.94). A large standard deviation (SD = 2.31) reflects contrasting beliefs about personal vulnerability, with some acknowledging risk and others denying it.

Table 4. Summary of the Subscales of the Diabetes-related Instrument to Assess Beliefs of Adolescents Among Respondents

Risk Categories	Subcales	*M* (SD)	Description
Low risk	Perceived self-efficacy	4.46 (.22)	Above the mean
	Behavioral beliefs	4.18 (.65)	Above the mean
	Perceived severity	4.67 (.14)	Above the mean
	Perceived susceptibility	3.66 (.18)	Above the mean
Slightly elevated risk	Perceived self-efficacy	4.63 (.15)	Above the mean
	Behavioral beliefs	4.21 (.65)	Above the mean
	Perceived severity	4.69 (.16)	Above the mean
	Perceived susceptibility	3.83 (.28)	Above the mean
Moderate risk	Perceived self-efficacy	4.70 (.25)	Above the mean
	Behavioral beliefs	4.26 (.63)	Above the mean
	Perceived severity	4.69 (.18)	Above the mean
	Perceived susceptibility	3.65 (.31)	Above the mean
High risk	Perceived self-efficacy	4.61 (.07)	Above the mean
	Behavioral beliefs	4.24 (.52)	Above the mean
	Perceived severity	4.69 (.09)	Above the mean
	Perceived susceptibility	3.50 (.27)	Above the mean
Very high risk	Perceived self-efficacy	4.53 (.18)	Above the mean
	Behavioral beliefs	3.67(.94)	Above the mean
	Perceived severity	4.58 (.50)	Above the mean
	Perceived susceptibility	3.67 (2.31)	Above the mean

Note. N = 372

Subphase 2: Presentation

To support T2DM prevention, the study anchored its digital risk assessment system on Administrative Order No. 2012-0029, which institutionalizes the PhilPEN framework for managing hypertension and diabetes at primary healthcare facilities. The system complements existing paper-based screening used by the DOH, which targets individuals aged 40 and above or those with risk factors such as obesity, hypertension, or family history of NCDs. Screening outcomes guide referrals or management at the primary care level following WHO PEN protocols.

The developed system integrates the validated FINDRISC tool into an automated, user-friendly platform, streamlining data collection, reducing manual errors, and generating real-time risk scores. The implementation process begins with initial client engagement, where BHWs confirm prior screenings, gather personal information, and secure consent. For new clients, household registration is completed in the system to ensure proper tracking.

Next, anthropometric measurements, including height, weight, and waist circumference, are collected to evaluate body composition and identify central obesity. BHWs then administer the risk assessment using the digital system, which evaluates BMI, physical activity, dietary habits, antihypertensive medication use, history of elevated blood glucose, and family history of diabetes. The system generates an overall risk score, classifying individuals into low, slightly elevated, moderate, high, or very high risk.

Following risk classification, BHWs provide tailored health education and counseling based on the client’s risk level, covering lifestyle modifications such as weight management, physical activity, nutrition, and adherence to medications if applicable. Finally, the system supports structured follow-up and referrals for high-risk individuals, ensuring timely interventions and alignment with PhilPEN protocols for preventive care.

DISCUSSION

The results of the study revealed that the developed risk assessment system was highly usable, with respondents finding it intuitive, easy to learn, and efficient for task completion. This aligns with Ferreira et al. (2022), who noted that user-friendly systems tailored to individual preferences enhance productivity. Similarly, Ritonummi (2020) and Kishabale (2021) emphasized that platforms providing user control and immediate feedback increase user confidence, reduce errors, and strengthen engagement. The positive usability ratings therefore highlight the system’s potential as a practical tool for health workers, as its design promoted smooth navigation and encouraged greater intent to use (De Mesa et al., 2024).

Respondents also evaluated the information quality as clear, organized, and reliable. Despite one outlier concerning error messages, most agreed that the information presented was helpful, understandable, and effective for guiding tasks. This finding is supported by Cachata et al. (2024), Dubale et al. (2023), and Srimulyo et al. (2024), who emphasized that well-structured and accurate information enhances decision-making and efficiency. The integration of the FINDRISC tool, a globally validated instrument (Seidel-Jacobs et al., 2022), further reinforced the system’s reliability. Since FINDRISC is based on established risk factors such as obesity, hypertension, and physical inactivity (CDC, 2024b; Mayo Clinic, 2024; Shirinzadeh, 2020), the system provided content that was both accurate and clinically relevant (Anil et al., 2024; Ekure et al., 2022; Guru et al., 2023).

Equally important, the interface quality received strong feedback, with respondents appreciating its structured and visually appealing layout. Features such as a sidebar menu, modular interface, and color-coded risk indicators reduced cognitive overload and supported usability. These design choices echo the findings of Ritonummi (2020) and Kishabale (2021), who highlighted the value of clear layouts and legible formatting in preventing user disorientation. The absence of distracting colors and the emphasis on consistent design further promoted engagement and satisfaction, contributing to long-term usability (Imtihan et al., 2024; De Mesa et al., 2024; Cachata et al., 2024). Taken together, these elements indicate that the system was not only functional but also fostered a productive and engaging digital experience suited for healthcare delivery.

When applied in the community setting, most respondents were categorized as low-risk for T2DM. This suggests that many individuals were already engaging in preventive behaviors, including maintaining physical activity, consuming a healthy diet, avoiding tobacco use, and managing blood pressure and cholesterol levels, which are consistent with WHO (2024) recommendations for diabetes prevention. Additionally, the absence of family history among some respondents may have reduced their overall susceptibility (Mayo Clinic, 2024). However, a notable portion of the population fell into the slightly elevated to very high risk categories, highlighting the need for continued screening and preventive interventions. Previous studies by Barcial (2022) and Zhang et al. (2020) emphasize that early lifestyle modification, routine glucose monitoring, and dietary changes such as reducing sugar, fats, and processed foods can delay or prevent the onset of diabetes. Similarly, Karomo (2020) and Patel et al. (2024) demonstrated that a diet rich in fiber and regular aerobic activity significantly lowers T2DM risk, with consistent exercise shown to reduce risk by up to 67%.

In analyzing specific risk factors, age emerged as the strongest non-modifiable factor, with most respondents being 45 years or older, a demographic shown to have greater vulnerability to diabetes and cardiovascular complications (CDC, 2024b). This underscores the importance of addressing modifiable factors such as BMI, waist circumference, and physical activity. While many respondents had normal BMI, a considerable proportion were overweight or obese, which is a strong predictor of diabetes (Shirinzadeh, 2020; WHO, 2024). Waist circumference data also revealed cases of central obesity, which directly contributes to insulin resistance (Ekure et al., 2022). Encouragingly, several respondents reported regular physical activity, consistent with CDC (2024b) guidelines recommending at least 150 minutes of moderate exercise per week. Proper nutrition also plays a key role, as diets rich in fruits, vegetables, and fiber are proven to reduce diabetes risk (Karomo, 2020; Shirinzadeh, 2020). On the other hand, the use of antihypertensive medication among some respondents suggested an overlap with hypertension, a condition that independently increases the likelihood of T2DM by 2.5 times (Shirinzadeh, 2020). Similarly, a subset of respondents reported a history of elevated blood glucose, which signals prediabetes according to ADA and WHO standards (Austria, 2023). For those with family histories of diabetes, the DOH (2016) recommends regular screening every three to six months, underscoring the need for targeted education and lifestyle interventions.

Beyond physiological risks, behavioral and psychosocial factors played an important role. Respondents generally reported high self-efficacy, which is associated with stronger persistence, better goal-setting, and improved adherence to healthy practices such as diet and exercise (McEwen et al., 2022; Boskey, 2024). These factors align strongly with the theoretical constructs of the Health Belief Model (HBM), which asserts that a person's belief in their ability to act and their recognition of the seriousness of a disease are powerful motivators for health action (Lumen Learning, 2025; Boskey, 2024). However, variations were noted in resisting unhealthy foods and quitting smoking, behaviors influenced by reward pathways and insufficient awareness of risks (Calcaterra et al., 2023; Grech et al., 2024). While many respondents recognized the importance of sleep, cholesterol, and mental health in managing diabetes risk, there was a tendency to underestimate the impact of prolonged screen time. This contrasts with Schmid et al. (2021), who found that sedentary behaviors such as TV viewing significantly reduce physical activity and increase caloric intake. A strong recognition of diabetes severity was also observed, consistent with WHO (2023) and CDC (2024b), who emphasize that acknowledging the seriousness of diabetes is critical in motivating preventive action. These findings align with the Health Belief Model, which asserts that perceived severity and susceptibility together shape health-promoting behaviors (Lumen Learning, 2025).

Finally, the DIABA assessment showed that perceived self-efficacy and perceived severity were the highest-scoring constructs, reinforcing respondents' confidence in adopting preventive behaviors and their awareness of diabetes' potential impact on health and quality of life. These results mirror Boskey (2024) and WHO (2023), who emphasized that self-efficacy and acknowledgment of severity drive performance outcomes and timely health-seeking behaviors. However, perceived susceptibility was the lowest, suggesting that many underestimated their personal risk despite the presence of modifiable and non-modifiable factors. According to the HBM, an individual must first perceive themselves as susceptible to a condition before they are sufficiently motivated to adopt a healthy behavior. The data suggest that despite being presented with an objectively calculated FINDRISC score, many individuals, even those in the high-risk group, significantly underestimated their personal vulnerability. The analysis of the high variability also further highlights the divergent and often inaccurate self-assessment of personal risk. This disconnect between objective data and subjective perception highlights an important barrier in preventive care. As Du et al. (2024) explain, misconceptions and underestimation of risk can limit health-seeking behaviors and reduce the effectiveness of self-care practices. Addressing this gap requires targeted education, consistent counseling, and stronger communication strategies to align personal beliefs with actual health risks.

CONCLUSION

In conclusion, this study highlights the substantial potential of integrating a digital risk assessment system into community-based diabetes prevention strategies. By developing a computerized tool grounded in the validated FINDRISC model, the study addressed the practical barriers to early detection. The system streamlined the screening process, enhanced user experience, and offered a cost-effective, non-invasive alternative to traditional diagnostic approaches.

Aside from that, the system effectively stratified individuals according to their risk for T2DM, identifying prevalent modifiable and non-modifiable risk factors within the community. However, the study revealed a key insight: awareness of risk factors and knowledge of personal risk scores do not automatically translate into meaningful behavioral change. Despite varying risk categorizations, respondents reported similarly high health behavior scores and strong personal beliefs in their overall wellness, indicating a disconnect between objective health data and subjective risk perception. This finding underscores the need for more comprehensive strategies beyond simple risk identification.

To address this, the study emphasizes a multidimensional approach to diabetes prevention. Strengthening health education, particularly at the preventive stage, and providing personalized counseling on modifiable risk factors such as diet, physical activity, and weight management can deepen individuals' understanding of their personal vulnerabilities. These strategies, consistent with the PhilPEN framework, require proactive risk communication that goes beyond awareness alone. Additionally, awareness campaigns targeting younger populations, alongside continuous monitoring and evaluation of program outcomes, are essential to ensure national health goals are effectively translated into community-level action.

For successful implementation, comprehensive and structured orientation and training for BHWs are recommended. This training should cover system operation, accurate data collection, interpretation of risk scores, and communication of results to clients. Establishing clear communication channels between BHWs, CHNs, and IT support is also essential for technical assistance, timely troubleshooting, and regular system updates. Periodic monitoring and refresher training will help maintain system reliability, address challenges, and reinforce knowledge during implementation.

Certain limitations of the study should also be acknowledged. As the research was conducted in a single community utilizing a cross-sectional design, the findings are limited in terms of generalizability and the ability to establish causal relationships. Additionally, the system's storage was restricted to a single local device, which limits accessibility and broader integration. Enhancing the system with online synchronization across multiple devices could further support integration at the national level. Nonetheless, the study still demonstrates the value of integrating the digital risk assessment system into existing health programs such as PhilPEN and other Department of Health initiatives. Incorporation into Local Government Unit screening activities is recommended, with BHWs as primary users and CHNs as administrators.

Future studies should consider longitudinal assessments to evaluate long-term effectiveness, usability testing with larger and more diverse populations. Additionally, the minimal differences in health behavior scores among individuals across risk levels suggest the need for further investigation into the multifactorial predictors of health behavior change to promote proactive lifestyle modification and risk management.

Conflict of Interest

The authors declared that there are no conflicts of interest regarding the publication of this paper.

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