A mHealth adoption model for diabetes self-management: patient-centered insights from UNRWA clinics

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ABSTRACT

This study develops and validates a mobile health (mHealth) adoption model to enhance diabetes self-management among type 2 diabetes mellitus (T2DM) patients in UNRWA primary healthcare clinics across Palestinian refugee camps. This study fills a gap in research on mHealth adoption in low-resource settings by combining the technology acceptance model (TAM), task-technology fit (TTF), and self-efficacy theory (SET). A descriptive, cross-sectional design was employed using a structured, validated questionnaire administered to 503 T2DM patients. Reliability analysis yielded high internal consistency (Cronbach's α = 0.808–0.966). Structural equation modeling (SEM) using SPSS and AMOS validated the model fit, evidenced by a comparative fit index (CFI) of 0.941 and a root mean square error of approximation (RMSEA) of 0.048. Out of the eleven factors that were examined, Perceived Usefulness had the most positive impact on self-care management (β = 0.67, $p < 0.001$), while Task Requirement had the least. Notably, Perceived Self-Efficacy showed no significant effect on behavior ($p > 0.05$). These findings highlight usability, usefulness, and tool functionality as central to promoting mHealth use. The validated model can be modified for other chronic disease settings in comparable healthcare environments and provides practical advice for creating patient-centered mHealth interventions.

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1. INTRODUCTION

The chronic illness known as diabetes mellitus (DM) is characterized by the body's incapacity to properly metabolize glucose, which leads to continuously increased blood glucose levels [1]. Insulin resistance and a progressive decrease in insulin production are symptoms of type 2 diabetes mellitus (T2DM), the most common type, often associated with sedentary lifestyles and high BMI [1]. In Palestine, the ongoing Israeli-Palestinian conflict has intensified psychological and social distress, particularly among vulnerable populations. These conditions have led to higher prevalences of anxiety, depression, and post-traumatic stress disorder [2], which in turn complicate the management and progression of chronic illnesses such as T2DM [3].

Mobile health (mHealth) solutions have demonstrated great promise in promoting diabetes management and self-care on a global scale. For example, a Moroccan study found that mHealth tools are widely accepted, which got 89.3% of doctors and 82% of patients acknowledging their potential to enhance diabetes care [4]. Similarly, even in environments with limited resources, a mobile-based educational program in Indonesia greatly improved the self-care skills of T2DM patients [5]. Nonetheless, a few enduring obstacles prevent the successful deployment of mHealth. Patients' knowledge of managing their diabetes is frequently limited by inadequate diabetes education, particularly in communities with limited resources [6]. Furthermore, the usability and relevance of many mHealth applications are compromised by their lack of user-centered design.

These obstacles are particularly noticeable in the Palestinian context, especially in the UNRWA-run Palestinian refugee camps, where there are significant economic, psychological, and educational limitations. These camps report the highest prevalence of T2DM in the country, yet few studies have specifically targeted these populations [7], [8]. While earlier studies have explored the impact of mHealth on general diabetic care, they have not explicitly addressed its influence on patient behavior, self-efficacy, and technological fit within government-regulated refugee camp healthcare systems. This study examined how mHealth adoption among T2DM patients in Palestinian primary healthcare facilities was affected by task-technology fit (TTF), user perceptions, and self-efficacy. While earlier studies have explored the impact of mHealth on general diabetes management, they have not explicitly addressed its influence on individual behavioral intention (BI) and tool usage in government-run settings such as UNRWA camps.

The technology acceptance model (TAM) [9], [10], TTF [11]-[13] and self-efficacy theory (SET) [14]-[16] are three theoretical frameworks that are incorporated into this study's proposed and validated integrated mHealth adoption model to fill this gap. The models were designed to look at eleven elements that affect how people use mHealth tools. They include what the task requires, how well the tool functions, how often it is used, the intention to use it, how easy and useful users think it is, their behaviors and performance, as well as their confidence and expectations of the results.

By answering the following research questions: (1) What are the key factors influencing self-care management among T2DM patients? (2) How does mobile health (mHealth) usage affect diabetes self-care management? (3) Which theoretical model best explains mHealth adoption for improving self-care in UNRWA healthcare centres? and (4) Can the proposed model be validated to support diabetes self-care among T2DM patients? This research offers a new, situation-specific framework. The validated model intends to guide future digital health solution implementation in underserved and resource-constrained healthcare settings, like UNRWA clinics in Palestine, and inform the design of user-centric mHealth interventions.

This research is novel because it was investigated in a high-barrier scenario. The information was gathered from T2DM patients in UNRWA refugee camps, a government-run healthcare system in Palestine where access and research require negotiating intricate legal and ethical processes. Few studies have looked at T2DM patients' adoption of mHealth in such limited, politically sensitive, and underserved settings.

2. PROPOSED MODEL

The suggested model combines three well-known models, which are TAM, TTF, and SET, in order to better understand and improve mHealth technology adoption among patients with type 2 diabetes. The TTF model assesses how well technology fits task requirements and user capabilities, highlighting the significance of customizing mHealth features to meet the unique requirements of patients with type 2 diabetes, including blood glucose management, physical activity tracking, and educational resource access. Task requirements, which are specific tasks that patients with type 2 diabetes must manage, technology characteristics, which are the features of mHealth applications, and TTF, as the degree to which mHealth satisfies patient needs, are important model constructs [17].

Perceived utility (PU) and perceived ease of use (PEOU) are the two main constructs that the TAM uses to explain user acceptance of technology. PEOU refers to the ease of use of mHealth applications without requiring a high level of technical expertise, while PU represents patients' opinions regarding the technology's advantages in improving diabetes self-management in the context of mHealth for type 2 diabetes [18], [19]. Furthermore, the intention to embrace and regularly use mHealth solutions is captured by BI [20]. According to TAM, users' BI regarding the adoption of new technology is greatly influenced by PU and PEOU [21].

The SET points out people's confidence in their capacity to carry out tasks, like using mHealth to manage type 2 diabetes. It consists of two main components which the first one is outcome expectancy, as the conviction that using mHealth will result in favorable health outcomes, and the second is efficacy expectancy, as the assurance that mHealth will produce the intended results [22]. This theory supports the development of mHealth interventions that give T2DM patients more control over their self-care skills, even when they question their capacity to carry out necessary behaviors [23]. However, self-efficacy in low-income diabetic populations is poorly studied. Sociodemographic factors such as income, education, and cultural beliefs may affect self-management practices and make it more difficult for T2DM patients in Palestine to achieve successful outcomes.

Both PU and PEOU are impacted by task requirements and technological features; a greater TTF raises opinions about the advantages and usability of mHealth. The association between PEOU and BI is moderated by self-efficacy beliefs, since patients who have higher levels of self-efficacy are more likely to embrace mHealth despite usability issues. Furthermore, BI is directly impacted by positive outcome expectancy, which increases motivation for regular mHealth use.

TTF, TAM, and SET are combined in Figure 1 to explain why T2DM patients use mobile health. It draws attention to how task requirements, technological features, perceived utility, usability, and self-efficacy all affect BI, real mobile use, and individual performance. The following hypothesis is used in this combined model to address psychological preparation, technological alignment, and confidence-building elements that are essential for successful mHealth:

H1: Task requirements will affect T2DM patients on Task Technology Fit.
H2: Task Technology Fit among T2DM patients will be impacted by tool functionality.
H3: Task Technology Fit will affect how T2DM patients use their phones.
H4: T2DM patients' actual tool use for mobile devices will be influenced by their intention to use the tool.
H5: Patients with type 2 diabetes will use tools more frequently if they intend to use them.
H6: Patients with type 2 diabetes will behave differently depending on their intention to use the tool.
H7: T2DM patients' intention to use the tool will affect how well they use it.
H8: Among T2DM patients, perceived usefulness will affect their intention to use the tool.
H9: T2DM patients' intention to use the tool will be influenced by their perception of its ease of use.
H10: Among T2DM patients, perceived usefulness will be influenced by PEOU.
H11: T2DM patients' actual tool use for mobile devices will be influenced by their intention to use the tool.
H12: Patients with type 2 diabetes will behave differently depending on their perceived level of self-efficacy.
H13: The use of smartphones and mobile health by T2DM patients will be influenced by outcome expectations.

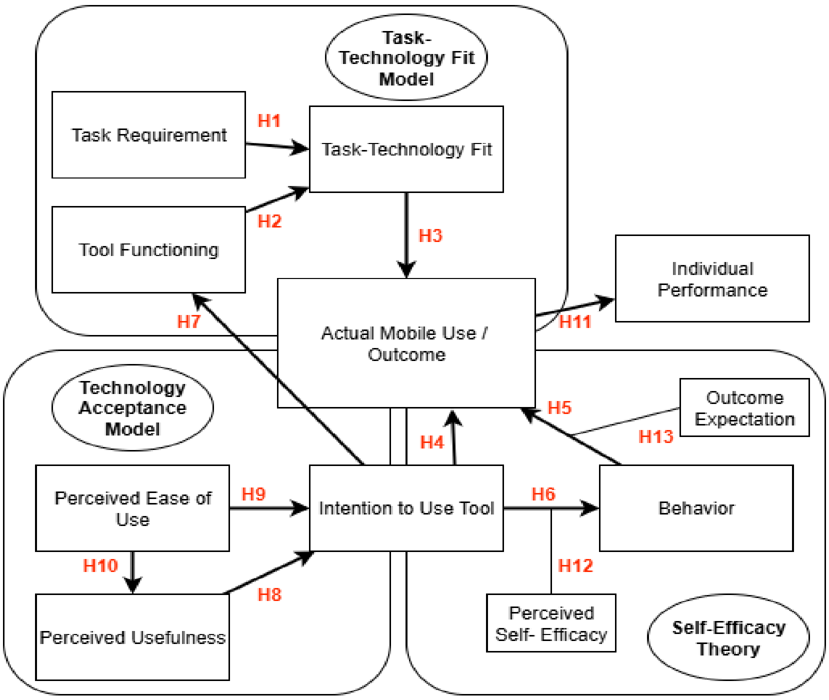

Figure 1. Model of mobile health use for self-management among T2DM patients

3. RESEARCH METHOD

3.1. Research design

This study adopts a quantitative research design to examine the factors influencing mHealth use and diabetes self-management among T2DM patients in UNRWA healthcare centers in Palestine. The study is exploratory in nature, given the limited existing research on mHealth adoption for self-care in the context of refugee populations and government-run healthcare sectors in Palestine. The design is also categorized as cross-sectional and descriptive, which uses structured questionnaires to gather empirical data at a specific moment in time. This method makes it possible to identify the main behavioral, technological, and psychological elements influencing the use of mHealth and the management of diabetes self-care.

The hypotheses based on three reliable theoretical frameworks like TAM, TTF, and SET are tested using a deductive approach. The development of the ideas and connections that will be investigated in the study is driven by these models. The study acknowledges the importance of mixed-methods research even though its main's focus is quantitative [24]. The study's preliminary nature and its challenging and unique research environment at UNRWA-managed refugee camps make for a more comprehensive viewpoint. Therefore, even though the main tool for gathering data is still a structured, closed-ended questionnaire for T2DM patients, data from these patients is valued for model development [25].

3.2. Study setting and population

The study focuses on T2DM patients who are treated at UNRWA primary healthcare clinics spread throughout Palestine's West Bank refugee camps. Adult T2DM patients who live in these camps and are enrolled in UNRWA healthcare services make up the target population. The government-run refugee health system, which provides care for a vulnerable and underprivileged population, monitors UNRWA clinic operations. Due to strict laws and regulations, restricted patient access, and the private nature of health-related data in refugee communities, conducting research in this context is technically and legally difficult. Despite these obstacles, this setting presents a special chance to investigate diabetes self-care management and mHealth adoption in one of the most understudies in digital health research.

This study is unique because it focuses on gathering empirical data directly from T2DM patients in these government-run refugee camps, an environment in which few studies of this kind are carried out because of logistical, administrative, and political limitations. It is believed that the results will provide historically based insights into how mHealth can help refugees in environments with limited resources manage their diabetes.

3.3. Sampling technique and sample size

Given the logistical difficulties in locating and reaching T2DM patients in UNRWA medical clinics in Palestinian refugee camps, this study will use a non-probability sampling approach, which is more realistic. To find T2DM patients who are available and willing to participate during clinic visits, convenience sampling will be employed. Given the sensitive nature of healthcare data in refugee settings and the limited access to patient lists and contact information, this approach is most suitable and appropriate.

Guidelines from earlier studies were used to determine the proper sample size. Sekaran and Bougie (2016) state that for survey-based quantitative research, a sample size of 30 to 500 respondents is adequate [26]. While some research indicates that 200 respondents is typically enough for most survey research designs, other studies have suggested a sample size of 100 to 200 for regression analysis [27]. This study aims to include at least 300 T2DM patients, with an oversampling goal of 350 participants, in accordance with these recommendations and to take into consideration non-responses, outliers, and missing values. This will guarantee the validity of statistical analyses and the strength of the conclusions about the adoption of mobile health and the management of diabetes self-care.

3.4. Development of research instrument

Data from T2DM patients will be obtained via a closed-ended, structured questionnaire. Using any of the three models taken into consideration in the theoretical framework, the questionnaire will be created based on the findings of previous relevant research. Additionally, the relevance of each questionnaire item for the Palestinian context will be evaluated. There will be five sections to the questionnaire. Items necessary for gathering participant demographic information, including gender, age, occupation, household income, number of dependents, and residential areas, will be included in Part 1. Items aimed at assessing patients' perceptions of the value and usability of mobile health for diabetes self-management will be making up Part 2. Items for assessing participants' social and clinical support will be included in Part 3. In the meantime, data on self-efficacy and self-care practices will be obtained in Part 4. The dependent variable, mobile health use for diabetes self-management, will be the focus of Part 5 of the questionnaire. The five-point Likert scale, which ranges from 1 = strongly disagree to 5 = strongly agree, will be used to evaluate each item. This format is well-known for its accuracy in behavioral studies [28].

3.5. Instrument validity and reliability

Expert review was carried out as advised by to guarantee the validity of the instrument [29]. A panel of academic and clinical experts used a validation form to evaluate the questionnaire items created for T2DM patients. The questionnaire was improved after their feedback was reviewed. Strong content validity was demonstrated by the expert validation's outstanding agreement rate of more than 90%.

A pilot study was conducted with a sample of 30 T2DM patients chosen from UNRWA healthcare clinics to further assure face and construct validity. According to [30], using about 10% of the planned sample size is adequate for pilot studies. Cronbach's Alpha, a statistical indicator of internal consistency, was used to evaluate the instrument's reliability. A Cronbach's Alpha value of 0.70 or higher is regarded as acceptable; values less than 0.60 suggest poor reliability and require the removal or revision of the important items [31]. The instrument's acceptable reliability was confirmed by the pilot experiment, indicating that it is appropriate for large-scale data collection.

3.6. Data collection procedure

T2DM patients who satisfied the inclusion requirements and visited UNRWA primary healthcare clinics in Palestine were the focus of the data collection. During their regular clinic visits, eligible participants were approached, briefed about the study's goals, given the assurance that their answers would remain private, and told that they could withdraw at any time without facing any penalties. Prior to participation, consent was obtained both orally and in writing. A self-administered questionnaire with clear instructions for completion was then given to each participant who had given their consent. To facilitate participant comprehension, the researchers' contact details were provided for any inquiries or clarifications pertaining to the survey. Data collection took place between January 2024 and May 2024, a span of five months.

3.7. Data analysis

The Statistical Package for Social Science (SPSS) Version 24 and AMOS for SEM were used to analyze all the data. The dataset was evaluated for non-response bias, common method bias, missing data, and normality of distribution prior to analysis. Kurtosis and skewness values were used to assess normality. The T2DM patient sample was characterized using descriptive statistics. Whereas frequencies and percentages were used for categorical data, means and standard deviations were reported for continuous variables. SEM was used with AMOS to investigate the connections between mHealth adoption and the identified behavioral, psychological, and technological factors. This made it possible to assess model fit, construct validity, and the direction and strength of proposed paths. The suggested model's goodness-of-fit was evaluated using model fit indices like Chi-square (χ^2), RMSEA, CFI, and TLI.

4. RESULTS AND DISCUSSION

Using the statistical program SPSS version 24, the reliability and internal consistency of the observed variables were assessed using Cronbach's test method prior to confirming the first developed SEM. The Cronbach's α values for T2DM patients of the observed variable used in the study are displayed in Table 1. According to the results below, Cronbach's α values range from 0.808 to 0.966, with T2DM patients having a total alpha value of 0.986. According to certain research, Cronbach's α value that greater than 0.7 indicates high internal consistency and reliability [32], [33]. Thus, it can be said that the samples are trustworthy for confirming the SEM.

Table 1. Reliability test results of T2DM patients

Factors	Number of observed variables	Cronbach's (α)
Task requirement (TR)	5	0.903
Task Technology Fit (TT)	5	0.948
Tool functioning (TF)	4	0.808
Actual tool use (AT)	6	0.878
Intention to use tool (IT)	4	0.942
Perceived ease of use (PE)	6	0.848
Perceived Usefulness (PU)	5	0.955
Behavior (B)	6	0.956
Individual performance (IP)	5	0.960
Perceived self-efficacy (PSE)	5	0.961
Outcome expectation (OE)	5	0.966
Total	56	0.986

4.1. Descriptive analysis of the sample data

The study samples consist of 503 individuals with T2DM, participants additional demographic characteristics were obtained including gender, age, educational level, and so on. Participants were 59.7 years old on average with a standard deviation of 10.3 years. The majority (60.0%) of T2DM sample were females and (36.6%) males, most (71.0%) of the participants are of high school education level or less, (11.5%) of them have a diploma, while (7.6%) of them were illiterate, and (1.6%) only of then holding Master or PhD degree. Majority of the respondents (46.5%) have suffered from diabetes mellitus for over 10 years. Table 2 show the summarize of demographic characteristics.

Table 2. T2DM patient's demographic characteristics

Variable	Characteristics	Amount	Percent
Gender	Male	184	36.6%
	Female	302	60.0%
	Missing	17	3.4%
Education	Illiterate	38	7.6%
	High school or less	357	71.0%
	Diploma	58	11.5%
	Bachelor degree	31	6.2%
	Master or doctor	8	1.6%
	Missing	11	2.2%
Duration of T2DM	Less than year	45	8.9%
	From 1 to 5 years	142	28.2%
	More than 5 to 10 years	75	14.9%
	More than 10 years	234	46.5%
	Missing	7	1.4%

The SEM taken into consideration in this study was developed using IBM analysis of moment structures (AMOS). SEM was used to calculate the causal relationships between each latent variable [34]. As in many other studies, it was used to evaluate how construction, stakeholders, materials, design, and external factors relate to project quality [35].

4.2. Statistical analysis

Potential influencing factors were gathered through a scientific research review to study the impact of all potential factors on self-care management among T2DM patients. 11 primary categories were used to group these factors: 'Task Requirement' (TR), 'Task Technology Fit' (TT), 'Tool Functioning' (TF), 'Actual Tool Use' (AT), 'Intention to Use Tool' (IT), 'Perceived Ease of Use' (PE), 'Perceived Usefulness' (PU), 'Behavior' (B), 'Individual Performance' (IP), 'Perceived Self-Efficacy' (PSE), and 'Outcome Expectation' (OE). 12 latent variables were created by combining those categories with 'Self-Care Management' (SCM) as the outcome variable. A Likert scale with a range of 1 (strongly disagree) to 5 (strongly agree) was used to measure the observed variables that made up each latent variable.

Based on the results shown in Table 1, the second phase of the analysis is SCM for T2DM. Cronbach's α values were higher than 0.7. This would demonstrate the final model's internal validity and dependability. Additionally, the models fit taken into consideration in this study are shown in Table 3. In accordance with a prior study's recommendation [36], while the incremental fit index (IFI), tucker lewis index (TLI), and comparative fit index (CFI) could have a minimum of 0.9 to show the model has an acceptable fit, the goodness of fit index (GFI) and the adjusted goodness of fit (AGFI) could have values greater than 0.80. Additionally, the root mean square error of approximation (RMSEA) value needs to be below 0.07. Moreover, Chi-Square was measured. Thus, the final models are acceptable.

Table 3. T2DM Model's Goodness-of-Fit

Goodness of fit measure	Parameter estimate	Cut-off
GFI	0.931	> 0.8
AGFI	0.883	> 0.8
IFI	0.952	> 0.9
CFI	0.927	> 0.9
TLI	0.936	> 0.9
RMSEA	0.0483	< 0.07
Chi-square = 5954.502	Degrees of freedom = 1314	p-value < 0.001

Figure 2 represents the SEM models for factors affecting SCM among diabetes patients (T2DM SEM Model). Certain factor loadings fall below the study's threshold [37], indicating the use of greater cut-offs ranging from 0.32 (poor), 0.45 (fair), 0.55 (good), 0.63 (very good), or 0.71 (excellent). The variables of TF and PE (Q3_3, Q6_1, and Q6_2) have since been removed from the model. Table 4 results show that every component of the T2DM model affects SCM, with the most influential being the factor Perceived Usefulness (PU) and the least influential being the Factor Task requirement (TR).

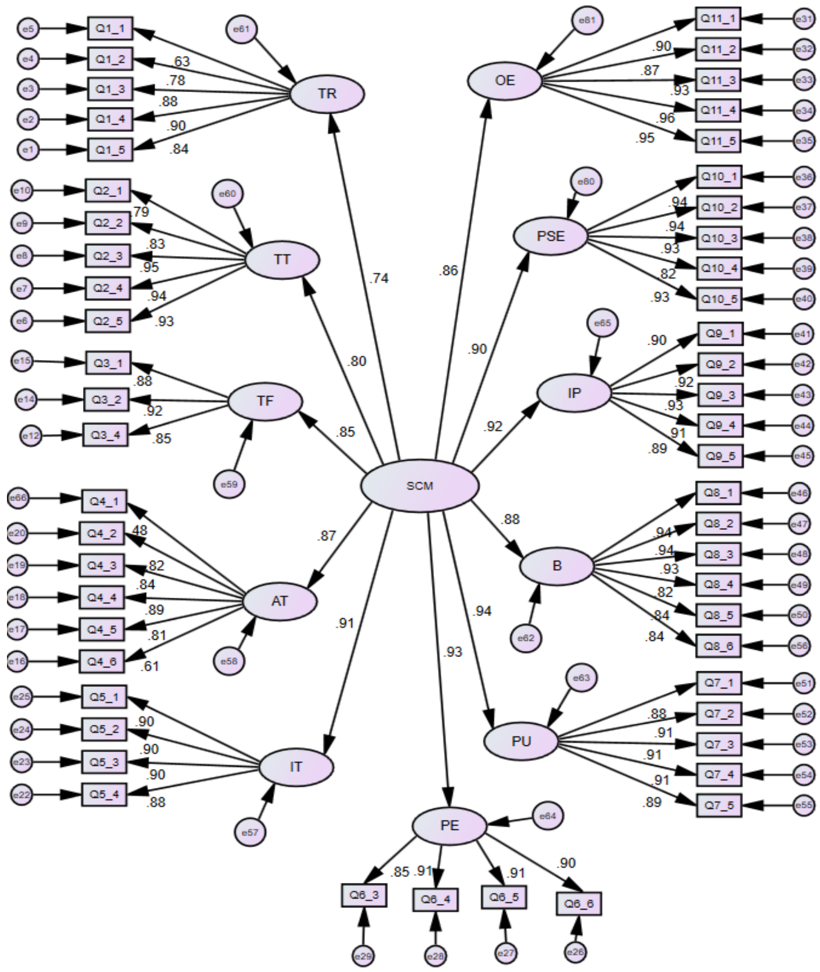

Figure 2. T2DM SEM model

Table 4. Path coefficient and t-statistics of T2DM model

Hypothesized path	Standardized (β)	t-test	p-value
PU □ SCM	0.939	22.852	.000
PE □ SCM	0.927	23.382	.000
IP □ SCM	0.92	23.093	.000
IT □ SCM	0.908	22.6	.000
PSE □ SCM	0.903	23.812	.000
B □ SCM	0.881	22.85	.000
AT □ SCM	0.872	13.737	.000
OE □ SCM	0.86	21.259	.000
TF □ SCM	0.854	20.032	.000
TT □ SCM	0.8	19.996	.000
TR □ SCM	0.738	16.255	.000
Level of Significant $\alpha \leq 0.05$			

The third stage of analysis is the hypothesis models for T2DM, factor loadings in the AMOS and the standardized β coefficient in the regression analysis were similar. The β denoted the expected variation in the dependent construct for a unit variation in the independent constructs. Each path in the proposed model had its β value calculated which the higher the β value, the more significant the impact on the internal hidden construct. All the observed variables in the T2DM SEM Model in Figure 2 have β values greater than 0.4, indicating that they measure and have an impact on their latent variables.

The hypotheses testing of this research were tested partially for each path of the analysis result using the SEM. Standardized path coefficients of T2DM path Model are shown in Table 5 revealed that the path model's factor loadings of latent and observed variables as in previous SEM model were found to be greater than 0.4 and positive, indicating that all observed variables were positive impact on their latent variables.

Table 5. Path coefficient and t-statistics of T2DM final model

Hypothesized path	Standardized (β)	S.E.	t-test	p-value
TT □ TR	.641	.035	17.150	.000
TT □ TF	.499	.031	14.777	.000
AT □ TT	.208	.024	6.930	.000
AT □ IT	.697	.050	9.878	.000
AT □ B	.121	.033	2.223	.026
B □ IT	.870	.044	22.564	.000
IT □ PU	.850	.034	23.585	.000
IT □ PE	.065	.030	2.214	.027
PU □ PE	.889	.036	24.006	.000
IP □ AT	.884	.040	23.958	.000
B □ PSE	.836	.076	13.716	.000
TR □ OE	-.010	.027	-.385	.700

Additionally, the standardized path coefficient value (0.641) and the t-value (17.51) were obtained from the analysis of the impact of TR on TT among T2DM patients. As a result, it was assumed that TR positively affects TT ($p < .001$) (H_1 supported). The results also confirm the hypothesis that TF significantly improves TT ($p < .001$) (H_2 supported). However, the results showed that B is not significantly affected by the PSE ($p > .05$) (H_12 Not Supported).

4.3. Discussion

The purpose of this study was to create and validate a mHealth adoption model for SCM among patients with T2DM who visit Palestinian primary healthcare facilities. The study evaluated how different theoretical constructs based on the TAM, TTF, and SET affect actual mHealth use among T2DM patients using a structural equation modeling (SEM) approach with SPSS and AMOS.

With a concentration on discovering what variables best predict the perceived benefit and use of mHealth, the model assessed 11 important dimensions. The main predictor of mHealth benefits according to the results, was PU. This is consistent with earlier TAM-based research that emphasizes PU as a key factor in technology adoption. This implies that T2DM patients are more likely to adopt and stick with mHealth applications when they believe they are helpful for managing their condition, such as monitoring blood glucose or getting medication reminders.

It's interesting to note that TR was found to be the least reliable predictor. This indicates that while patients acknowledge the value of mHealth, the alignment between their specific self-care tasks and the functionalities offered by mobile tools may still be lacking. This finding may point to a need for better customization or culturally relevant design features in mHealth applications tailored for Palestinian T2DM patients. Table 6 provided a summary of the hypothesis testing. The results indicate that while TTF will have an impact on actual mobile use among T2DM patients, TR will have an impact on TTF among T2DM patients as well as TF. Once more, among T2DM patients, IT will affect AT use for mobile use, whereas B will affect AT use for mobile use.

Table 6. Summary of hypothesized relationships of T2DM hypotheses

Hypotheses	Decision	Standardized (β)	p-value
H_1: Task requirements will affect T2DM patients on Task Technology Fit	Supported	.641	.000
H_2: Task Technology Fit among T2DM patients will be impacted by tool functionality	Supported	.499	.000
H_3: Task Technology Fit will affect how T2DM patients use their phones	Supported	.208	.000
H_4: T2DM patients' actual tool use for mobile devices will be influenced by their intention to use the tool	Supported	.697	.000
H_5: Patients with type 2 diabetes will use tools more frequently if they intend to use them	Supported	.121	.026
H_6: Patients with type 2 diabetes will behave differently depending on their intention to use the tool	Supported	.870	.000
H_7: T2DM patients' intention to use the tool will affect how well they use it	Supported	.850	.000
H_8: Among T2DM patients, perceived usefulness will affect their intention to use the tool	Supported	.065	.027
H_9: T2DM patients' intention to use the tool will be influenced by their perception of its ease of use	Supported	.889	.000
H_{10}: Among T2DM patients, perceived usefulness will be influenced by perceived ease of use	Supported	.884	.000
H_{11}: T2DM patients' actual tool use for mobile devices will be influenced by their intention to use the tool	Supported	.836	.000
H_{12}: Patients with type 2 diabetes will behave differently depending on their perceived level of self-efficacy	Not Supported	-.010	.700
H_{13}: The use of smartphones and mobile health by T2DM patients will be influenced by outcome expectations	Supported	.638	.000

The findings also supported other hypothesized relationships such as TR and TF significantly influence TTF, confirming that perceived alignment between the mHealth tool and the users' self-care needs contributes to perceived fit. TTF had a positive impact on actual mHealth usage, reinforcing that the better the tool matches the patient's health tasks, the more likely it is to be adopted. B and IT were both found to have a significant impact on actual mHealth usage, highlighting the direct influence of BI and health-related behaviors on technology use in the management of chronic diseases.

PSE had little impact on B, which was unexpected. This could be explained by the fact that confidence itself is insufficient in the absence of useful assistance, instruction, or user-friendly app design. The impact of self-efficacy may also be reduced for T2DM patients in refugee settings by external barriers like digital literacy, device access, or cultural factors. The theoretical framework was validated in the environment of Palestinian T2DM patients by the SEM model's overall good fit indices. These results highlight the significance of creating mHealth tools that address gaps in user confidence and accessibility while giving attention to perceived usefulness and task alignment.

5. CONCLUSION

The outcomes of this study support the original goal of creating and verifying a mHealth adoption model for T2DM patients' self-care management in Palestine's primary healthcare facilities. The robustness of the model in capturing key variables influencing adoption was confirmed by SEM, which showed significant connections among the 11 dimensions of mHealth use. The most significant factor was found to be PU, underscoring the significance of creating mHealth applications that are not only useful but also viewed favorably by users. The practical implication is obvious, which is to improve patient engagement and facilitate efficient self-management of chronic diseases, mHealth tools must focus on user-centric design.

This study adds to the expanding corpus of information on the adoption of digital health and offers a validated model that can guide the creation of focused mHealth interventions. Future research could build on this work by using the model in a variety of healthcare settings or for other chronic conditions. Predictive analytics and AI-driven personalization could enhance mHealth solutions even more by making sure they adjust to users' changing requirements and preferences. Through implications for healthcare policy, app development, and patient empowerment, the study concludes by highlighting the transformative potential of mobile health in enhancing chronic disease self-management.

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CONFLICT OF INTEREST STATEMENT

According to the authors, there is no conflict of interest.

ETHICAL APPROVAL

The Director General of UNRWA Primary Health Care Clinics in Palestine and the Al-Quds University Ethics Committee granted ethical approval for this study. Only after both authorities gave their approval did data collection begin, and all participating T2DM patients gave their written and verbally informed consent. Participants were made aware of the confidentiality of their answers prior to data collection, and the researcher issued a formal statement about data confidentiality. No personally identifiable data was gathered. Only the researcher and the supervisory team have access to the password-protected personal computer where all datasets are safely kept. After the study is finished, the data will be kept for three years before being permanently erased.

DATA AVAILABILITY

Because of limitations pertaining to participant confidentiality and ethical approval, the data supporting the study's conclusions are not publicly accessible. The Director General of UNRWA Primary Health Care Clinics in Palestine and the Al-Quds University Ethics Committee have established restrictions on access to the data.

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