Enhanced Technology Adoption Model for Diabetes Self-Management using Mobile Health: Insights from UNRWA Healthcare Providers

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ABSTRACT

This study aimed to develop and validate a mobile health (mHealth) adoption model for self-care management of type 2 diabetes mellitus (T2DM) from the perspective of healthcare providers (HCPs) in primary United Nations Relief and Works Agency (UNRWA) healthcare centers. A structured questionnaire was administered to HCPs, capturing socio-demographic information and eleven dimensions of mHealth use: Task Requirement, Task Technology Fit, Tool Functioning, Actual Tool Use, Intention to Use, Perceived Ease of Use, Perceived Usefulness, Behavior, Individual Performance, Perceived Self-Efficacy, and Outcome Expectation. Data was analyzed using Structural Equation Modeling (SEM) in AMOS 21. The results showed that Perceived Ease of Use ($\beta = 0.928$, $p < .001$) was the most influential factor affecting Actual Tool Use, whereas Task Requirement ($\beta = 0.528$, $p < .001$) had the lowest impact on Task Technology Fit. Task Technology Fit was significantly influenced by Task Requirement and Tool Functioning but did not directly affect Actual Mobile Use. These findings confirm the robustness of the proposed model in capturing key determinants of mHealth adoption and provide actionable insights for designing effective, user-centric mHealth interventions to support diabetes self-management among HCPs.

Keywords- Mobile Health, Type 2 Diabetic Mellitus, Structural Equation Model, Healthcare Provider, Self-care Management

INTRODUCTION

Type 2 diabetes mellitus (T2DM) is one of the most prevalent chronic diseases worldwide, posing significant health, social, and economic challenges [1]. The International Diabetes Federation's latest report indicates that approximately 589 million adults aged 20–79 years are living with diabetes, and this number is projected to rise to 853 million by 2050 [2]. Effective self-care management, including lifestyle modification, medication adherence, and regular monitoring, is essential to prevent complications and improve quality of life [3]. Mobile health (mHealth) technologies, such as smartphone applications, wearable devices, and remote monitoring tools, offer promising support for diabetes self-care management by facilitating real-time communication, patient education, and data sharing [4], enabling healthcare providers (HCP) to deliver more personalized and continuous care. However, the successful adoption of mHealth in clinical practice depends largely on HCP's readiness, willingness, and ability to integrate these technologies into their workflows.

In UNRWA healthcare centres in Palestine, diabetes is a leading cause of morbidity and mortality, with T2DM accounting for most cases [5]. Despite the growing global use of mHealth in chronic disease management, adoption within the Palestinian healthcare system has been slow. UNRWA primary healthcare centers, which serve a large portion of the population, face resource constraints, limited digital infrastructure, and varying levels of technological literacy among HCP [6]. Previous research has primarily focused on patient perspectives, with limited attention to HCP, who serve as gatekeepers and enablers of mHealth adoption. Understanding their perceptions, readiness, and barriers is crucial for ensuring successful implementation and utilization of mHealth tools.

The purpose of this study is to investigate HCP's perceptions, readiness, and perceived barriers of the mHealth adoption for T2DM self-care management in UNRWA primary healthcare centers. Specifically, it aims to explore provider attitudes toward mHealth, identify barriers and facilitators influencing adoption, and examine the relationship between provider characteristics and willingness to integrate mHealth into practice. The study addresses the following research questions: (1) What factors influence HCP's ability and willingness to support self-care management in UNRWA primary healthcare centers? (2) What is the influence of mobile health use, from the healthcare provider perspective, on diabetes self-care management? (3) Which model is most appropriate for integrating mobile health into diabetes self-care management based on HCP's perspectives?

The study is significant for three main reasons. First, it contributes to the limited literature on provider-focused mHealth adoption in Palestine and other developing countries in the Middle East. Second, it provides policy-relevant evidence to guide the Palestinian Ministry of Health and UNRWA in designing strategies, policies, and training programs to enhance mHealth adoption among providers. Finally, understanding provider perspectives can improve the design and implementation of mHealth interventions, thereby enhancing patient communication, treatment adherence, and self-care outcomes.

The novelty of this research lies in its empirical investigation within UNRWA refugee camps, a government-regulated healthcare sector where access and data collection involve navigating complex bureaucratic and ethical procedures. There is a scarcity of studies examining mHealth adoption from the perspective of HCP in such constrained, politically sensitive, and underserved environments. This study not only fills a critical research gap but also provides actionable insights for improving mHealth implementation in similarly challenging contexts worldwide.

RELATED WORK

A. Healthcare Providers' Perspectives on Mobile Health for Diabetes Self-Management

HCP plays a crucial role in the adoption of mHealth technologies for diabetes self-management. Studies have consistently highlighted challenges such as patient non-adherence to medication, dietary and lifestyle recommendations, and misconceptions regarding treatment options, particularly insulin [7]. Effective patient-provider communication, shared decision-making, and early clarification of treatment concerns are key strategies to improve adherence [8].

The provider-patient relationship is also critical, good rapport enhances patient engagement and compliance, while limited consultation time negatively affects trust and self-care adherence [9]. Multidisciplinary approaches and increased access to specialized clinics have been suggested as strategies to overcome time constraints and improve diabetes outcomes [10]. HCP further acknowledges the potential benefits of mHealth apps in promoting self-management, but report concerns workload, liability, data privacy, and security [11], [12]. Addressing these issues is essential to facilitate successful implementation of mHealth solutions in clinical practice.

B. Mobile Health Applications and Self-Management for T2DM in the Middle East

Mobile health technologies are increasingly recognized as effective tools for managing chronic diseases such as T2DM [13]. The Middle East has seen rapid adoption of digital health solutions due to widespread smartphone use and internet access [14]. However, the prevalence of diabetes remains high, particularly in countries such as Saudi Arabia, Qatar, and Kuwait, driven by poor diet, obesity, and low physical activity [15].

Studies in the region have explored the use of mHealth to track physical activity, dietary intake, and enable communication with HCP [16]. Despite these efforts, challenges remain, including low health literacy, cultural lifestyle factors, and poor adherence to self-care practices [17]. Evidence suggests that patient self-efficacy strongly influences engagement in self-management behaviors [18], and mHealth interventions could potentially enhance self-efficacy and promote better adherence.

C. Mobile Health Applications and Self-Management for T2DM in Palestine

Research on mHealth for diabetes management in Palestine is limited. Some studies have addressed mobile health for mental health [19] or assessed medication adherence among T2DM patients [20]. These studies found that non-adherence is a major issue, often linked to patients' knowledge of the disease, beliefs about medications, and perceived ability to perform self-care behaviors. High mobile phone ownership (93.4%) and frequent use of social media (99.6%) suggest potential for mHealth interventions in Palestine [19]. Nonetheless, there is a paucity of research examining mHealth adoption for self-management among Palestinian T2DM patients, highlighting a clear gap that the present study seeks to address.

D. Conceptual and Theoretical Foundations

Previous studies have utilized multiple theoretical frameworks to guide diabetes self-management research, including Self-Efficacy Theory [18], Orem's Self-Care Deficit Nursing Theory (SCDNT) [21], the Technology Acceptance Model (TAM) [22] and Task-Technology Fit [23]. These frameworks emphasize the interplay between patient characteristics, technological capabilities, behavioral intention, self-efficacy, and social support in facilitating effective self-management. The integration of these theories allows for a comprehensive understanding of the factors influencing mHealth adoption and use and provides a foundation to develop and validate a context-specific model for T2DM self-management in Palestine.

Despite the growing evidence on mHealth applications for diabetes self-management in Middle Eastern countries, few studies focus specifically on Palestine. Most research addresses mental health or general chronic disease management, leaving gaps in understanding patient self-efficacy, lifestyle behaviors, cultural influences, and healthcare provider perspectives on mHealth adoption. Consequently, there is a need to develop and validate a context-specific model for mobile health use that addresses both patient- and provider-related factors for T2DM self-management in Palestine.

METHODOLOGY

A. Research Design

This study adopts a quantitative research design to examine the factors influencing mobile health (mHealth) adoption to support diabetes self-care management among healthcare providers (HCPs) in UNRWA primary healthcare centers in Palestine. Given the scarcity of studies exploring mHealth adoption in refugee healthcare settings, the study is exploratory in nature. The design is descriptive and cross-sectional, involving the collection of empirical data at a single point in time using structured questionnaires. This approach enables the identification of technological, behavioral, and organizational factors that affect HCP's willingness to integrate mHealth into diabetes care.

A deductive approach is employed to test hypotheses derived from three theoretical frameworks: the Technology Acceptance Model (TAM), Task-Technology Fit (TTF), and Self-Efficacy Theory (SET). These models guided the development of constructs and relationships to be examined. While the primary method is quantitative, the study acknowledges the contextual complexities of healthcare provision in refugee settings, which warrant careful adaptation of the research instruments to fit the unique environment of UNRWA clinics [24].

B. Study Setting and Population

The study was conducted in UNRWA primary healthcare centers located within refugee camps in the West Bank, Palestine. These camps, established in 1948, include Al-Jalazon, Al-Amari, Qalandiya, Shu'fat, Dheisheh, and Al-Arroub. The target population consisted of HCPs, including physicians, nurses, laboratory technicians, and health educators, who are directly involved in the management and care of patients with T2DM.

UNRWA clinics operate under a government-regulated refugee health system, serving a vulnerable population with limited healthcare resources. Conducting research in this context is challenging due to administrative restrictions, heavy workloads of medical staff, and the sensitivity of health-related data in refugee communities. Despite these constraints, the setting provides a rare opportunity to investigate mHealth adoption among HCPs in one of the most underrepresented healthcare environments.

C. Sampling Technique and Sample Size

Due to logistical constraints and limited access to comprehensive staff rosters, a non-probability sampling method was employed. Convenience sampling was used to recruit HCPs who were available and willing to participate during the data collection period. This approach was appropriate given the restricted administrative access and the operational demands faced by HCPs in UNRWA clinics.

In determining sample size, previous survey-based studies in healthcare settings were consulted. The study from [25] suggest a sample size between 30 and 500 for such studies. For structural equation modeling (SEM), another study from [26] recommends a minimum of 200 respondents, with larger samples preferred to improve statistical power. To ensure robustness and account for non-responses or incomplete questionnaires, the study targeted at least 300 respondents, with an oversampling goal of 350 HCPs.

D. Development of Research Instrument

A structured, close-ended questionnaire was developed to gather data from HCPs. The instrument was informed by previous studies on mHealth adoption using TAM, TTF, and SET, and adapted to fit the Palestinian refugee healthcare context. The questionnaire consisted of demographic and occupational questions—such as occupation, gender, and educational level—followed by perception-based items. These items assessed opinions on whether patient income influences mHealth use, whether mHealth helps patients gain more control and knowledge about their disease, whether mHealth improves patient health ratings, and the extent to which patients seek diabetes information from clinics versus mHealth platforms. Other items explored whether HCPs themselves use mHealth for delivering health services, and whether family influence affects patient adoption of mHealth. All perception-based items were measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), a widely used format in behavioral research for measuring attitudes and perceptions [27].

E. Instrument Validity and Reliability

In this study, the instrument designed for healthcare providers was validated based on expert recommendations after reviewing the questionnaire items. A validation form was created and sent to the experts, and their comments and feedback were retrieved, analyzed, and used to refine the instrument accordingly. The expert validation process indicated excellent agreement, with more than 90% approval of the instrument's content and structure.

Pre-testing was conducted to ensure the face validity of the instrument. Construct validity was further achieved through a pilot study involving a selected group of healthcare providers (n = 30). According to [28], 10% of the main study sample size is considered sufficient for pilot testing. Therefore, 30 participants were deemed appropriate. Feedback from the pilot test was used to make minor modifications to enhance clarity and relevance.

F. Data Collection Procedure

Data collection was carried out between January 2024 and May 2024. Eligible HCPs were approached in person during their working hours and provided with information about the study's objectives, confidentiality measures, and voluntary nature of participation. Informed consent was obtained before distributing the self-administered questionnaires. To minimize disruption to clinical duties, participants were allowed to complete the questionnaire at their convenience and return it to the research team within a specified period.

G. Data Analysis

All data were analyzed using IBM SPSS Statistics Version 24 and AMOS for SEM. Prior to analysis, the dataset was screened for missing values, outliers, and normality, using skewness and kurtosis as indicators. Descriptive statistics were calculated to summarize the demographic and professional characteristics of the HCP sample. SEM was used to test the hypothesized relationships between constructions. Model fit was assessed using standard indices following the guidelines [29], including Chi-square (χ^2), the Root Mean Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI), and the Tucker–Lewis Index (TLI).

RESULT AND DISCUSSION

A. Reliability Analysis

Before testing the Structural Equation Model (SEM), the internal consistency and reliability of observed variables for HCP were assessed using Cronbach's α. Table 1 shows that the Cronbach's α values for HCP of observed variable used in the study.

TABLE I. Reliability Test Results For HCP

Factor	Number of Observed Variables	Cronbach's (α)
Task requirement (TR)	5	0.894
Task Technology Fit (TT)	5	0.900
Tool functioning (TF)	4	0.781
Actual Tool use (AT)	6	0.804
Intention to Use Tool (IT)	4	0.886
Perceived ease of use (PE)	6	0.781
Perceived Usefulness (PU)	5	0.888
Behavior (B)	6	0.937
Individual Performance (IP)	5	0.918
Perceived self-efficacy (PSE)	5	0.878
Outcome expectation (OE)	5	0.906
Total	56	0.976

Results indicate that Cronbach's α values ranged from 0.781 to 0.937, with an overall α of 0.976 for HCP, suggesting high reliability and internal consistency. Following [30] and [31], values exceeding 0.7 indicate acceptable reliability, confirming that the dataset is suitable for SEM analysis.

B. Demographic Profile of Healthcare Providers

The HCP sample consisted of 76.8% females and 21.1% males, with a mean age of 42.4 years (SD = 11.3). Occupational roles included nurses (50.5%), doctors (21.1%), and other healthcare staff such as pharmacists or laboratory technicians (26.3%). These demographics reflect the diversity of clinical roles contributing to mobile health adoption within UNRWA primary healthcare centers. Demographic characteristics are summarized in Table 2.

TABLE II. HCP Sample Demographic Characteristics.

Variable	Characteristic	Count (n)	Percent (%)
Occupation	Doctor	20	21.1%
	Nurse	48	50.5%

	Other	25	26.3%
	System	2	2.1%
Gender	Female	73	76.8%
	Male	20	21.1%
	System	2	2.1%
Educational Level	Diploma	32	33.7%
	Bachelor's degree	41	43.2%
	Master or PhD	20	21.1%
	System	2	2.1%

IBM Analysis of Moment Structures (AMOS) was utilized to develop the SEM considered in this study. The causal relationships between each latent variable were measured using SEM [32]. Like many previous studies, SEM was utilized to evaluate the relationships between construction, stakeholders, materials, design, and external factors, and how these relate to project quality [33].

C. Structural Equation Modeling (SEM) Approach for HCP

AMOS 21 was employed to evaluate the hypothesized SEM, which included twelve latent variables: 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), Outcome Expectation (OE), and Self-Care Management (SCM). Each latent variable comprised multiple observed variables, measured using a five-point Likert scale.

The SEM analysis followed a two-step approach: evaluation of the measurement model (validity and reliability) and evaluation of the structural model (path relationships between latent variables) [34]. Table 3 presents the model's goodness-of-fit indices considered in this study.

TABLE III. HCP Model Goodness-Of-Fit

Goodness of Fit Measure	**Parameter Estimate**	**Cut-Off**
GFI	0.845	> 0.8
AGFI	0.821	> 0.8
IFI	0.911	> 0.9
CFI	0.912	> 0.9
TLI	0.904	> 0.9
RMSEA	0.052	< 0.07

The goodness-of-fit indices, including GFI, AGFI, IFI, TLI, CFI, and RMSEA, were within acceptable thresholds, indicating that the final HCP model adequately fits the data.

Figure 1 illustrates the HCP SEM model. During model refinement, three observed variables which are Q3_3 (Tool Functioning), Q4_1 (Actual Tool Use), and Q6_1 (Perceived Ease of Use) were removed due to poor loading values.

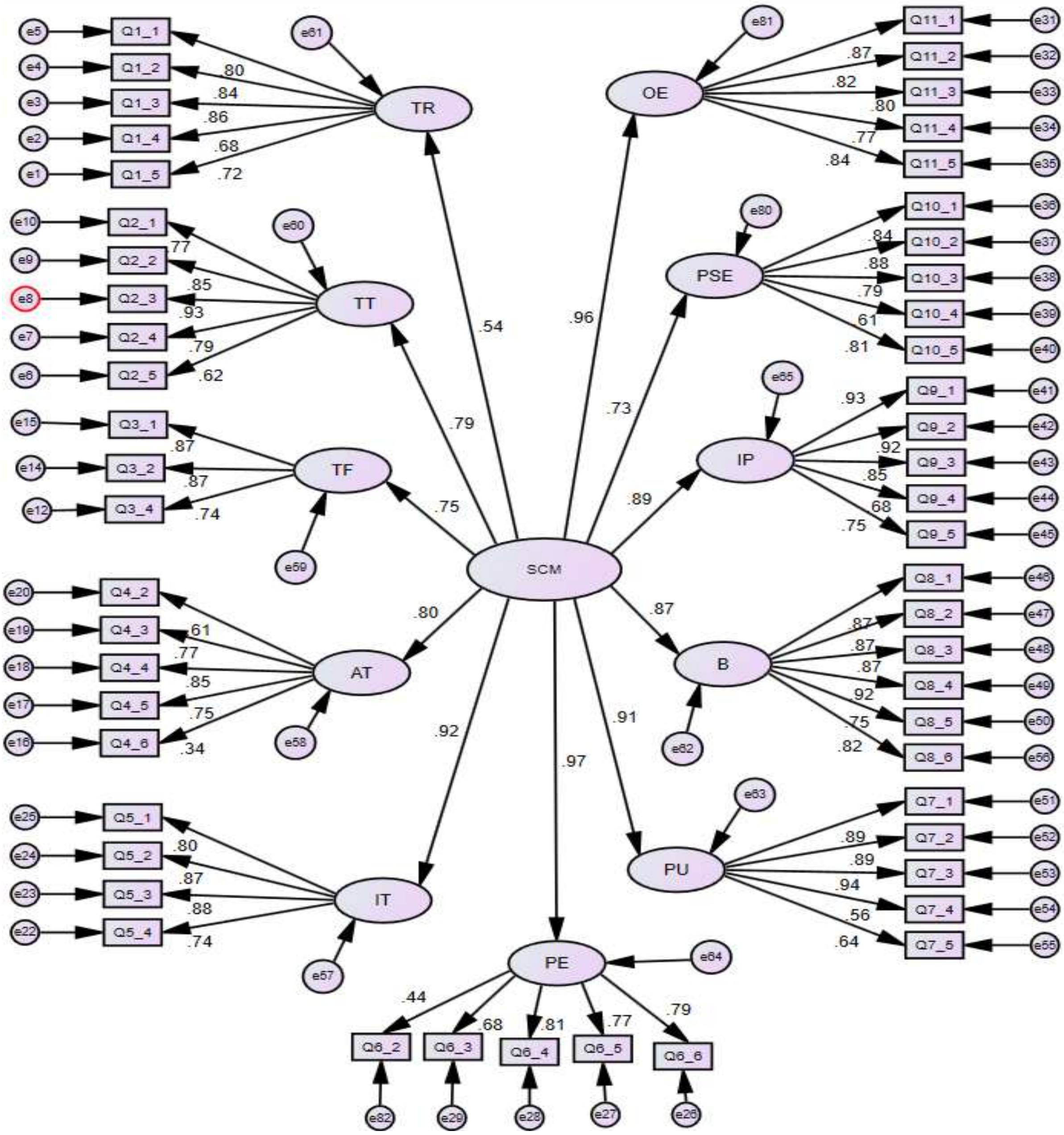

Figure 1. HCP SEM Model

The model highlights that usability and perceived benefits of mobile health are central to adoption among HCP, whereas task alignment plays a smaller role. These findings reflect the critical importance of designing intuitive mobile health tools to ensure effective use in clinical workflows.

The standardized path coefficients and t-statistics for the HCP model are summarized in Table 4. All factors in the model demonstrated significant influence on SCM at $\alpha \leq 0.05$, with Perceived Ease of Use (PE) emerging as the most influential factor ($\beta = 0.973$, $t = 8.836$, $p < .001$) and Task Requirement (TR) being the least influential ($\beta = 0.545$, $t = 4.678$, $p < .001$).

TABLE IV. Path Coefficient And T-Statistics Of HCP Model

Hypothesized Path	Standardized (β)	t-test	p-value
PE ← SCM	0.973	8.836	.000
OE ← SCM	0.956	9.928	.000
IT ← SCM	0.921	8.379	.000

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PU ← SCM	0.91	9.558	.000
IP ← SCM	0.885	9.768	.000
B ← SCM	0.868	8.812	.000
AT ← SCM	0.795	3.06	.002
TT ← SCM	0.787	5.634	.000
TF ← SCM	0.752	7.194	.000
PSE ← SCM	0.728	6.842	.000
TR ← SCM	0.545	4.678	.000

The last stage of analysis involved testing the hypothesized model for HCP. Factor loadings obtained from the SEM analysis showed that all observed variables had standardized β values greater than 0.4, indicating that each observed variable contributed positively to measuring its respective latent construct. The standardized β coefficient in the regression analysis denoted the expected variation in the dependent construct for a unit variation in the independent construct, where higher β values reflect a stronger effect on the endogenous latent construct.

Hypothesis testing was performed for each path in the model, and the results are presented in Table 5. The analysis revealed that Task Requirement (TR) had a significant positive effect on Task Technology Fit (TT) ($\beta = 0.528$, $t = 4.448$, $p < .001$), supporting H1. Tool Functioning (TF) also positively influenced TT ($\beta = 0.700$, $t = 5.266$, $p < .001$), supporting H2. However, TT did not have a significant effect on Actual Tool Use (AT) ($\beta = 0.130$, $t = 1.636$, $p = .102$), leading to the rejection of H3.

TABLE V. Path Coefficient And T-Statistics of HCP Final Model

Hypothesized Path	**Standardized (β)**	**S.E.**	**t-test**	**p-value**
TT ← TR	.528	.080	4.448	.000
TT ← TF	.700	.069	5.266	.000
AT ← TT	.130	.062	1.636	.102
AT ← IT	.725	.114	3.241	.001
AT ← B	.184	.062	1.327	.185
B ← IT	.872	.042	9.213	.000
TF ← IT	.793	.121	8.180	.000
IT ← PU	.077	.094	.862	.388
IT ← PE	.928	.153	11.351	.000
PU ← PE	.887	.100	9.152	.000
IP ← AT	.870	.482	3.955	.000
B ← PSE	-.116	.056	-1.920	.055
TR ← OE	.501	.105	4.268	.000

Further results showed that Intention to Use Tool (IT) significantly influenced AT ($\beta = 0.725$, $t = 3.241$, $p = .001$), while Behavior (B) did not have a significant effect on AT ($p > .05$). IT was significantly predicted by Perceived Ease of Use (PE) ($\beta = 0.928$, $t = 11.351$, $p < .001$), whereas Perceived Usefulness (PU) did not show a significant effect ($p = .388$). PU, however, was significantly influenced by PE ($\beta = 0.887$, $t = 9.152$, $p < .001$). Actual Tool Use (AT) strongly influenced Individual Performance (IP) ($\beta = 0.870$, $t = 3.955$, $p < .001$), and TR was significantly influenced by Outcome Expectation (OE) ($\beta = 0.501$, $t = 4.268$, $p < .001$).

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DISCUSSION

This study aimed to develop and validate a structural equation model to explain HCP's adoption of mobile health for self-care management of T2DM in primary healthcare centers in Palestine. The model incorporated eleven dimensions such as 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). Among HCPs, PE emerged as the most influential predictor of Intention to Use Tool, while TR was the weakest predictor within the model. This suggests that ease of interaction with the mobile health system, rather than the specific nature of their work tasks, was more critical in influencing adoption.

The hypotheses testing results for HCP indicate that TR and TF both had significant positive effects on TTF (H_1 and H_2 supported), aligning with Task-Technology Fit theory, which emphasizes the importance of aligning technology capabilities with task demands. However, TTF did not have a significant effect on AT (H_3 not supported), this suggests that even when healthcare providers perceive a good alignment between the tasks they perform and the technology available, this perception does not necessarily translate into actual usage of mobile health tools. One possible explanation is that external barriers, such as institutional policies, limited infrastructure, or lack of organizational support, may inhibit actual adoption despite a favorable task–technology alignment. IT significantly influenced AT (H_4 supported), underscoring the role of intention as a strong driver of actual usage, consistent with the Technology Acceptance Model (TAM).

Behavior did not significantly influence AT (H_5 not supported). This may reflect a gap between intended or stated behavior and real-world practice, possibly due to contextual barriers such as lack of time, training, or system reliability. The finding underscores that behavioral intention alone may not be sufficient to drive sustained use without supportive infrastructure and institutional encouragement. Instead, IT had a strong positive effect on B (H_6 supported), indicating that intention shapes behavioral tendencies even if these tendencies do not always translate directly into actual use. Furthermore, IT significantly influenced TF (H_7 supported), highlighting the potential for user motivation to drive perceptions of system capability. While PU did not significantly influence IT (H_8 not supported), a potential explanation is that healthcare providers may already recognize the general usefulness of digital tools, but their actual intention is shaped more strongly by ease of use and organizational readiness. In resource-constrained environments, perceived convenience and effort reduction may outweigh usefulness in shaping adoption decisions. PE had a substantial positive effect on IT (H_9 supported) and on PU (H_{10} supported), reinforcing the idea that system usability is a key determinant of perceived benefits among HCPs.

In addition, AT had a strong positive effect on IP (H_{11} supported), demonstrating that actual use of mobile health tools translates into perceived performance improvements. PSE did not significantly influence B (H_{12} not supported), this could be due to systemic barriers, such as rigid workflows, institutional priorities, or limited integration of mHealth into daily clinical practice. It highlights that individual confidence must be reinforced by external enablers for actual behavioral transformation to occur. Taken together, those unsupported relationships highlight that individual perceptions are not always sufficient drivers of adoption. Instead, organizational context, infrastructure, and external support mechanisms may play a more critical role in shaping actual mHealth use among healthcare providers. Finally, OE significantly influenced TR (H_{13} supported), implying that expectations of positive outcomes encourage alignment between tasks and technology use. Summary of hypotheses testing was presented in Table 6.

TABLE VI. Summary Of Hypothesized Relationships Of HCP Hypotheses

Hypotheses	Decision	Standardized (β)	p-value
H_1: Task requirement will have an influence on Task Technology Fit among T2DM Patients and healthcare providers (TTF).	Supported	.528	.000

H_2: Tool functioning will have an influence on Task Technology Fit among T2DM patients and healthcare providers (TTF).	Supported	.700	.000
H_3: Task Technology Fit will have an influence on actual mobile use among T2DM patients and healthcare providers (TTF).	Not Supported	.130	.102
H_4: Intention to Use Tool will have an influence on Actual Tool use for Mobil use among T2DM patients and healthcare providers (TTF) (TAM).	Supported	.725	.001
H_5: Behavior will have an influence on Actual Tool use for Mobile use among T2DM Patients and healthcare providers (TTF) (Banadora).	Not Supported	.184	.185
H_6: Intention to Use Tool will have an influence on Behavior of the T2DM patients and healthcare providers (TTF) (Banadora).	Supported	.872	.000
H_7: Intention to Use Tool will have an influence on Tool functioning among T2DM patients and healthcare providers (TTF)(TAM).	Supported	.793	.000
H_8: Perceived Usefulness will have an influence on Intention to Use Tool among T2DM patients and healthcare providers (TTF) (TAM).	Not Supported	.077	.388
H_9: Perceived ease of use will have an influence on Intention to Use Tool among T2DM patients and healthcare providers (TTF) (TAM).	Supported	.928	.000
H_{10}: Perceived ease of use will have an influence on Perceived Usefulness Among T2DM patients and healthcare providers (TAM).	Supported	.887	.000
H_{11}: Actual mobile will have an influence on the individual performance for the T2DM patients and healthcare providers.	Supported	.870	.000
H_{12}: Perceived self-efficacy will have an influence on Behavior of the T2DM patients and healthcare providers	Not Supported	-.116	.055
H_{13}: Outcome expectation will have an influence on the use of the mobile health /smartphone for the T2DM patients and healthcare providers.	Supported	.501	.000

Overall, the findings highlight that for HCP, ease of use is central to driving intention and perceived usefulness, while actual use is more strongly linked to intention than to perceived task-technology fit. This suggests that adoption strategies should prioritize improving system usability and fostering user motivation rather than focusing solely on matching technology to tasks.

CONCLUSION

The findings of this study align with the initial objective of developing and validating a mHealth adoption model for self-care management of T2DM from the perspective of HCP in primary healthcare centers in Palestine. SEM revealed significant relationships among the eleven dimensions of mHealth use, confirming the model’s robustness in capturing key determinants of adoption among HCPs.

Perceived Ease of Use emerged as the most influential factor for HCPs, underscoring the importance of designing mHealth applications that are intuitive, accessible, and seamlessly integrated into clinical workflows. While Task Requirement was found to have the weakest influence, the results indicate that usability and user motivation outweigh strict alignment between technology and job demands in adoption of driving. This research contributes to the growing body of knowledge on digital health adoption by providing a validated, HCP-specific model that can guide the development of targeted mHealth interventions. Future studies could apply this model to other healthcare roles or chronic conditions and explore the integration of AI-driven personalization to enhance clinical decision-making and patient support.

This study has some limitations that should be acknowledged. First, the sampling was limited to healthcare providers working in UNRWA primary healthcare centers in Palestine. While this setting is important for understanding mHealth adoption in refugee contexts, it may not fully represent the perspectives of all healthcare providers in Palestine or in other healthcare systems. As such, the generalizability of the findings is restricted. Future research should consider expanding the sample to include providers from different types of institutions, as well as incorporating patient perspectives, to provide a more comprehensive understanding of mHealth adoption in diabetes care. Additionally, for future research, the focus on longitudinal or mixed-method approaches could offer deeper insights into how attitudes and practices toward mHealth evolve over time.

In conclusion, the study highlights the potential of mHealth to transform chronic disease care by empowering healthcare providers with efficient, user-friendly tools, offering valuable insights for healthcare policy, app design, and implementation strategies.

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