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Exploring mobile health service adoption among diabetic patients using an integrated UTAUT-PMT model

Ragil Saputra[1], Satriyo Adhy[1], Hasbi Yasin[2]
[1]Department of Informatics, Faculty of Science and Mathematics, Diponegoro University, Semarang, Indonesia
[2]Department of Statistics, Faculty of Science and Mathematics, Diponegoro University, Semarang, Indonesia

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ABSTRACT

Mobile health services (MHS) have emerged as vital tools for delivering accessible and cost-effective healthcare, particularly for managing chronic conditions such as diabetes. This study investigates the behavioral factors influencing MHS adoption by integrating the unified theory of acceptance and use of technology (UTAUT) and protection motivation theory (PMT) into a unified model. A total of 189 valid responses were collected through both offline surveys (23 diabetic outpatients from 4 clinics) and online surveys (166 members of an Indonesian diabetes forum). Structural equation modeling was used to test the proposed relationships. The results show that self-efficacy (SE), effort expectancy (EE), and perceived vulnerability (PV) significantly influence behavioral intention (BI), while BI strongly affects MHS usage behavior (UB). Conversely, perceived severity (PS) and response cost (RC) were not significant. The study offers a novel theoretical contribution by demonstrating how the interaction between cognitive and motivational factors affects technology adoption in healthcare. Practical implications are provided for app developers and policymakers to improve MHS engagement through personalized interventions.

Corresponding Author:

Ragil Saputra
Department of Informatics, Faculty of Science and Mathematics, Diponegoro University
St. Prof. Soedarto SH, Tembalang, Semarang, Indonesia
Email: ragil.saputra@live.undip.ac.id

1. INTRODUCTION

The integration of digital technologies into healthcare systems has transformed how medical services are accessed and delivered [1]. Among these innovations, mobile health services (MHS) have emerged as promising solutions to facilitate remote monitoring, disease management, and patient engagement-particularly for chronic conditions such as diabetes [2]. Despite their growing availability, the adoption rate of MHS remains inconsistent, especially in developing countries like Indonesia. Barriers such as limited awareness, technological literacy, and perceptions of health risks contribute to suboptimal utilization.

In Indonesia, the prevalence of diabetes has continued to rise, with 20 million cases recorded by 2024 [3]. Although mobile internet penetration is high, adoption of MHS applications remains limited [4]. This paradox reveals a gap between access and usage behavior (UB), especially among chronic patients who could benefit most from digital interventions.

One common challenge faced by mobile healthcare developers is engaging and retaining users, making the study of user adoption behavior in health services a crucial area for researchers. Previous research has extensively explored the acceptance of e-health technology, primarily focusing on the perspectives of healthcare professionals or physicians [5], [6]. However, research exploring the behavioral acceptance of health technology from the patients' or consumers' perspectives remains relatively scarce. This lack of consumer-focused research has limited efforts to improve the acceptance and effectiveness of healthcare technologies among patients.

Several studies have employed technology acceptance models to explore MHS adoption. The unified theory of acceptance and use of technology (UTAUT) has been widely used to explain user behavior by incorporating variables such as performance expectancy (PE), effort expectancy (EE), and behavioral intention (BI) [7], [8]. For instance, Venkatesh *et al.* [9] demonstrated that PE and EE significantly influence BI in various contexts. In mobile health settings, Alam *et al.* [10] confirmed that these constructs play a significant role in shaping users' intention to adopt MHS.

However, relying solely on technology-oriented models neglects the role of health beliefs in shaping user decisions. Protection motivation theory (PMT) introduces constructs such as perceived severity (PS), perceived vulnerability (PV), and self-efficacy (SE), which have been shown to affect BI in mHealth contexts [11], [12]. The study of [12] found that SE and response efficacy are strong predictors of MHS acceptance, while [13] demonstrated that health threat appraisals significantly shaped telemedicine usage during the COVID-19 pandemic.

While both models offer explanatory value, few studies have attempted to integrate UTAUT and PMT into an integrated framework to explain MHS adoption, particularly in the context of diabetes care in Indonesia. This study aims to fill this gap by proposing a combined UTAUT-PMT model and empirically testing its relevance. Our contribution lies in demonstrating how cognitive and motivational factors jointly influence MHS adoption, and how PV and SE outperform other constructs in this context.

This study contributes to the existing literature by introducing a unified UTAUT-PMT model to explain MHS adoption behavior among diabetic patients in Indonesia, an area that remains underexplored. While UTAUT captures the cognitive and social drivers of technology acceptance, PMT introduces health-related motivational factors. The main novelty of this study is applying this integrated model in a real-world health context in a developing country, thereby extending the generalizability and applicability of both theories.

To address the aforementioned research gap, this study adopts a structured approach. The remainder of this paper is structured as follows. Section 2 provides a theoretical overview of the UTAUT and PMT frameworks. Section 3 presents the research model and methodology. Section 4 discusses the hypothesis testing results, and interprets the findings and their implications. Section 5 concludes the paper and outlines future research directions.

2. LITERATURE REVIEW

2.1. Protection motivation theory

A theoretical model, PMT is widely used as a foundational theory for studying an individual's protective behavior. PMT was first proposed in a study [14] which claimed that those undergoing treatment will face a threat assessment and coping assessment process to cope with self-protection. PMT uses PV, PS, response costs (RC), and efficacy to reflect PS, perceived susceptibility, perceived barriers, and perceived benefits in health belief model (HBM). Additionally, PMT introduces new factors, such as SE, which describes an individual's confidence in their capability to carry out tasks, achieve goals, and plan actions to achieve a goal [15]. PMT divides these factors into two categories according to an individual's stages of decision-making: threat assessment and coping assessment. Threat assessment consists of PS and PV, while coping assessment includes SE, response efficacy, and RC. In general, PMT is considered a more comprehensive theory than HBM for explaining health behavior [11].

In the context of adopting mobile health technologies, PMT includes key variables such as PS, PV, SE, and RCs play critical roles in shaping users' motivations. For instance, Changizi and Kaveh [16] found that mobile health technologies significantly enhance SE among elderly individuals, leading to improved health behaviors and quality of life. Similarly, Alharbi *et al.* [17] demonstrated that perceived benefits and SE were crucial determinants affecting the adoption of health mobile applications during the COVID-19 lockdown, highlighting the importance of users' confidence in their ability to utilize these technologies effectively. According to Chiu *et al.* [18], response efficacy, as part of coping appraisals, exerts a greater predictive power over attitudes and intention to adopt than threat-based appraisals. Similarly, Luo *et al.* [19] examined how PV, response efficacy, and SE affect user behavior.

2.2. Unified theory of acceptance and use of technology

According to Davis [20], the technology acceptance model (TAM) is a theory that can be utilized to clarify the effects of outer variables on behavior intention. However, Venkatesh *et al.* [8] pointed out that many of these variables have unique characteristics that can be applied in various fields, which has led to expand of UTAUT model. This model identifies three variables as key components of behavioral intent, namely PE, EE, and social influence (SI).

Derived from TAM, UTAUT includes the constructs of facilitating conditions (FC) and BI. Perceived usefulness and perceived ease of use are considered important elements of UB. The variable perceived ease of use is included in the EE configuration, while perceived usefulness is included in the PE configuration. Subjective norms, variables not included in TAM, are included in the composition of SI. Simply put, perceived ease of use describes the level of ease of use of a specific information technology, and the concept usefulness describes the level of performance improvement achieved through the use of a specific information tecnology (IT). Subjective norms refer to the extent of consideration of whether a key person needs to perform a specific behavior [8].

The UTAUT model has proven effective in research involving diverse health technologies, such as information systems [21], telehealthcare services [22], telemedicine during COVID-19 [23], and MHS [10]. Based on [24], the acceptance of mHealth among individuals with diabetes is significantly influenced by the four external constructs of UTAUT: FC, PE, EE, and SI. These studies demonstrate that the UTAUT model is a reliable approach for determining health technology UB.

2.3. Combining protection motivation theory and unified theory of acceptance and use of technology in mHealth research

An increasing number of studies have emphasized the importance of combining psychological models with technology adoption frameworks in explaining mHealth usage [11]-[13]. While UTAUT focuses on perceived system characteristics (ease of use and usefulness), PMT captures deeper motivational factors related to personal health beliefs. An integrated framework enables a more integrated understanding of behavior, particularly in health-sensitive contexts where emotional, psychological, and cognitive evaluations all influence decision-making. However, integration of these two models remains underexplored, especially in developing countries and for specific high-risk populations such as diabetic patients.

As shown in Table 1, previous studies have applied UTAUT and PMT across diverse contexts and populations. However, only a few have integrated both frameworks to explain m-Health adoption among chronic-disease patients in developing countries. To address this gap, the present study examines diabetic patients in Indonesia, providing both theoretical integration and contextual contribution.

Table 1. Summary of previous studies on m-health adoption

No	Authors and year	Country	Model	Key findings	Identified gap
1	[10] (2020)	Bangladesh	UTAUT	PE, EE, and SI strongly affected mHealth adoption intention.	Focused on general mHealth users; did not include health-threat or coping variables from PMT.
2	[11] (2020)	China	TPB+PMT	PV and SE influenced BI through attitude and perceived behavioral control.	Theoretical overlap between TPB and PMT, limited application in chronic-disease context.
3	[12] (2017)	China	TAM+PMT	SE and response efficacy significantly predicted BI to use MHS.	Did not combine with UTAUT constructs such as PE or EE.
4	[13] (2021)	Middle east	UTAUT2 +PMT	PV, PE, and trust were significant during the COVID-19 pandemic.	Temporary (crisis) context; limited to telemedicine, not long-term adoption.
5	[17] (2022)	Saudi Arabia	HBM	Perceived benefits and SE strongly influenced health-app use during lockdown.	Used HBM instead of PMT; lacks integration with UTAUT constructs.
6	This study	Indonesia	UTAUT +PMT	SE, PV, and PE significantly influenced BI among diabetic patients.	Addresses integration of cognitive (UTAUT) and motivational (PMT) factors in a chronic-disease, developing-country context.

Unlike prior hybrid frameworks such as UTAUT2-HBM [17] or PMT-TAM [12], this study uniquely integrates UTAUT's cognitive determinants with PMT's coping-appraisal components to capture both technological and psychological readiness among diabetic patients.

3. METHOD

3.1. Research design

This study employed a quantitative cross-sectional survey design to investigate the BI to adopt MHS among diabetic patients in Indonesia. This approach was deemed appropriate for testing hypothesized relationships within an integrated model of UTAUT and PMT using structured data collection.

3.2. Population and sample

The questionnaire was pilot-tested with 30 diabetic patients to assess item clarity, linguistic consistency, and cultural appropriateness. Minor wording revisions were made based on participants' feedback to ensure the instrument was understandable and contextually relevant. A total of 189 valid questionnaires were obtained from diabetic patients in Indonesia who were familiar with MHS. Respondents were recruited using purposive sampling through online diabetic communities and health-related social media groups.

The sample size exceeded the minimum threshold recommended for partial least squares structural equation modeling (PLS-SEM), which is typically 10 times the maximum number of inner or outer model paths [25]. This ensures sufficient statistical strength to test the proposed model and hypotheses. However, since the sample was drawn primarily from online diabetic communities, the results largely represent younger, well-educated, and technology-literate diabetic patients. Therefore, generalization to the broader diabetic population, particularly those with limited digital literacy or living in rural areas, should be made with caution. Similar limitations have been reported in previous m-health adoption studies using online survey data, where participants tend to overrepresent digitally literate and urban users [26], [27].

3.3. Instrument development

The questionnaire was developed based on validated scales from prior UTAUT and PMT studies [7], [11], [13]. A total of eight latent constructs, each measured by three items: PE, EE, PV, PS, SE, RC, BI, and UB. All items used a 5-point likert scale (1=strongly disagree to 5=strongly agree). SI and FC were excluded due to their conceptual overlap with SE. Response efficacy was also excluded to maintain model parsimony. Response efficacy reflects the perceived effectiveness of a recommended protective behavior in reducing health threats. However, in many mHealth contexts, response efficacy and SE often exhibit conceptual similarity because both constructs capture users' confidence in using technology to manage their health conditions. Several prior studies have similarly excluded response efficacy when its explanatory contribution overlapped with SE in technology adoption models [12], [13]. Furthermore, the primary objective of this study was to examine the combined role of technological acceptance factors UTAUT and key coping-appraisal constructs from PMT while maintaining a parsimonious structural model suitable for PLS-SEM analysis. Maintaining model parsimony is recommended in PLS-SEM studies to avoid unnecessary model complexity and improve interpretability [25]. Table 2 shows all questionnaire items along with variable measurements adapted from prior studies.

Table 2. Research constructs

Construct	Code	Items	References
PS	PS1	If i face a health problem, like diabetes, then it will get worse	[11], [19]
	PS2	If i face a health problem, then it will be very serious	
	PS3	If i face a health problem, then it will be severe	
PV	PV1	I have a risk of experiencing health problems, such as diabetes mellitus	[11], [19]
	PV2	Chances are I could have health problems	
	PV3	It's possible that I can suffer from health problems	
PE	PE1	I find the MHS beneficial in my everyday life	[9], [10]
	PE2	Using the MHS helps me to know my health status	
	PE3	Using the MHS boosts my life productivity	
EE	EE1	Learning how to use the MHS is easy for me	[9], [10]
	EE2	Interaction with MHS is clear and easy to understand	
	EE3	It's easy to become proficient at using the MHS	
SE	SE1	I can easily learn to use MHS	[17], [19]
	SE2	I am capable of using the MHS for self-monitoring my health	
	SE3	I can use the MHS with little effort	
RC	RC1	MHS apps are costly to purchase	[11], [13]
	RC2	I find it challenging to learn how to use MHS, requiring a lot of effort	
	RC3	Using MHS will lead to a change in my lifestyle	
BI	BI1	I have the intention to use the MHS in the next three months	[9], [10]
	BI2	I foresee using the MHS in the next three months	
	BI3	I have plans to use the MHS in the upcoming three months	
UB	UB1	MHS is an enjoyable experience	[9], [10]
	UB2	I actually want to use MHS to take care of my health	
	UB3	I use MHS on a regular basis	

3.4. Proposed research model

Based on the integration of UTAUT and PMT, this study proposes a conceptual model as shown in Figure 1. The model posits that BI is influenced by both technological factors (PE and EE) and psychological factors (PS, PV, SE, and RC).

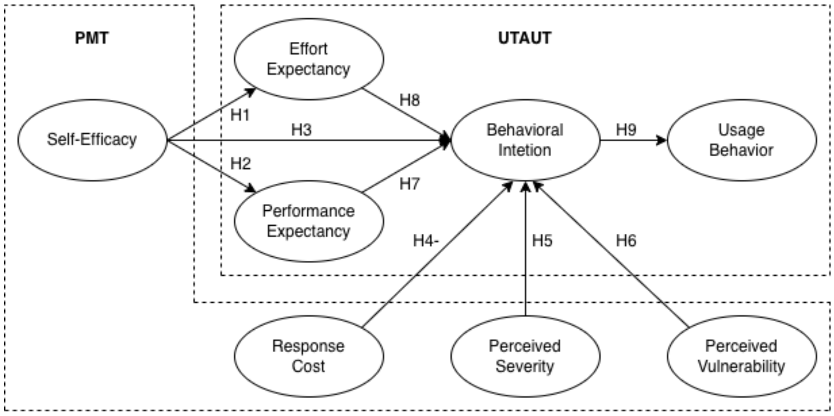

Figure 1. Proposed conceptual model

SE in this research describes the user's confidence in their ability to learn and operate MHS. When users believe in their capability to adopt technology, they are more likely to intend to use it. Additionally, users' belief in the technology's reliability and functionality reinforces their SE. This relationship has been highlighted in previous studies on technology acceptance [8]. Study [12] shows that SE has is positively associated with EE. Similarly, studies [11], [17] demonstrate that SE positively impacts BI to use MHS. Thus, we proposed following hypotheses:

- H1: SE is positively associated with PE.
- H2: SE is positively associated with EE.
- H3: SE is positively associated with BI.

In this context, RC is related to external constraints because it involves resources such as money, effort, and time required to learn and use MHS applications. When individuals are required to spend significant money on services or make substantial efforts to learn the technology, they may be less likely to adopt the technology, showing a contrary correlation linking RC and intention to adopt [11], [13], [28]. Furthermore, for older users who are more aware of expenditures, RCs become a significant factor influencing their choices. This leads to the following hypothesis:

- H4: RC negatively impacts BI.

Based on PMT, health behavior is triggered not only by threat assessments and threat severity (i.e., needs) but also by coping assessments that evaluate how a person responds to a situation [28]. Therefore, in addition to coping assessments, threat assessments should be regarded as an important factor. Based on PMT, threat appraisals consist of two variables: PV and PS. PV relates to the potential for loss, meanwhile, PS describes the level of danger from unhealthy behavior [28], [29]. Thus, we propose following hypotheses:

- H5: PS has a positive impact on BI.
- H6: PV has a positive impact on BI.

PE refers to the extent to which an individual considers that employing an information system enhances work performance [7]. Users are more likely to adopt new technology when they view it as beneficial and supportive [7], [20]. PE in the context of eHealth represent user expectations of the technology's problem-solving capabilities. Studies such as [10] have found that PE positively affects BI to use mobile health. EE refers to the degree of simplicity involved in utilizing an information system [7]. Users typically feel more comfortable and are more inclined to adopt technology when they perceive it as user-friendly. EE has been recognized as a key factor that directly impacts the intention to adopt healthcare monitoring systems, eHealth services, and mobile health [30]. In the context of mobile health [10], [31], UTAUT has been confirmed as a framework for mHealth adoption. Thus, this study proposes the following hypotheses:

- H7: PE significantly influences BI.
- H8: EE significantly influences BI.
- H9: BI significantly influences UB.

4. RESULTS AND DISCUSSION

4.1. Profile of respondents

The questionnaire results obtained through the online platform included 167 respondents, with one invalid data entry. Of the 25 offline (paper-based) questionnaires distributed, two were returned incomplete.

In total, data from 189 respondents were collected, representing diverse demographic information. Most respondents were aged between 31 and 40 years (61.6%), and the majority were male (61.4%). Regarding education, more than 80% of respondents were higher education graduates. Additionally, 50.8% of respondents had been using a smartphone for 4 to 7 years.

4.2. Measurement model

The model evaluation was carried out using confirmatory factor analysis (CFA), which involved tests for validity and reliability. Reliability was evaluated using cronbach's alpha (CA), average variance extracted (AVE), and composite reliability (CR). Table 3 shows that strong reliability is suggested by CA values for the variables exceeding 0.7. The validity assessment included both discriminant and convergent validity. Convergent validity was evaluated using AVE values and standardized item loadings. The test results indicate that all loading factors are greater than 0.55, and AVE values exceed 0.5, demonstrating strong convergent validity [25].

Table 3. Measurement model

Construct	Item	Loading	CA	AVE	CR
PS	PS1	0.904	0.771	0.604	0.819
	PS2	0.673			
	PS3	0.620			
PV	PV1	0.871	0.810	0.725	0.888
	PV2	0.879			
	PV3	0.801			
PE	PE1	0.831	0.726	0.642	0.850
	PE2	0.673			
	PE3	0.905			
EE	EE1	0.868	0.833	0.751	0.900
	EE2	0.888			
	EE3	0.549			
SE	SE1	0.618	0.727	0.514	0.760
	SE2	0.798			
	SE3	0.794			
RC	RC1	0.569	0.742	0.642	0.842
	RC2	0.552			
	RC3	0.832			
BI	BI1	0.870	0.716	0.640	0.842
	BI2	0.791			
	BI3	0.680			
UB	UB1	0.657	0.737	0.557	0.790
	UB2	0.802			
	UB3	0.693			

4.3. Structural model and testing results

The inner model, also known as the structural model, was assessed to evaluate the hypothesized relationships among the latent variables in the integrated UTAUT-PMT framework. The analysis was conducted using PLS-SEM with SmartPLS, focusing on both path coefficients and explanatory power (R^2 values).

Table 4 presents the hypothesis testing results, including path coefficients and t-values. A two-tailed test at a 5% significance level (critical t-value=1.98) was applied. Of the nine hypotheses proposed, seven were supported by the data. SE significantly predicted PE (H1), EE (H2), and BI (H3), confirming its central role in the model. PE (H7) and EE (H8) also had significant positive effects on BI, while BI strongly influenced UB, supporting (H9). Among the PMT constructs, PV significantly influenced BI (H6), whereas PS and RC did not exhibit significant effects, leading to the rejection of (H4) and (H5).

Table 4. Hypothesis testing

Hypothesis	Path	Path coefficient	t-value	Support
H1	SE->PE	0.872	3.649	Yes
H2	SE->EE	0.208	3.240	Yes
H3	SE->BI	0.122	2.278	Yes
H4	RC->BI	0.058	0.249	No
H5	PS->BI	0.201	0.019	No
H6	PV->BI	0.289	2.634	Yes
H7	PE->BI	0.268	3.149	Yes
H8	EE->BI	0.083	2.037	Yes
H9	BI->UB	0.775	2.469	Yes

The R^2 value for BI is 0.874, indicating that 87.4% of the variance in BI is explained by SE, PE, EE, PS, PV, and RC. This high explanatory power demonstrates the robustness of the integrated UTAUT-PMT model in predicting user intention toward MHS. In addition, the R^2 values for PE and EE are 0.785 and 0.764, respectively, indicating that SE is a strong predictor of these constructs. The UB construct has an R^2 of 0.595, suggesting that BI accounts for a substantial portion of the variability in actual usage. Collectively, these results provide strong empirical support for the model's predictive validity in the context of MHS adoption among diabetic patients.

For the PMT components, one coping appraisal variable (SE) significantly influences BI, PE, and EE, confirming H1, H2, and H3. Hypothesis H4 is not supported, while RC was hypothesized to negatively influence BI, the result was not significant (β=0.058, t=0.249). This may indicate that cost concerns are less relevant in the Indonesian context, possibly due to the availability of free or low-cost MHS applications. This contrasts with prior research [12], where RC was a barrier among older populations. The path coefficient for threat appraisals indicates that PV demonstrates a statistically significant positive influence on BI, with a path coefficient of 0.289 and a t-value of 2.634. These results support H6, indicating that diabetic patients who perceive themselves as more vulnerable to health threats are more motivated to adopt MHS. This finding suggests that interventions emphasizing personal health risk can be effective in enhancing user engagement with mobile health solutions. However, PS did not significantly correlate with BI, meaning H5 was not supported.

For the UTAUT variables, PE and EE positively impact BI, supporting H7 and H8. A significant effect was also observed between BI and UB, confirming H9.

4.4. Discussion

The findings confirm the theoretical relevance of combining PMT and UTAUT. First, PV from PMT had a significant effect on BI, while PS did not. This aligns with [11], who found that PV had a stronger predictive power than PS in determining user motivation, especially among chronic disease patients. In contrast, Zhang *et al.* [12] reported significant effects for both PS and PV, suggesting that cultural or contextual differences—such as the perceived accessibility of healthcare services—may influence the role of threat perception. Our study, conducted in Indonesia, supports the view that individuals may not be strongly influenced by severity unless they perceive themselves personally at risk PV. This finding is supported by [1], who emphasized in their foundational work on PMT that PV tends to exert a more direct and consistent influence on BI than PS. Similar results have been reported in non-health domains, such as safe ride adoption [32] and information security behavior [33], where PS was found to be a weaker or non-significant predictor compared to PV.

In contrast, PS and RC showed no significant influence on BI. Although H4 proposed a negative relationship, the insignificant result suggests that perceived barriers such as time or effort may no longer deter adoption, possibly due to users' growing familiarity with mobile applications. Future research could further examine subgroup differences (e.g., age, gender, or digital literacy) to better understand these non-significant relationships. The non-significant effect of PS may also be explained by contextual factors in Indonesia. Many diabetic patients already perceive diabetes as a serious chronic condition; therefore, variations in PS may not strongly differentiate BI. Instead, PV appears to be a stronger motivational trigger because individuals are more likely to adopt preventive technologies when they personally feel at risk. This finding is consistent with PMT, which suggests that PV often has a stronger influence on protective behavior than PS [11], [28]. The non-significant effect of RC may also reflect the increasing accessibility of mobile health applications in Indonesia. Many MHS applications are either free or provided at minimal cost through public or private health initiatives. In addition, the high penetration of smartphones and widespread familiarity with mobile applications may reduce the perceived effort required to learn and use such systems. Consequently, economic, and effort-related barriers may no longer represent a major deterrent for technology adoption among digitally literate users [10], [34].

Second, our findings show that SE plays a central role in both PMT and UTAUT paths. As noted in [12], SE significantly predicts BI by enhancing users' confidence in managing health through mobile technology. These results align with studies [35], but they contradict findings from other studies where SE was not significant [36]. This is consistent with [11], [13], who found SE to be a critical determinant during the COVID-19 pandemic, when digital health adoption increased out of necessity. To situate our findings within a broader context, we benchmarked them against international studies from various healthcare settings. A study in Austria–Germany integrating UTAUT2 for diabetic patients found that trust and perceived disease threat are essential extensions to the model [24]. In the U.S., Chiu *et al.* [18] showed that coping appraisal constructs like response efficacy outperform threat appraisal among elderly users, aligning with our emphasis on self-efficacy. In Bangladesh, research among older adults emphasized performance and EE as primary drivers [37], consistent with our findings on EE's significance. Similarly, a study in Ethiopia demonstrated strong effects of perceived ease of use and usefulness in mHealth adoption [34]. Together, these comparisons underscore that while EE and PE are foundational, integrating psychological factors such as self-efficacy and vulnerability enhances the explanatory power of adoption models in diverse health contexts.

The variations observed across countries may stem from differences in cultural norms toward technology use and healthcare financing models. For example, Austria and the US benefit from well-established digital-health infrastructures and higher health literacy, while Indonesia and Bangladesh rely more on out-of-pocket payments, which may restrict affordability. Ethiopia's universal coverage emphasizes preventive public health rather than individualized digital services. These contextual factors partly explain why constructs such as PE and SE show stronger effects in Indonesia.

Third, the relationship between SE with two UTAUT constructs, PE and EE were confirmed. This result is conformable with a studies [8], [9], [12], [23]. BI was significant impact by users' perceived capability to use MHS (SE), perceived ease of use (EE), and perceived advantage of the system in improving performance (PE).

Lastly, PE and EE significant effects on BI, consistent with research on technology acceptance [9], [23], [31], but in contrast with another study [38]. The lack of significant influence of PE and EE on the BI in some studies may be attributed to the high technological proficiency of users, who have extensive experience with technology-based applications and have developed the necessary skills for their use.

These results suggest that BI in MHS usage is primarily driven by SE and PV, while RC and PS were not significant. This contrasts with previous findings from [12], [35], where both RC and PS significantly influenced user intentions. The divergence in findings may be attributed to cultural and contextual differences, including the availability of free MHS services and high smartphone penetration in Indonesia.

While the integrated UTAUT-PMT model provides a robust framework for analyzing MHS adoption, it does not account for all psychosocial and contextual variables, such as trust or cultural health beliefs, which may also play critical roles in influencing technology adoption decisions.

4.5. Implications for theory and practice

This study offers several significant theoretical insights. First, while previous research focused heavily on technological factors, this study explores how health threats influence individuals' decision to adopt MHS. PMT was applied as the foundation for building a threat-response assessment framework to investigate how health-related threats influence BI. Specifically, this study empirically demonstrated that PV and SE influence MHS usage behavioral. Additionally, from the perspective of technology acceptance, UTAUT was used to investigate how perceived system advantages, such as performance improvements, contribute to MHS adoption. Second, this study operationalizes and validates the MHS acceptance model by comprehensively integrating UTAUT and PMT. The integrated model provides an overview of individuals' intentions to use MHS and describes their beliefs about health threats, individual roles (e.g., SE), and the use and acceptance of technology. By doing so, this study bridges the gap in previous research [35], which primarily focused on one of these perspectives.

This study has several practical implications, as detailed below. First, MHS application providers must comprehensively understand the factors influencing individual adoption intentions. This model recommends examining MHS usage from both the technological and health protection motivation perspectives. Most individuals use MHS applications to safeguard themselves from illness. Consequently, MHS providers should strive to increase disease awareness susceptibility and highlight the benefits of MHS to address indifference among certain individuals toward using these applications. Second, SE plays a critical role in building BI toward MHS. Providers must enhance service quality to help users effectively manage and monitor their health. Improving ease of use, usability, and reliability can significantly boost SE, leading to higher adoption rates.

Beyond theoretical contribution, the findings have practical value for MHS developers, healthcare policymakers, and health practitioners. In particular, SE emerged as a key determinant of MHS usage, indicating the need for targeted educational initiatives and user training to enhance user confidence. Moreover, PV was more influential than PS, suggesting that awareness campaigns should focus on personal risk messaging rather than general warnings. Future applications may integrate personalized health feedback features in MHS apps to enhance these perceptions and sustain engagement. These recommendations are especially critical in developing countries, where disparities in digital literacy and healthcare access present ongoing challenges to MHS adoption.

Furthermore, while this study provides valuable insights into mobile health adoption among diabetic patients, several limitations should be acknowledged. The data on UB were self-reported rather than system-logged, which may introduce recall bias and limit the precision of behavioral measurement. Future studies could incorporate behavioral analytics or system usage logs to enhance measurement validity and provide a more objective understanding of actual technology use.

5. CONCLUSION

This study represents an initial empirical attempt to explore the adoption of MHS by integrating the UTAUT and PMT. The structural model demonstrated strong explanatory power, particularly for BI (R^2=0.874), confirming the robustness of the proposed framework in predicting MHS usage. The findings reveal that PE, EE, and BI are significantly influenced by SE, while PV also plays a crucial role in shaping users' intention. Conversely, PS and RC were found to be non-significant in this context.

These results suggest that, for patients, particularly those managing chronic conditions like diabetes, psychological readiness and confidence in technology (SE and PV) are more important than general threat perception. This insight is vital for designers of MHS applications and healthcare stakeholders: interventions should emphasize building user confidence and highlighting personal health benefits, rather than focusing solely on disease severity.

Theoretically, this research contributes to the field by demonstrating how integrating UTAUT and PMT can offer a more holistic understanding of health technology adoption, particularly in developing countries where factors such as digital literacy and healthcare accessibility are uneven. Practically, the results inform MHS developers and policymakers on how to better tailor engagement strategies for diverse patient populations.

This study extends UTAUT by incorporating PMT's coping-appraisal components, offering a comprehensive framework that can be applied to other chronic disease contexts such as hypertension. Beyond diabetic patients, the integrated model provides a conceptual foundation for examining digital-health adoption behaviors in broader healthcare domains, where users' psychological readiness and SE play critical roles. Practically, the findings underscore the need to enhance patient SE and personalize risk communication strategies to increase adoption.

Future research could extend this study by examining mHealth adoption among rural populations or elderly patients who may face different technological and healthcare access barriers. Longitudinal studies may also capture changes in BI and actual usage over time. In addition, comparative studies across different chronic diseases and the inclusion of constructs such as trust, perceived risk, or system quality may further enhance the explanatory power of the model.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ragil Saputra	✓	✓	✓	✓				✓	✓	✓				
Satriyo Adhy		✓				✓		✓	✓		✓	✓		
Hasbi Yasin			✓	✓	✓		✓			✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding this research.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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BIOGRAPHIES OF AUTHORS

Ragil Saputra received his Bachelor's degree in Mathematics and Master's degree in Computer Science from Diponegoro University and Gadjah Mada University in 2003 and 2010 respectively. Currently he is a Ph.D. student at Department of Computer Science and Electronics, Universitas Gadjah Mada. He was interested in information system, big data and computation. His current research focuses on spatial data mining for human mobility prediction. His other research interests include data science, and technology adoption. He can be contacted at email: ragil.saputra@live.undip.ac.id.

Satriyo Adhy received a Bachelor's degree at Department of Mathematics, Faculty of Science and Mathematics, Diponegoro University, Semarang Indonesia and a Master's degree in Informatics from Institut Teknologi Bandung, Indonesia. Currently he is a Ph.D. student at Department of Information Systems, Universitas Diponegoro. He is a lecturer, researcher, and project manager at Universitas Diponegoro, Indonesia. His areas of interest are information system, internet of things, database, and big data. He can be contacted at email: satriyo@live.undip.ac.id.

Hasbi Yasin received a Bachelor's degree in Mathematics from the Faculty of Science and Mathematics, Diponegoro University, and Master's and doctoral degrees from the Sepuluh Nopember Institute of Technology (ITS), Surabaya, Indonesia. He is a lecturer and researcher at the Department of Statistics, Faculty of Science and Mathematics, Diponegoro University, Semarang Indonesia. His current research interests include computational statistics and neural networks modeling. His current project is spatial analysis. He can be contacted at email: hasbiyasin@live.undip.ac.id.