The Study of Factors Influencing the Adoption of mHealth Applications among the Consumers of Health Services.

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ABSTRACT

Mobile-enabled health technologies let individuals obtain clinical guidance and assessments without an in-person visit and give public-health agencies a powerful channel for distributing programmes throughout a community. This study investigates how users' motivation to avoid perceived threats interacts with their attitudes to shape intentions to adopt mobile-health (mHealth) apps. To capture both acceptance and avoidance dynamics, the research unites the Technology Acceptance Model (TAM) with Technology Threat Avoidance Theory (TTAT). In the integrated framework, threat- and coping-appraisal processes feed avoidance motivation, whereas perceived ease of use and perceived usefulness foster a favourable attitude. The hypothesised paths are assessed with Partial Least Squares Structural Equation Modelling (PLS-SEM). By highlighting the most influential mHealth determinants from the perspective of key stakeholders, the findings offer actionable guidance for practitioners and policymakers overseeing mHealth roll-outs.

KEYWORDS

mHealth, TAMTTAT, Self-efficacy, Adoption intention

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INTRODUCTION

mHealth denotes delivering healthcare services through wireless devices to improve individual health outcomes. mHealth service could be as basic as using the SMS function of a mobile phone to send health-related alerts to complex services, such as using built-in mobile sensors to interpret clinical data (PricewaterhouseCoopers, n.d. 2024). In the current landscape, India is grappling with the challenge of making primary healthcare accessible to all, with a noticeable disparity between urban and rural areas, and private and subsidized healthcare. This has led to a significant burden on healthcare costs for the population. However, the emergence of mobile healthcare, or mHealth, offers hope. It has the potential to not only reduce healthcare costs but also bridge the gap in healthcare access, particularly in underserved areas (Healthcare at Your Fingertips: Case of mHealth in India. | Centre For Civil Society, n.d. 2024). India's digital landscape is rapidly evolving. In 2023, the country had over 1.2 billion internet users, the second-largest worldwide. A staggering 1.05 billion accessed the internet through mobile phones, predicted to reach 1.2 billion by 2050 (India: Mobile Phone Internet Users 2050 | Statista, n.d. 2024). This digital revolution is also reflected in the healthcare sector, with over 245 million health and fitness app downloads nationwide in 2021. The primary focus areas of Indians while using these apps were meditation, mental health, and fitness. However, despite the high internet and mobile phone penetration, the adoption of mHealth services in India is still relatively low. This could result from a variety of factors such as unawareness, information on data privacy concerns and the digital divide between urban and rural areas. Addressing these barriers is critical to drive mHealth uptake in India; this underscores the significance of the barriers that stand in the way of mHealth adoption in India which need to be addressed if we are to promote the introduction of mHealth (Rajak & Shaw, 2021). Intellectual mHealth involves the integration of advanced technologies like AI, blockchain, and cloud computing into mHealth offerings. On another note, machine learning has found utility in speech recognition for dysarthria patients (Swain et al., 2023). The potential applications of intellectual mHealth are far-reaching: clinical data collection, provision of health services to both practitioners and patients, research enhancement and support for healthcare education, as well as real-time patient monitoring (Addotey-Delove et al., 2022b).

A growing body of research underlines the importance of studying mHealth adoption among India's digitally native 18–35 age group due to their high technological fluency and proactive health behaviors (DeSouza et al., 2014). In India, where smartphone penetration continues to surge among young adults, leveraging mHealth has been shown to significantly enhance health promotion, disease prevention, and chronic disease management outcomes (Agarwal et al., 2023). Understanding adoption drivers enables developers to design scalable, user-centered apps that resonate with India's diverse youth demographic. The study presents an integrated model incorporating the Technology Acceptance Model (TAM, Davis 1989) and Technology Threat Avoidance Theory (TAAT) to elucidate the antecedents affecting intellectual healthcare technology adoption. TAM predicted perceived ease of use and perceived usefulness to determine the use intention, which further leads to the use of technology (Silva, 2015). Technology Threat Avoidance Theory (TTAT; Liang & Xue, 2009) discusses why individuals or organizations may feel reluctant to adopt or engage in a new technology or innovation.

LITERATURE REVIEW

Technological advances are reshaping how healthcare is delivered. Digital tools allow organizations to shift away from slow, centrally controlled workflows toward more agile, decentralized operations, provided the underlying business model still generates sustainable returns (Black & Cherrington, 2022). According to Tajudeen et al. (2022), mobile health (mHealth) services function as communication platforms that expand key care features, giving patients greater autonomy in selecting and managing their own treatment options. While strong marketing visibility encourages uptake, factors such as app complexity and limited use cases can deter adoption. Tajudeen et al. (2022) ultimately conclude that personal motivation is the primary catalyst driving consumers to embrace mHealth. In a wide-ranging review of 427 studies, Goel and Taneja (2023) catalogued the latest innovations in phone-based health services, whereas Riley et al. (2011) argue that prevailing theoretical models still fail to capture all the organizational factors influencing adoption.

Considering Table 1, the contemporary mHealth adoption literature paints a multifaceted picture in which classic technology-acceptance logics interweave with risk–benefit appraisals, quality judgments, and demographic contingencies. Early empirical work by Guo et al. (2015) used Protection Motivation Theory (PMT) to show that Chinese smartphone users' coping appraisals (self-efficacy and response efficacy) outweighed threat appraisals in shaping intention. This insight foreshadowed a wave of studies arguing that perceived capability and perceived usefulness trump purely fear-based drivers. For example, Mouloudj et al. (2023) extended the Technology Acceptance Model (TAM) with self-efficacy and trust in an Algerian consumer sample, confirming that perceived ease of use and trust jointly bolster usefulness perceptions, which in turn drive adoption intention.

Parallel efforts refined the Unified Theory of Acceptance and Use of Technology. Palas et al. (2022) verified that performance expectancy, effort expectancy, and hedonic motivation explain 71 % of variation in Bangladeshi elders' intention when augmented with service quality and perceived quality of life. Yang et al. (2024), working with a large Indonesian Telegram cohort, showed that perceived product value moderates most UTAUT2 paths, implying that value framing can amplify technology beliefs. A generational lens emerged in Rahman and Uddin (2025): their SEM-ANN study of Malaysian millennials found habit and social influence to be the strongest predictors of intention, but post-hoc importance-performance mapping revealed effort expectancy as the most actionable managerial lever.

Table 1: mHealth Studies

Study	Context / Sample	Model Highlights
Palas et al. (2022) – "Factors Influencing the Elderly's Adoption of mHealth"	Bangladesh, elders (n = 493)	UTAUT2 + Service Quality & Quality of Life predictors
Yang et al. (2024) – "Predicting m-Health Acceptance"	Indonesian Telegram users (n = 2 068)	Moderating role of Perceived Product Value within UTAUT
Chai et al. (2025) – "mHealth Adoption Intention Among Gen Y"	Malaysian millennials	Integrated UTAUT + Health Belief Model (HBM); analysed via SEM-ANN-IPMA
Vu et al. (2022) – "Self-Efficacy & Privacy Concerns in mHealth"	China	Adds self-efficacy & privacy constructs to UTAUT for app adoption
Lee et al. (2024) – "mHealth Adoption & Mental Well-Being"	Multinational survey	Modified UTAUT2; shows links to psychological well-being
Chiu, Won & Chen (2025) – "Older Adults' Adoption Behaviour of mHealth Apps"	US seniors (n = 600)	Technology Readiness + PMT; coping appraisals trump threat appraisals
Guo et al. (2015) – "Investigating m-Health Acceptance from a PMT Perspective"	Chinese smartphone users	Threat & coping appraisals predict adoption intention
Marikyan & Papagiannidis (2020) – "Health Concerns About Emerging Wearables"	UK consumers	Applies TTAT to explain avoidance vs. adoption of mHealth wearables
Zhao et al. (2024) – "Quality Factors Affecting Continued Use of mHealth Apps"	Ethnic-minority users in Southwest China	ECM + PLS-SEM & ANN hybrid analysis
Sultana et al. (2024) – "Community Health Workers' Continuance of mHealth Applications"	Bangladesh CHWs	ECM + IS-Success model; highlights system quality & confirmation science
Fan et al. (2023) – "Comprehensive Picture of Factors Affecting mHealth Use"	TAM + privacy-concern & demographic moderators	Eight-country SEM study (n = 1 669); digital literacy strongest predictor
JMIR Human Factors (2024) – "Provider Adoption of mHealth in Rural Care"	TAM × TPB × organisational factors	Illuminates provider-side barriers in low-resource settings, human factors.

Risk and security concerns remain prominent yet do not necessarily deter adoption if counter-balanced by capability beliefs. Liu et al. (2022) integrated privacy concerns into UTAUT and observed that privacy exerts an indirect negative effect—weak enough to be offset by self-efficacy and performance expectancy among Chinese users. At the same time, Chiu, Won, and Chen (2025) combined Technology Readiness with PMT to explore older US adults: technology readiness dimensions influenced coping more than threat appraisals, underlining the importance of empowerment narratives when targeting seniors.

Research on post-adoption behaviour now runs parallel to the early adoption literature. For instance, Deng et al. (2024) blended the Expectation–Confirmation Model with an artificial-neural-network approach and showed that, for ethnic-minority Chinese users, a combination of confirmation, perceived service quality and overall satisfaction is decisive for ongoing engagement. Tian and Wu (2022) reached a similar conclusion with older adults living with chronic illness: by integrating ECM and UTAUT they found that confirmation bolsters both effort and performance expectations, which together lead to sustained use. Evidence from the supply side paints a different picture. Weichelt et al. (2024) observed that in rural U.S. healthcare organisations, management backing and the perceived benefit to patients outweigh effort expectancy, implying that institutional drivers diverge from those affecting consumers.

Hybrid models underscore the idea that a single theory cannot fully explain mHealth dynamics. Fan et al. (2023) combined TAM with privacy concerns and demographic moderators across eight nations, concluding that digital literacy is the dominant predictor of willingness to adopt. Looking beyond individual factors, Marikyan and Papagiannidis (2020) applied Technology Threat Avoidance Theory to wearables and found that adoption and avoidance can exist side by side when users perceive adequate safeguards.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), introduced by Davis (1989), is one of the most widely used frameworks for predicting user acceptance of information systems. TAM posits that two primary beliefs—perceived ease of use and perceived usefulness—directly influence users' attitudes toward technology, which in turn affect their behavioral intentions to adopt (Davis, 1989; Venkatesh & Davis, 2000). Numerous studies have validated TAM across various contexts, demonstrating that when users perceive a technology as easy to use and useful, they are more likely to develop positive attitudes and intentions toward its adoption (Venkatesh & Bala, 2008).

Technology Threat Avoidance Theory (TTAT)

While TAM effectively explains utilitarian motivations, it does not address users' concerns about risks or threats. The Technology Threat Avoidance Theory (TTAT), developed by Liang and Xue (2010), addresses this gap by focusing on how individuals respond to perceived threats in technology use, particularly in security and privacy contexts. TTAT introduces constructs such as self-efficacy—the belief in one's ability to execute threat avoidance behaviors—and perceived effectiveness—the belief that these behaviors will successfully mitigate threats (Liang & Xue, 2010; Ifinedo, 2012). These constructs are critical in contexts where security, privacy, or risk are salient, as they shape both attitudes and intentions toward adopting protective technologies.

Integrated Model: TAM and TTAT

Integrating TAM and TTAT provides a more holistic understanding of technology adoption. Recent research supports the inclusion of threat avoidance constructs alongside traditional acceptance variables. For example, Ifinedo (2012) found that both self-efficacy and perceived effectiveness significantly influenced attitudes toward security-related technologies, complementing the effects of perceived usefulness and ease of use. Similarly, Anderson and Agarwal (2010) demonstrated that users' confidence in their ability to manage threats and their belief in the effectiveness of protective actions were pivotal in shaping positive attitudes and intentions.

The adoption of mobile health (mHealth) technologies has gained prominence due to their potential to improve healthcare accessibility, efficiency, and patient engagement. The theoretical foundation of mHealth adoption is frequently examined using the Technology Acceptance Model (TAM), Social Cognitive Theory, and related frameworks. The following literature supports the hypothesis that perceived ease of use, perceived usefulness, self-efficacy, and perceived effectiveness significantly influence users' attitudes, which in turn influence mHealth adoption intentions. Perceived ease of use refers to the degree to which a person believes that using a system would be free of effort. It is a core component of TAM and has been empirically linked to user attitudes toward technology. In a recent study, Huang et al. (2025) found that PEOU significantly influenced clinicians' positive perceptions of mHealth tools, particularly in image-based assessments in remote diagnostics. Users reported that simple and intuitive interfaces increased their willingness to engage with mHealth apps (Huang et al., 2025). This supports earlier findings by Davis (1989), emphasizing the centrality of PEOU in shaping attitudes. Perceived usefulness, another TAM construct, is defined as the degree to which a person believes that using a system enhances their performance. PU has been consistently shown to shape favorable user attitudes. In the study by Ferreira and Caldeira (2024), perceived usefulness emerged as a dominant factor influencing healthcare professionals' and patients' willingness to use mobile health apps.

Apps perceived as beneficial in improving decision-making and reducing time for diagnosis elicited stronger positive attitudes toward continued use (Ferreira & Caldeira, 2024). Self-efficacy is an individual's belief in their ability to perform specific tasks. Bandura's Social Cognitive Theory posits that self-efficacy directly influences behavior and attitudes. Ferreira and Caldeira (2024) highlighted that patient confidence in their ability to navigate mHealth apps was significantly associated with favorable attitudes. Those with higher digital self-efficacy were more likely to adopt and recommend mHealth tools.

Perceived effectiveness relates to users' belief that mHealth applications achieve desired health outcomes. Empirical findings suggest that effectiveness perceptions are central to the evaluation of technological interventions. Huang et al. (2025) reported that users who found mobile imaging apps effective in real-time trauma assessment held a more positive attitude towards adoption. The alignment of app functionality with user expectations for clinical effectiveness is crucial in this context. Attitude acts as a mediating variable between beliefs and behavioral intention. According to both studies reviewed, a favorable attitude was the most consistent predictor of mHealth adoption intention. Positive perceptions of usefulness, ease of use, and confidence culminated in a strong intention to use these technologies in routine healthcare practices. Based on the above, the following hypotheses are proposed and represented in Figure 1. The presented model reflects this integration: perceived ease of use and perceived usefulness (from TAM), along with self-efficacy and perceived effectiveness (from TTAT), are posited to influence attitude, which subsequently predicts adoption intention.

H1: Perceived ease of use significantly influences attitude.

H2: Perceived usefulness significantly influences attitude.

H3: Self-efficacy significantly influences attitude.

H4: Perceived effectiveness significantly influences attitude.

H5: Attitude significantly influences mHealth adoption intention.

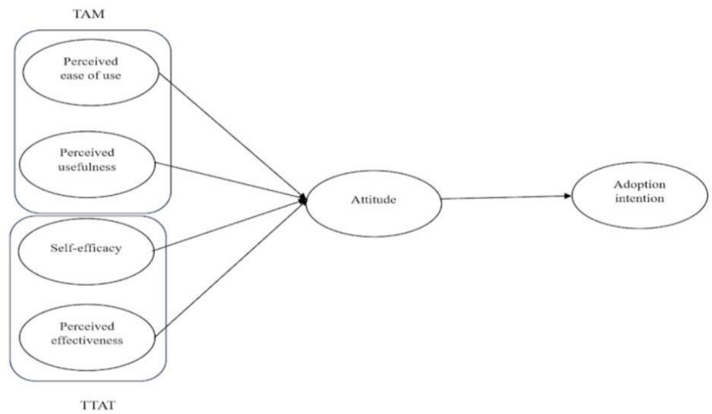

Figure 1: Conceptual framework

METHODOLOGY

A cross-sectional survey-based quantitative research design was employed. This design allows for the collection of primary data from a large sample at a single point in time, making it ideal for studying relationships among constructs such as perceptions, attitudes, and behavioral intentions. A structured questionnaire, adapting the variables from literature was used to measure the constructs in the hypotheses:

Table 2: Measurement Scale

Construct	Measurement Source	Scale
Perceived Ease of Use (PEOU)	Davis (1989) – TAM	5 point Likert scale
Perceived Usefulness (PU)	Davis (1989) – TAM	5 point Likert scale
Self-Efficacy (SE)	Liu et al. (2020)	5 point Likert scale
Perceived Effectiveness (PE)	Adapted from Lin (2007), Venkatesh et al. (2012)	5 point Likert scale
Attitude toward mHealth (AT)	Ajzen & Fishbein (1980)	5 point Likert scale
Adoption Intention (INT)	Venkatesh et al. (2003)	5 point Likert scale

Respondents include Individuals who have used or are potential users of mobile health (mHealth) applications (e.g., patients, general users, and healthcare professionals). The qualifying questions for respondents were related to their awareness and use of any of the fitness trackers, telemedicine apps, medication reminders, or health monitoring apps in the past 6 months. A convenience sampling approach has been used to ensure representation across age groups, gender, health status, and mHealth usage experience. 343 respondents participated in the study. Sample size determination was based on Hair et al.'s rule: 10 respondents per observed variable. Data was collected online via survey platforms, distributed through social media, health forums, or mHealth platforms. Informed consent was obtained prior to participation.

Non-response bias

The reported response rate was 69%, which is below the 85% threshold. It is crucial to test for non-response error to ensure the external validity of the study. The sample was divided into three distinct categories: early respondents (those who responded without a reminder), late respondents, and non-respondents. The χ^2 test confirms that the results of the groups are similar based on the respondents' characteristics and the constructs considered in the study, indicating that there is no significant non-response bias.

Common method bias

Common method bias is often a concern in cross-sectional studies where respondents report on their own experiences. To assess this, we conducted a Harman single-factor test on the constructs involved. The results showed that no single factor accounted for more than 50 percent of the variance across all variables, indicating that our dataset does not exhibit common method bias.

Demographic Profile

The demographic profile (Table 3) of the respondents (N = 343) reveals a predominance of male participants, accounting for 58.60%, while females comprised 41.39% of the sample. This indicates a slightly higher inclination or accessibility toward mHealth applications among males in the studied population. In terms of age distribution, individuals between 26–35 years represented the majority (51.89%), closely followed by those aged 18–25 years (48.10%). This suggests that mHealth usage is more prevalent among younger adults, potentially due to their higher familiarity with mobile technologies and proactive health-seeking behaviors. Educational qualifications indicate that over half of the respondents (53.93%) were postgraduates, with graduates forming 40.81% and a smaller proportion (5.24%) falling into other categories. This reflects a user base that is relatively well-educated, aligning with previous findings that suggest education level significantly influences digital health technology adoption. Regarding the purpose of mHealth use, the majority (64.43%) reported using mHealth for patient-centric services such as self-care and engagement, whereas 35.56% utilized it for provider-supporting tools aimed at clinical practice. This indicates a strong preference for personal health management tools among users, emphasizing the role of mHealth in enabling individuals to monitor and manage their own health proactively. Collectively, these insights underscore the growing reliance on mHealth among young, educated individuals, particularly for self-directed healthcare support.

Table 3: Demographic Profile

	Number	Percentage (%)
Gender		
Female	142	41.39
Male	201	58.60
Age		
18-25	165	48.10
26-35	178	51.89
Education Qualification		
Graduate	140	40.81
Postgraduate	185	53.93
Others	18	5.24
Purpose for mHealth		
Patient-centric Services (Self-care, engagement)	221	64.43
Provider-supporting tools (Clinical Practice)	122	35.56
TOTAL	343	100

RESULTS

Partial Least Squares Structural Equation Modelling (PLS-SEM) is the most appropriate analytic technique for this investigation because it excels at estimating intricate frameworks that contain many latent variables and indicators, yet prioritise prediction. Smart PLS 3 has been used for analysis. Unlike covariance-based SEM, PLS-SEM performs well with modest samples and data that fall short of strict multivariate-normality requirements. This makes it ideal for an emerging research domain such as mobile-health adoption, where representative data can be limited and distributional assumptions are rarely satisfied. The approach evaluates the measurement model and the structural paths in a single procedure, letting researchers verify construct reliability and validity while simultaneously testing hypothesised relationships among latent factors. Moreover, PLS-SEM accommodates both reflective and formative indicators and remains stable in the presence of multicollinearity, features that map neatly onto the mixed construct types and overlapping psychological and technological drivers examined here. Given the study's exploratory stance and its aim to predict how perceptions translate into usage intentions, PLS-SEM offers the necessary methodological flexibility and statistical power.

Measurement Model

The measurement model (Table 4) results provide strong evidence supporting the reliability and validity of the constructs used in the study. For the Perceived Ease of Use (PEOU) construct, all indicator loadings range between 0.763 and 0.884, which surpasses the recommended threshold of 0.70, indicating high indicator reliability. The Average Variance Extracted (AVE) is 0.735, confirming convergent validity, while Composite Reliability (CR = 0.867) and Cronbach's Alpha (α = 0.855) reflect excellent internal consistency. Similarly, Perceived Usefulness (PU) shows acceptable loadings (0.711 to 0.854), with AVE = 0.635, CR = 0.844, and α = 0.722—all supporting its reliability and validity.

In the case of Self-Efficacy (SE), three items (SE1 to SE3) load well, but SE4 has a very low loading of 0.237, indicating it does not adequately measure the construct and should be removed. Despite this, the construct's AVE (0.611), CR (0.799), and α (0.655) remain within acceptable limits, although the reliability would likely improve upon excluding SE4. For Perceived Effectiveness (PEF), all items have acceptable loadings (0.682–0.777), and the construct exhibits its good convergent validity (AVE = 0.714) and reliability (CR = 0.775, α = 0.757). The Attitude (AT) construct shows high internal consistency, with loadings above 0.762, AVE = 0.876, CR = 0.877, and α = 0.852, although the exceptionally high AVE warrants a recheck. Lastly, the Adoption Intention (AI) construct performs well, with item loadings between 0.761 and 0.778, an AVE of 0.722, CR = 0.782, and α = 0.797, confirming its robust measurement properties.

Table 4: Measurement Model

Construct	Item	Loading	AVE	CR	α
Perceived Ease of Use (PEOU)	PEOU1	0.852	0.735	0.867	0.855
	PEOU2	0.763			
	PEOU3	0.883			
	PEOU4	0.854			
Perceived Usefulness (PU)	PU1	0.854	0.635	0.844	0.722
	PU2	0.833			
	PU3	0.711			
Self-Efficacy (SE)	SE1	0.711	0.611	0.799	0.655
	SE2	0.821			
	SE3	0.865			
	SE4	0.237			
Perceived effectiveness (PEF)	AM1	0.776	0.714	0.775	0.757
	AM2	0.777			
	AM3	0.682			
Attitude (AT)	AT1	0.779	0.876	0.877	0.852
	AT2	0.762			
	AT3	0.874			
Adoption intention (AI)	AI1	0.761	0.722	0.782	0.797
	AI2	0.766			
	AI3	0.773			
	AI4	0.778			

Structural Model

The structural model results (Table 5) confirm that all proposed relationships among the constructs are statistically significant and positively associated. Perceived ease of use has a positive influence on attitude, as indicated by a path coefficient of 0.277 and a t-value of 3.515. This implies that when users find a mobile health (mHealth) application easy to use, they are more likely to develop a favorable attitude toward it. Similarly, perceived usefulness shows a significant positive effect on attitude, with a path coefficient of 0.387 and a t-value of 4.515, suggesting that users who perceive the app to be helpful in achieving health-related outcomes tend to have a more positive attitude.

Self-efficacy also demonstrates a strong influence on attitude, with a coefficient of 0.432 and a t-value of 5.242. This means that users who feel confident in their ability to use mHealth apps are more inclined to view them positively. Notably, perceived effectiveness has the strongest effect on attitude, with a path coefficient of 0.467 and a t-value of 6.424, highlighting that users' belief in the app's ability to deliver health benefits plays a critical role in shaping their attitude. Attitude, in turn, significantly influences adoption intention, as shown by a path coefficient of 0.332 and a t-value of 4.423. Although the effect size for this relationship is smaller, it still confirms that a positive attitude contributes to the intention to adopt mHealth technologies.

The model explains 58.6% of the variance in attitude and 42.8% in adoption intention, which are considered substantial and moderate, respectively. Furthermore, all constructs demonstrate predictive relevance, as reflected in Q^2 values above zero (0.347 for attitude and 0.284 for adoption intention). All variance inflation factor (VIF) values are well below the threshold of 3.3, indicating no multicollinearity issues. Overall, the structural model demonstrates good predictive strength and reliability in capturing the factors influencing mHealth adoption. The structural model is presented in Figure 2.

Table 5: Structural Model

Hypothesis	Relationship	Path Coefficient	t Value	Decision	VIF	f^2	Q^2	R^2
H1	PEOU→AT	0.277**	3.515	Accepted	1.354	0.088	0.347	0.586
H2	PU→AT	0.387**	4.515	Accepted	1.354	0.088		
H3	SE→AT	0.432**	5.242	Accepted	1.647	0.121		
H4	PEF→AT	0.467**	6.424	Accepted	1.448	0.262		
H5	AT→AI	0.332**	4.423	Accepted	1.323	0.043	0.284	0.428

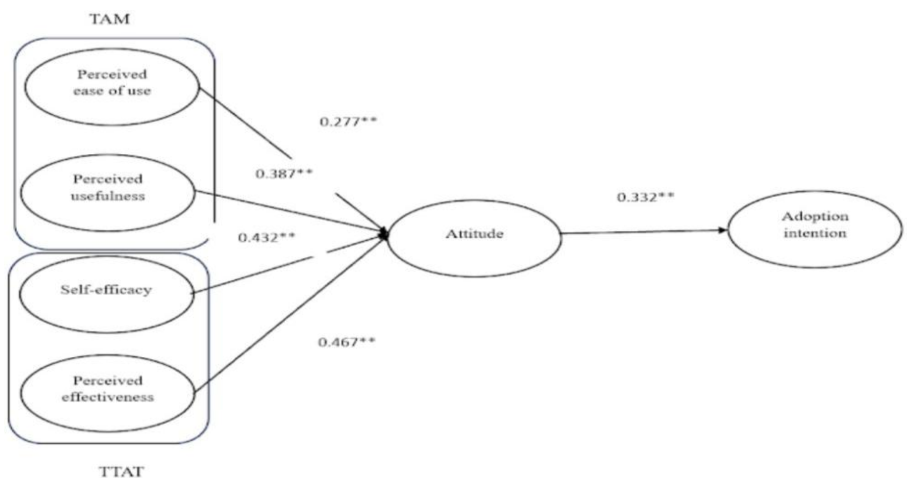

Figure 2: Structural model

DISCUSSION

The structural-path estimates shed nuanced light on what propels or hinders people's readiness to embrace mobile-health apps. First, the robust, positive link between perceived ease of use (PEOU) and user attitude reiterates Davis's original Technology Acceptance Model (1989), yet the present context adds specificity: when navigation flows are friction-free, screen layouts are uncluttered, and onboarding cues are self-explanatory, potential users translate that experiential comfort into an affective "thumbs-up." Contemporary mHealth evidence echoes this view; Alam et al. (2021) showed that even marginal gains in interface clarity measurably boost attitudinal scores among chronic-care patients. Perceived usefulness (PU) proved similarly consequential. In health settings, usefulness is rarely abstract; it materialises as faster symptom logging, personalised feedback loops, or easier appointment scheduling. The data confirm that such concrete benefits strongly colour attitudes—mirroring findings by Zhou (2011) on tele-consultations and by Liu et al. (2023) on AI-driven wellness coaching. Thus, designers who foreground outcome-centric value propositions are more likely to foster early enthusiasm. Self-efficacy emerged as another decisive lever. Rooted in Bandura's social-cognitive theory (1997), the construct captures a user's conviction that "I can master this app if I try." Our results align with Chao (2019), who reported that older adults' confidence in basic smartphone skills directly lifted their openness to digital pharmacies. Elevated self-efficacy dampens technophobia, reduces dropout during onboarding, and ultimately cultivates a more favourable outlook toward continued use. Of all antecedents, perceived effectiveness (PE) exerted the greatest weight on attitude. This variable reflects outcome expectancy—users' belief that engaging with the app will tangibly improve their health status. Prior work has underscored its salience: Tajudeen et al. (2022) linked high PE perceptions to persistent engagement in diabetes-management apps, while Goel and Taneja (2023) found that PE eclipsed both PEOU and PU in predicting retention among fitness-tracker users. Our findings reinforce the idea that, in a domain where stakes are literally life-and-health, expected efficacy trumps convenience.

Downstream, attitude significantly shaped adoption intention, echoing the Theory of Reasoned Action (Ajzen & Fishbein, 1980) and later TAM extensions (Venkatesh et al., 2003). Although the standardized path coefficient was more modest than those feeding into attitude, its statistical strength confirms attitude's role as a mediating pivot between cognitive assessments and behavioural resolve. Model diagnostics buttress these insights. The structural equation explains 58.6 % of the variance in attitude and 42.8 % in intention—figures that compare favourably with past mHealth TAM replications. Stone–Geisser Q^2 values exceeded zero, evidencing predictive relevance, while all inner-VIF statistics stayed below the 3.3 threshold, ruling out harmful multicollinearity. Together, these metrics validate the decision to extend classical TAM with self-efficacy and perceived effectiveness, yielding a richer explanatory lens tailored to healthcare technology.

In sum, analysis highlights four practical imperatives: (1) craft interfaces that feel instantly familiar; (2) articulate concrete health gains, not abstract features; (3) embed scaffolding that nurtures user confidence (e.g., step-by-step tutorials, peer support); and (4) rigorously substantiate perceived effectiveness through evidence-based functionalities. Addressing these fronts simultaneously is likely to accelerate both positive attitudes and real-world uptake of mHealth solutions.

IMPLICATIONS

The study provides a deeper understanding of how various cognitive and psychological constructs influence user attitudes and their subsequent intention to adopt mobile health (mHealth) applications. The significant roles of perceived ease of use, perceived usefulness, self-efficacy, and perceived effectiveness offer both theoretical advancement and actionable strategies for practice.

Theoretical implications

These results both confirm and extend the original Technology Acceptance Model (TAM; Davis, 1989). For mobile-health apps, the familiar drivers—perceived ease of use and perceived usefulness—still matter, yet they do not fully capture what shapes user attitudes. Adding self-efficacy and perceived effectiveness markedly boosts the model's explanatory power, showing that adoption decisions in healthcare hinge on more than usability and utility alone. In contexts where health outcomes are paramount, researchers should therefore enrich TAM with variables that tap users' psychological readiness and expectations of tangible benefits (Liu et al., 2023). The analysis also highlights self-efficacy—the belief that one can use the technology competently—as a particularly strong predictor of positive attitudes toward mHealth. This supports Bandura's (1997) Social Cognitive Theory, which emphasizes the importance of individual agency in behavioral outcomes. Its significance in the mHealth context indicates that future theoretical models should consistently include self-efficacy when investigating digital health behaviors. The results substantiate the mediating role of attitude between user beliefs and behavioral intention, aligning with the Theory of Reasoned Action (Ajzen & Fishbein, 1980). This indicates that attitudes are not merely outcomes but serve as essential intermediaries in converting perceptions (such as ease of use or effectiveness) into actual intent to use. Researchers exploring technology use behavior in healthcare or other emerging sectors should consider this mediating mechanism. The model's explanatory power, reflected its robustness. This supports the model as a theoretically grounded yet practically meaningful framework for analyzing user acceptance of digital health technologies, especially in under-researched or evolving contexts.

Practical implications

Since perceived ease of use significantly impacts attitude, mHealth developers must ensure that interfaces are clean, navigation is logical, and onboarding is smooth. Features such as voice input, simplified layouts, and language localization can help users with varying digital literacy levels engage effectively with the app. The influence of perceived usefulness suggests that users need to see clear, value-added benefits. Marketing materials, in-app notifications, and product descriptions should clearly communicate how the app supports users in managing conditions (e.g., medication reminders, symptom tracking) or improves their healthcare experience. Adding evidence from clinical trials, user testimonials, or integration with real-world outcomes can enhance trust. The significant effect of self-efficacy implies that simply offering a useful app is not enough—users must feel capable of using it. Developers and healthcare providers should offer user guides, video tutorials, FAQs, and in-app support to increase user confidence, particularly for elderly or non-tech-savvy populations. Public health initiatives can also include digital literacy training sessions to address this gap. As perceived effectiveness had the strongest influence on attitude, it is vital that users are convinced the app will yield real health benefits. This can be achieved by integrating progress tracking features, providing regular health insights, and visualizing improvements (e.g., reduced blood pressure, improved sleep) in simple, motivating formats. Policymakers can support mHealth adoption by funding awareness campaigns, ensuring internet connectivity in rural areas, and providing incentives for digital health usage. Additionally, integrating mHealth apps into public healthcare systems or insurance platforms can promote credibility and widespread adoption. Policies should also ensure data privacy and compliance to build user trust. Insights from this model can inform segment-specific strategies.

CONCLUSION

These findings deepen insight into mobile-health uptake by empirically testing an augmented Technology Acceptance

Model. The analysis shows that perceived ease of use, perceived usefulness, self-efficacy, and perceived effectiveness all foster a positive attitude toward mHealth, and that this attitude, in turn, strengthens the intention to adopt. Perceived effectiveness exerts the greatest influence, underscoring how strongly users weigh expected health outcomes when evaluating such apps. The extended model explains a considerable share of the variance in both attitude and behavioural intention, attesting to its robustness in digital-health settings.

Adding self-efficacy and outcome expectancies to the classic TAM enables the framework to capture both cognitive judgements and motivational beliefs that shape mHealth behaviour. Theoretically, the work broadens technology-adoption scholarship by validating a multi-factor structure that positions psychological confidence and outcome assessment alongside traditional TAM drivers. Practically, the findings encourage developers and health-sector policymakers to create mHealth solutions that are intuitive, visibly beneficial, and supportive. Interfaces should minimise user effort, demonstrate measurable health gains, and build confidence through clear guidance and training. Overall, the study pinpoints the key levers of mHealth adoption and invites future research to examine demographic, cultural, and contextual moderators, paving the way for more inclusive and effective mobile-health interventions.

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