Contents lists available at Science-Gate

International Journal of Advanced and Applied Sciences

Journal homepage: https://www.science-gate.com/IJAAS.html

Determinants of continued mHealth usage in Vietnam: An integrated S-O-R and UGT approach

Nam Hoang Trinh *

Faculty of Management Information Systems, Ho Chi Minh University of Banking, Ho Chi Minh City, Vietnam

ARTICLE INFO

Article history:
Received 13 October 2025
Received in revised form
6 March 2026
Accepted 10 March 2026

Keywords:
Mobile health applications
Continuance intention
Hedonic motivation
Technology responsiveness
Vietnamese users

ABSTRACT

With the rapid pace of digital transformation, mobile health (mHealth) applications have become an important tool in the healthcare sector. This study aims to improve the theoretical understanding of Vietnamese consumers' intention to use mHealth applications and to provide practical guidance for service providers in the design, implementation, and management of these systems. A conceptual research framework was developed by integrating the Stimulus–Organism–Response (S-O-R) model with the Uses and Gratifications Theory (UGT), while also considering key characteristics of mobile technology. Survey data were collected from 256 Vietnamese mobile phone users and analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method. The results show that the continued use of mHealth applications is mainly driven by intrinsic psychological rewards, particularly playfulness and enjoyment, which have a stronger influence on future usage intention than utilitarian benefits. This finding suggests that users' feelings of fun and pleasure play a more important role in sustaining long-term engagement than functional efficiency alone. In terms of technological features, responsiveness was identified as the most important factor, as it enhances both enjoyment and gratification, while observability promotes playfulness. Interestingly, the study also found a negative relationship between personalization and gratification. Overall, the findings highlight the stronger role of hedonic factors compared to utilitarian factors in predicting continuance intention. The study also provides a validated framework indicating that responsiveness and observability are key features for encouraging sustained use, while suggesting that developers should be cautious when implementing strong or generalized personalization features in health technologies.

1. Introduction

The rapid adoption of smartphones and a young, tech-savvy population have revolutionized healthcare in Vietnam, making mobile healthcare (mHealth) applications an essential part of the industry. The most significant trend is the rise of telehealth, which allows users to consult with doctors remotely via video call. Platforms like BookingCare and Med247 have become top choices, particularly following the COVID-19 pandemic. A survey (statista.com) in 2024 revealed that 45% of Vietnamese people were interested in telemedicine services. Additionally, electronic health record management is gaining popularity. The Ministry of Health's "Electronic Health Book" app has seen over 80 million downloads, becoming a crucial tool for managing medical history and vaccination records. Finally, personal health monitoring apps such as Samsung Health and Apple Health are now integral to the lifestyle of many modern Vietnamese. A 2022 report by Google and Temasek found that 75% of internet users in Vietnam apply these applications to manage their sleep, diet, and daily physical metrics (Tran et al., 2025). This growing trend reflects a more useful approach to health and wellness among the population.

The impressive growth of the mHealth market in Vietnam is driven by many factors. First, with a smartphone penetration rate of over 84%, Vietnam has a solid digital foundation for healthcare solutions. The Government's National Digital Transformation Policy, which prioritizes healthcare, has further facilitated this shift. The COVID-19

* Corresponding Author.
Email Address: namth@hub.edu.vn
https://doi.org/10.21833/ijaas.2026.03.012
Corresponding author's ORCID profile:
https://orcid.org/0009-0005-3270-5130

pandemic has also played a strong catalytic role, forcing both the population and the healthcare system to deploy digital solutions to ensure continuity of care (Shaver, 2022). As a result, remote healthcare platforms have emerged and gradually reduced the burden on hospitals while addressing the severe shortage of healthcare professionals in rural areas. Vietnam's digital healthcare market is expected to reach a value of 3 billion USD by 2025. This finding not only shows significant economic prospects but also highlights that technology is actively improving the quality of life for millions of people.

The rise of mobile technology and the growing demand for healthcare have made the adoption of mHealth apps an important area of research for scientists. The decision to use these apps depends on a complex interplay of psychological, social, and technological factors. At their core, users are motivated by both utilitarian and emotional values (Chakraborty and Paul, 2023). Hedonic motivation, or the pleasure derived from interaction, is particularly important for older adults (Palas et al., 2022), while time-saving features also positively influence intention to use (Tanantong and Wongras, 2024).

In addition to these values, user confidence, or their confidence in using technology, is a key determinant of adoption, especially among older populations (Uncovska et al., 2023). Similarly, emotional intelligence plays a role, especially with AI-enabled health apps, as it influences users' comfort in sharing sensitive information with technology (Yadegari et al., 2024). The core design of the app is also important. Perceived usefulness and perceived ease of use are fundamental to acceptance; an app must provide real health benefits with a simple, intuitive interface to ensure long-term retention (Alkhwaldi and Abdulmuhsin, 2022). Finally, data security and privacy are significant barriers to technology adoption (Pigera et al., 2025). Users must be able to trust the vendor and the technology, as this trust reduces their concerns about risk and is a fundamental prerequisite for long-term use (Jia et al., 2024).

Previous research on mHealth app adoption has identified two primary categories of factors: user-centric and application-centric. User factors include perceived value (both utilitarian and emotional), personal motivations such as enjoyment and habit, and individual traits like self-confidence and emotional intelligence. Application-centric factors, on the other hand, focus on perceived usefulness, ease of use, service quality, and, crucially, user security and trust. While existing literature acknowledges that emotional value and hedonic motivation influence users, there is a notable gap in understanding the specific mechanisms through which they operate, particularly in the context of mobile technology and gamification. The precise contributions of elements like enjoyment, gratification, and playfulness have not been specifically analyzed as distinct drivers of user intention. This study will address this gap by investigating how these specific mechanisms, facilitated by mobile technology and gamification, influence the intent to use mHealth apps. This will provide a more nuanced understanding of the factors that shape user behavior in the digital health landscape.

2. Literature review

2.1. Mobile healthcare application adoption

The development of mobile technology and the increasing demand for healthcare have made medical applications an inevitable trend. However, creating an application is just the beginning. What is more important is how users accept and use them effectively. Therefore, the field of research on the acceptance of mobile medical applications has become the focus of attention of scientists, developers, and medical professionals. These studies help us delve into the psychological, social, and technological factors that influence users' intention to use. From there, there is a new era for personalized medicine, where healthcare becomes closer and more suitable to each individual than ever before.

Behind the decision to download and use a health app is a series of values that we expect to receive. Research by Chakraborty and Paul (2023) has shown that users are attracted by two main types of values: utilitarian value and emotional value. Utilitarian value is easy to understand, which is when an app helps us manage our health daily, such as tracking steps, planning workouts, or managing diabetes. However, what is interesting is that emotional value is the most powerful factor. We want an app to bring us positive feelings, such as joy, satisfaction, or confidence (Chakraborty and Paul, 2023). In addition, hedonic motivation plays an important role, especially for older adults. They tend to use apps not only for health purposes but also because they feel joy and pleasure when interacting with them (Palas et al., 2022). When an app becomes an integral part of our lives, using it becomes habitual. This habit is a strong indicator that users will continue to use the app long-term (Palas et al., 2022). Finally, another point worth noting is time saving. If the app helps us get things done more quickly, like making an appointment or looking up information without having to wait, it will positively impact our intention to use it (Tanantong and Wongras, 2024).

Personal confidence in our ability to use technology is also a key factor. Self-efficacy is the belief that we can master the app without difficulty, without feeling "overwhelmed" or "lost" when interacting. Studies have confirmed that the more confident users are in their abilities, the more willing they are to adopt and use e-health applications (Uncovska et al., 2023). This is especially important for those new to technology or older populations, where anxiety about use can be a major barrier.

Another unique aspect is the role of emotional intelligence, especially in the acceptance of medical applications using artificial intelligence. Research by Yadegari et al. (2024) suggested that how we understand and manage our emotions and empathize with others can directly influence our intention to use AI technology in healthcare. This suggests that an application should not only be smart but also be designed to interact in a friendly and pleasant way, helping users feel more comfortable and confident when sharing their sensitive health issues.

When evaluating a health app, the first two questions we often ask are "Is it really useful?" and "Is it easy to use?" Perceived usefulness refers to whether the app helps us improve our health or manage our lives more effectively (Alkhwaldi and Abdulmuhsin, 2022). For example, a sleep tracking app should provide accurate and understandable data so we can adjust our habits. At the same time, perceived ease of use is equally important. No matter how useful an app is, if its interface is complicated, functions are difficult to find, or it crashes frequently, it will be difficult to accept (Alkhwaldi and Abdulmuhsin, 2022). Research has shown that developing a user interface (UI) and user experience (UX) that is intuitive, simple, and engaging is key to encouraging long-term user retention. Finally, service quality also plays a decisive role, especially for older adults (Palas et al., 2022). The app must function reliably, provide accurate information, and provide support when needed.

One of our biggest concerns when using health apps is whether our sensitive personal and medical information is safe. Data security and privacy are major barriers, as no one wants their information to be leaked or misused (Pigera et al., 2025). Privacy concerns can negatively impact the intention to use e-health systems (Pan et al., 2024). For this reason, trust becomes a core factor. We are only willing to accept an online health service when we trust the provider, the application, and the system (Liu et al., 2024). Trust helps to reduce concerns about risks and encourages acceptance. Research on older adults in Hong Kong also highlighted that trust is extremely important to their use of mHealth applications. To build trust, developers need to be transparent about their privacy policies, how data is collected and used, and apply strong data protection measures (Pigera et al., 2025).

In summary, the factors influencing the use of mHealth applications are divided into two main groups: user factors and application-related factors. User factors include perceived value (usefulness and emotion), personal motivation (pleasure and habit), along with self-confidence and emotional intelligence. Meanwhile, application and technology-related factors focus on usefulness, ease of use, service quality, as well as user safety, security, and trust. All these factors combined shape the behavior and intention to use health applications. However, previous studies have not provided insights into the contribution of mobile technology and mobile gamification to the intention to use. While the literature has shown that hedonic motivation and emotional value influence users, there has been no specific analysis of which mechanisms, such as enjoyment, gratification, and playfulness, are effective. This study will fill the above research gaps.

2.2. Theoretical framework

The Stimulus-Organism-Response (S-O-R) model gives us a great way to understand why people decide to use mHealth apps. It's a powerful framework that breaks down user behavior into three distinct parts, allowing us to analyze how complex factors work together. First, there's Stimulus, which refers to the external things - the objective characteristics of the mHealth app itself, like its features, design, and usability. Next is the Organism, which is all about the user's internal world. This is where a person processes the stimulus through their thoughts and emotions. Do they see the app as trustworthy, easy to use, or helpful? Finally, the Response is the result of that internal processing - the user's action or intention to act. This model lets us do more than just list what influences a decision; it helps us understand the full chain of events, from an initial impression to the final choice of whether to use the app.

The Uses and Gratifications Theory (UGT) is uniquely suited for examining the adoption of any new technology because it recognizes users as active agents rather than passive recipients (Katz et al., 1973). Instead of focusing solely on technology's inherent features, UGT centers on the user's conscious decision-making process: why they select a new platform and what specific needs they seek to fulfill (Bawack et al., 2023). This holistic approach allows researchers to model a diverse range of motivations - including hedonic needs like enjoyment and novelty, social needs like connection, and utilitarian needs like information. By capturing the full spectrum of sought gratifications, UGT provides a far deeper explanation for sustained engagement than traditional utility-based models, making it ideal for understanding the long-term success of innovative and discretionary platforms.

Combining S-O-R and UGT yields a powerful, synergistic model that provides a holistic understanding of technology adoption. The S-O-R model offers the necessary process structure, delineating how external environmental features (the stimulus, such as an app's aesthetics or responsiveness) lead to internal user states (the organism), which ultimately drive behavioral outcomes (the response, like intended use). However, S-O-R is mechanistic and needs theoretical grounding for the "Organism" stage. UGT steps in to fill this gap, providing the psychological content and explanatory power by defining the Organism. UGT focuses on the user as an active, goal-directed agent, supplying the specific gratifications sought - such as enjoyment, playfulness, or gratification - that mediate the relationship. By merging them, researchers can move beyond simply listing features and instead demonstrate how specific technological stimuli activate conscious psychological motives defined by UGT. This integrated approach is essential for modern, discretionary technologies, allowing researchers to model not only if a feature is present, but how it successfully addresses the user's underlying need for both fun and function, resulting in a more robust prediction of sustained usage (Fig. 1). The initial part of the story, described by the S-O-R Stimulus, focuses on the mobile app's core features. It's not just about a pretty face (aesthetics). It's the immediate snap-back from the app (responsiveness) that makes the entire experience frictionless. It's also about what you can see (observability), whether that's real-time information or social cues, making the world feel more connected. And finally, there's the feeling that the app truly knows you (personalization), making every interaction relevant. These technical and design features are the external cues that first grab the user's attention and set the stage for engagement.

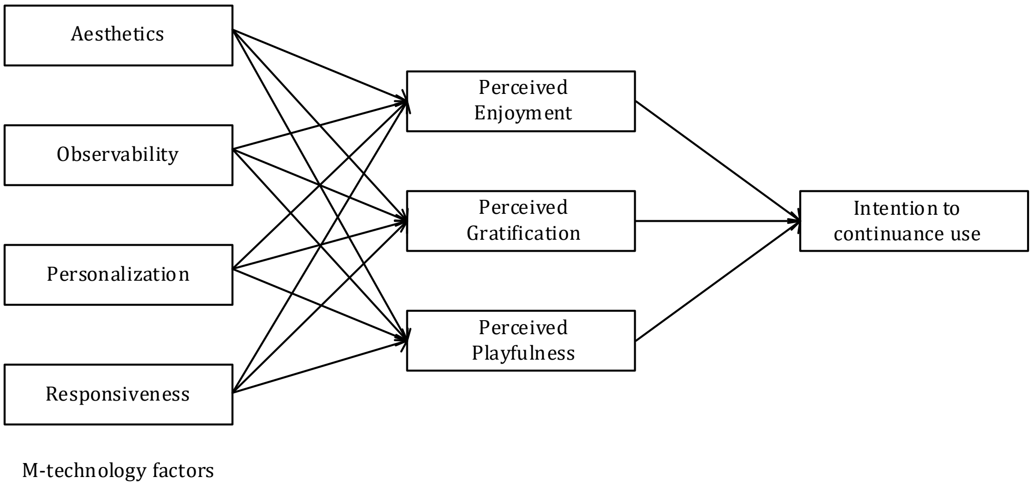

Fig. 1: Proposed research model

Next comes the Organism, which is where UGT takes over, diving into the user's mind and motives. Users aren't passive; they're actively seeking specific gratifications. These aren't just about utility (e.g., tracking steps), but about the pleasure derived from the interaction itself. This includes enjoyment (the simple pleasure of using the app), gratification (the satisfying feeling of achievement from earning a badge or seeing progress), and playfulness (the freedom to explore the app like a sandbox). These internal, psychological feelings are the user's conscious response to the features.

The final stage is the response: consistent, active use of the mHealth app. In a model combining S-O-R and UGT, the app's features (Stimulus) don't directly cause use; instead, they must first successfully activate the user's conscious needs for pleasure, achievement, and exploration (gratifications). This powerful blend explains that for mHealth apps to succeed, their technical and design features must be finely tuned to tap into the user's intrinsic desires, turning a simple tool into a compelling, long-term habit.

2.3. Research hypotheses development

2.3.1. Mobile aesthetics

Mobile aesthetics serve as a foundational component in the design and evaluation of digital interfaces across both mobile commerce and mHealth systems. Aesthetic quality - including layout structure, color harmony, imagery, symmetry, typography, and overall visual coherence - significantly shapes users' first impressions and ongoing emotional responses. Prior studies demonstrate that visually pleasing interfaces stimulate positive feelings such as enjoyment, pleasure, and comfort, which collectively form the hedonic value of digital interactions (Olivar et al., 2025; Perrig et al., 2023). When users encounter a harmonious and professionally designed interface, they tend to perceive the system as more trustworthy, competent, and user-centered. This generates favorable expectations and promotes deeper, more sustained engagement. The S-O-R model helps explain this effect: aesthetic features act as stimuli that evoke emotional and cognitive transformations within the user, leading to subsequent behavioral reactions. Aesthetic stimuli satisfy hedonic motives under UGT by providing entertainment, visual pleasure, and sensory stimulation (Bazi et al., 2023). In mobile commerce, visually appealing product layouts increase viewing time, support better decision-making, and enhance perceivability of recommendations (Sulikowski et al., 2022). Similarly, in mHealth applications, a polished visual design contributes directly to engagement, gratification, and overall perceived quality, as confirmed by evaluations using the Mobile App Rating Scale (Mustafa et al., 2022). Users frequently associate aesthetic refinement with clinical professionalism and care quality, which strengthens their willingness to trust the application for health-related actions. Aesthetics also play a central role in stimulating perceived playfulness, curiosity, and exploratory behavior. Rich visual elements - icons, illustrations, animated transitions, reward badges, avatars, or progress indicators - create a game-like environment that encourages playful interaction. In consumer contexts, aesthetic enhancements have been shown to reinforce flow states, which increase voluntary exploration and extend interaction duration (Jo, 2023). In mHealth apps, visually dynamic gamified features such as progress rings, levels, and animated rewards further support motivation and playful engagement (Schwarz et al., 2023). These elements help transform routine self-tracking tasks into enjoyable activities. Ultimately, both mobile commerce and mHealth studies converge in showing that mobile aesthetics directly strengthen users' positive emotional states - enjoyment, gratification, and playfulness. Aesthetics not only enhance intuitive usability but also enrich the experiential dimension of digital interaction, making users more willing to continue using the system. Thus, we propose the following hypotheses:

H1: Mobile aesthetics positively affect perceived enjoyment.
H2: Mobile aesthetics positively affect perceived gratification.
H3: Mobile aesthetics positively affect perceived playfulness.

2.3.2. Mobile observability

Mobile observability refers to the degree to which users can view, monitor, and interpret either their own activities or the actions of others through real-time, visible cues. In mobile commerce, this often includes observable social signals such as purchase notifications, like ratings, and comments, whereas in mHealth apps, it includes symptom visualizations, progress charts, goal completion meters, and physiological trends. Across contexts, observability functions as a potent psychological stimulus that influences enjoyment, gratification, and playfulness.

In mobile commerce, observability enhances enjoyment by strengthening the sense of social presence. Visibility of peer behaviors - such as others buying the same product or leaving favorable reviews - creates an interactive and lively environment that fosters emotional enjoyment (Huang et al., 2024). It also activates mechanisms of social learning and imitation, encouraging users to explore new products based on cues observed from others (Jia et al., 2024). Observability features such as leaderboards or activity badges further increase operational enjoyment by fostering competition and reinforcing dynamic participation (Kim and Ho, 2021). In mHealth, observability plays an even more fundamental role by helping users understand their healthy journeys. Being able to view real-time progress - changes in steps, heart rate, blood glucose levels, medication adherence, or symptom improvements - creates meaning and reinforces a sense of control. Progress visualizations satisfy competence needs and generate pleasure through achievement. Research in chronic disease apps shows that users derive substantial gratification from observable improvements because it validates their efforts and reassures them that the app is effectively guiding their condition (Honglin et al., 2024). Observable feedback thus enhances both utilitarian gratification (through information) and hedonic gratification (through emotional rewards). Observability also elevates perceived playfulness. Real-time visual cues - floating comments, viewer counts, badges, streaks, and progress rings - add a layer of dynamism and game-like feedback to the experience. These cues prompt curiosity, trial-and-error behavior, and playful experimentation. In gamified health applications, immediate visibility of points or achievements transforms otherwise mundane health tasks into interactive challenges (Wang et al., 2021). Observability reduces uncertainty by providing users with clear cues about their status, making them more confident and willing to interact with features creatively. Based on this evidence, we propose the following hypotheses:

H4: Mobile observability positively affects perceived enjoyment.
H5: Mobile observability positively affects perceived gratification.
H6: Mobile observability positively affects perceived playfulness.

2.3.3. Mobile personalization

Mobile personalization encompasses the adaptation of digital content, recommendations, reminders, feedback, and interface elements to users' unique preferences, habits, health profiles, and behavioral histories. Personalization is widely recognized as a central mechanism for improving digital user experiences because it elevates relevance, reduces cognitive effort, and enhances perceived usefulness (Gosetto et al., 2023; Mo et al., 2023). Personalization increases perceived enjoyment by aligning the app's content and functions with users' immediate needs. Tailored recommendations reduce irrelevant information and streamline the interaction, making the experience smoother and more pleasurable. Personalized notifications - such as customized medication reminders or daily exercise goals - also enhance user engagement by creating a sense of being understood and individually supported. According to Self-Determination Theory, personalization contributes to gratification of the autonomy and competence needs, both of which foster intrinsic enjoyment (Lambillotte et al., 2022). Personalization also enhances gratification, especially in mHealth environments where effectiveness and timeliness are crucial. When health advice, educational content, or feedback is tailored to individual characteristics, users perceive the information as more credible and actionable. Research confirms that personalization increases gratification because users feel their unique circumstances are acknowledged, which reinforces perceived value and strengthens health-related commitment (Gosetto et al., 2025). Personalized suggestions also help users achieve goals more efficiently, boosting their sense of accomplishment and reinforcing affective gratification. In addition, personalization is strongly associated with perceived playfulness. Features allowing users to choose avatars, adjust challenge levels, customize themes, or configure personal goals encourage creative exploration. Personalized gamification - aligning tasks or rewards with user ability - promotes flow states and increases willingness to experiment (Mustafa et al., 2022). Eye-tracking studies show that personalized interfaces draw greater attention and stimulate more interactive browsing (Lambillotte et al., 2022). This playful engagement promotes deeper attachment to the system and greater interaction frequency. Highlighting these connections, the evidence strongly supports the following hypotheses:

H7: Mobile personalization positively affects perceived enjoyment.
H8: Mobile personalization positively affects perceived gratification.
H9: Mobile personalization positively affects perceived playfulness.

2.3.4. Mobile responsiveness

Mobile responsiveness is defined as the system's ability to respond quickly, smoothly, and accurately to user inputs, including the stability of the interface, loading speed, real-time data processes, and immediate system feedback. Responsiveness is essential because it determines whether users perceive the interaction as fluid, reliable, and supportive. Responsiveness heightens perceived enjoyment by reducing cognitive and emotional friction. When the interface responds instantly to actions - taps, swipes, chatbot queries, or data updates - it maintains the rhythm of interaction and supports a sense of flow (Haley et al., 2025; Liu et al., 2023). Delays or lag frustrate users and diminish positive emotions, whereas rapid system feedback enhances pleasure and comfort. In conversational agents, quick replies are interpreted as empathy or attentiveness, increasing emotional enjoyment (Kim et al., 2026). Responsiveness significantly boosts perceived gratification. Many mHealth tasks require timely information - symptom assessment, medication tracking, glucose monitoring, or mood logging. Immediate feedback reassures users that the system is functioning accurately and supports decision-making. This strengthens utilitarian gratification by reducing uncertainty and providing just-in-time information (Kim and Yum, 2024). It also enhances hedonic gratification by generating a sense of connection and responsiveness from the system (Li et al., 2022). Mobile responsiveness also fosters playfulness. In gamified mHealth systems, instant animations, rapid display of rewards, and smooth transitions are crucial to maintaining immersion. Immediate feedback encourages trial-and-error behavior and motivates users to explore features more fully (Jiang et al., 2022; Jiang and Lau, 2023). Responsiveness enhances intrinsic value and promotes repeated, playful engagement by reinforcing the perception that the system is dynamic and interactive. These observations provide strong evidence supporting the following hypotheses:

H10: Mobile responsiveness positively affects perceived enjoyment.
H11: Mobile responsiveness positively affects perceived gratification.
H12: Mobile responsiveness positively affects perceived playfulness.

2.3.5. Enjoyment, gratification, playfulness, and continuance usage intention

Perceived enjoyment, gratification, and playfulness represent crucial psychological states that guide users' intentions to continue interacting with mHealth applications. These states influence perceptions of value, motivation, and willingness to adopt digital health tools over time. Perceived enjoyment is the immediate pleasure users derive from interactions. It is consistently identified as one of the strongest predictors of behavioral intention in mHealth adoption models (Huang et al., 2024; Schomakers et al., 2022). Enjoyment lowers perceived effort and makes app usage feel voluntary and self-motivated. When users perceive the app as fun, engaging, or inspiring, their likelihood of long-term adherence increases significantly. Hedonic motivation is also emphasized in UTAUT2, where it consistently drives usage intention across demographic groups (Yang et al., 2024). Perceived gratification captures the extent to which the app fulfills users' needs - informational, emotional, or functional. Numerous studies confirm that gratification (a proxy for gratification) is one of the strongest drivers of continuance intention, particularly in digital health contexts (Tian and Wu, 2022; Wang et al., 2022).

Users who feel that the app effectively supports their health goals, provides clear and timely information, or validates their progress are more likely to continue using it. Gratification bridges expectations with actual outcomes, reinforcing the perceived value of the app. Perceived playfulness reflects a sense of curiosity, enjoyment in exploration, and immersion in interaction. Playfulness increases intrinsic motivation by making the user experience entertaining and rewarding. Gamification studies find that playfulness enhances expectancy, gratification, and ultimately future usage intention (Wang et al., 2021; Wang et al., 2023). When health tasks are transformed into playful challenges, users experience greater engagement and show stronger long-term commitment. Given the robust evidence across digital health, information systems, and gamification research, we propose the following hypotheses:

H13: Perceived enjoyment positively affects the continuance usage intention of mHealth apps.
H14: Perceived gratification positively affects the continuance usage intention of mHealth apps.
H15: Perceived playfulness positively affects the continuance usage intention of mHealth apps.

3. Research methodology

This study employed a mixed-methods approach to investigate the relatively new topic of mobile health app adoption in Vietnam. The design included preliminary qualitative and formal quantitative approaches to ensure a comprehensive and contextually relevant study.

The qualitative research in this study used a focus group discussion (FGD) approach, in which participants were encouraged to share their perspectives on how external stimuli - specifically, mobile technology elements such as aesthetics, observability, personalization, and responsiveness - shaped their internal cognitive assessments of enjoyment, gratification, and playfulness associated with mobile health services. The discussion also examined how these perceptions influenced their behavioral responses, specifically their intention to use mHealth. Through this structured dialogue, FGD further clarified the relationship between technology characteristics, users' internal perceptions, and their behavioral intentions. The session was attended by 10 mobile technology experts, including 2 university lecturers, 3 healthcare workers from 3 hospitals that have implemented e-healthcare services, and 5 customers who have used this service in the past 3 months. The face-to-face session was designed to evaluate and refine the preliminary scale derived from previous studies (Zhang et al., 2023; Zhu et al., 2023). Based on the feedback from the participants, some items were adjusted to suit the healthcare sector in Vietnam, and the translation played an important role in helping the respondents understand correctly and answer easily. After the discussion was completed, the final scale was developed and used in the quantitative phase conducted in Ho Chi Minh City, Vietnam, to study consumer attitudes and behaviors in line with the proposed model and hypotheses.

Primary data used in the quantitative study were collected through an online questionnaire based on the scale identified from the qualitative study. A convenience sampling method was applied to select volunteers to participate in the survey. At the end of the data collection process, the study recorded 256 valid responses, ready for the next analysis steps. The quantitative study used the Partial Least Squares Structural Equation Modeling (PLS-SEM) method.

This method is especially effective for complex research models with intertwined relationships between research concepts. At the same time, this technique uses a relatively small sample size compared to other analysis techniques. According to the guidance of Hair et al. (2022), the minimum sample size for PLS-SEM should be at least five times the number of observed variables. With the official scale of 28 observed variables, the study required a minimum of 140 responses. With a data size of 256, the collected sample meets the sample size requirements well, ensuring stability and reliability for PLS-SEM analysis.

4. Analysis results

4.1. Measurement model validation

To evaluate the measurement model, this study tested the reliability of both observed variables and latent factors. The reliability of observed variables was assessed through the Cronbach's Alpha coefficient (CA) and the composite reliability coefficient (CR). The initial analysis results showed that variables AES1 and PSO3 had external loading factors less than 0.708, which is the minimum standard according to Hair et al. (2022). Due to not meeting the requirements for internal consistency reliability, these variables were removed from the measurement model. After removing the above two variables, all remaining observed variables had external loading factors greater than 0.708, ensuring the stability of the scale. Moreover, the factors in the research model all had CA coefficients greater than 0.721 and CR coefficients greater than 0.845 (Table 1).

These values all exceeded the recommended threshold, indicating that the measurement model of the study is reliable and has high internal consistency.

Table 1: Measurement model testing results

Code	Factor	Minimum outer loadings	CA	CR	AVE	Maximum outer VIF values
AES	Aesthetics	0.817	0.779	0.872	0.693	1.688
OBS	Observability	0.768	0.804	0.871	0.629	1.716
PSO	Personalization	0.735	0.721	0.845	0.614	1.312
RPO	Responsiveness	0.795	0.832	0.888	0.665	2.015
PEN	Enjoyment	0.801	0.832	0.888	0.665	1.894
PEG	Gratification	0.779	0.815	0.878	0.643	1.788
PEP	Playfulness	0.792	0.811	0.876	0.638	1.827
IU	Intended continuance use	0.787	0.836	0.893	0.652	1.729

Assessing convergent validity and discriminant validity are two important steps to confirm the reliability and validity of a scale in quantitative research. Convergent validity represents the extent to which observed variables within the same concept are closely correlated with each other. According to

Hair et al. (2022), the variance extracted (AVE) index is the main tool to assess this criterion. A scale is considered to have good convergent validity when the AVE value is greater than 0.5. The analysis results show that all concepts in the study have good convergent validity when the AVE value is greater than 0.5. Specifically, the Personalization factor (PSO) has the lowest AVE value (0.614), while the Aesthetics factor (AES) has the highest AVE value (0.693). These values confirm that all observed variables focus well on their respective concepts, thereby confirming that the scale of the study has convergent validity. Discriminant validity ensures that each concept is unique and distinct from the remaining concepts. The study used the Heterotrait-Monotrait (HTMT) correlation index to test this. The analysis results show that the HTMT indexes of all pairs of concepts in the study are in the range from 0.116 to 0.728 (Table 2). All these values are less than the threshold of 0.85, proving that the concepts in the research model are independent and clearly differentiated (Hair et al., 2022). This allows us to confirm that the research scale has achieved discriminant validity.

Table 2: Discriminant validity test results

	AES	IU	OBS	PEG	PEN	PEP	PSO	RPO
AES								
IU	0.630							
OBS	0.326	0.583						
PEG	0.123	0.552	0.415					
PEN	0.326	0.728	0.341	0.466				
PEP	0.519	0.717	0.523	0.282	0.331			
PSO	0.116	0.457	0.479	0.406	0.318	0.157		
RPO	0.281	0.631	0.261	0.515	0.599	0.377	0.274	

4.2. Structural model validation

The relationships between the concepts in the structural model are determined through estimating a series of regression equations. An important step before evaluating these relationships is to check for multicollinearity, as this phenomenon can distort the regression results. In PLS-SEM analysis, the variance inflation factor (VIF) is used to detect this phenomenon. The analysis results confirm that there is no serious multicollinearity problem between the observed variables because the VIF coefficients of all observed variables are less than 3.0. Similarly, the VIF coefficients of all factors in the research model are also less than 1.227. Thus, the independent variables do not have significant correlations, ensuring the stability of the model (Table 3). Next, this study uses the P-value to evaluate the statistical significance of the regression coefficients. Bootstrapping techniques are used to generate more stable standard errors, thereby helping to accurately determine the P-values for all path coefficients in the structural model.

In the business field, a relationship is considered statistically significant when the P-value is less than 0.05. The results from the bootstrapping analysis provide both standardized impact coefficients and P-values of the hypotheses, which serve as a basis for testing the relationship between research concepts.

Table 3: Structural model testing results

Hypothesis	Path	Std. coefficient	P-value	Result	Inner VIF index	f^2 index	Effect level
H1	AES -> PEN	0.127	0.029	Accepted	1.111	0.021	Very small
H2	AES -> PEG	-0.058	0.299	Declined	1.111	0.004	
H3	AES -> PEP	0.290	0.000	Accepted	1.111	0.11	Small
H4	OBS -> PEN	0.123	0.033	Accepted	1.227	0.018	Very small
H5	OBS -> PEG	0.220	0.000	Accepted	1.227	0.054	Small
H6	OBS -> PEP	0.331	0.000	Accepted	1.227	0.13	Small
H7	PSO -> PEN	-0.093	0.114	Declined	1.164	0.011	
H8	PSO -> PEG	-0.158	0.007	Accepted	1.164	0.029	Very small
H9	PSO -> PEP	0.063	0.215	Declined	1.164	0.005	
H10	RPO -> PEN	0.424	0.000	Accepted	1.110	0.232	Medium
H11	RPO -> PEG	0.361	0.000	Accepted	1.110	0.161	Medium
H12	RPO -> PEP	0.188	0.001	Accepted	1.110	0.046	Small
H13	PEN -> IU	0.404	0.000	Accepted	1.226	0.314	Medium
H14	PEG -> IU	0.198	0.000	Accepted	1.197	0.077	Small
H15	PEP -> IU	0.426	0.000	Accepted	1.103	0.389	Large

The analysis of the mHealth app adoption model reveals a complex, yet insightful, picture of how mobile technology characteristics influence user intentions through emotional and hedonic mechanisms. Overall, the findings underscore the dominant role of real-time interaction quality and intrinsic motivation in driving the continued use of digital health platforms. The relationships between the four technological characteristics and the three emotional outcomes - enjoyment, gratification, and playfulness - showed high variability, with a remarkable 12 out of 15 hypotheses being accepted at a significance level of $p<0.05$ (Fig. 2).

The most powerful driver across all outcomes was responsiveness, highlighting that low latency and timely system or agent feedback is critical to the mHealth experience. Responsiveness demonstrated the strongest relationships with both enjoyment (β = 0.424, p = 0.000) and gratification (β = 0.361, p = 0.000), affirming that a seamless, quick interaction is inherently pleasant and efficiently meets user needs. Observability - the visibility of social signals and activity traces - also proved to be a consistently strong catalyst, positively affecting playfulness (β = 0.331, p = 0.000), gratification (β = 0.220, p = 0.000), and enjoyment (β = 0.123, p = 0.033). This suggests that the feeling of a "less dead" and more social environment significantly enhances both the pleasure and utility of the app.

In contrast, the influence of aesthetics and personalization was more selective. While aesthetics positively impacted enjoyment (β = 0.127, p = 0.029) and, most strongly, playfulness (β = 0.290, p = 0.000), it failed to significantly affect gratification (β = −0.058, p = 0.299). This indicates that an aesthetically pleasing design is great for fun and exploration, but users do not necessarily equate beauty with the fulfillment of their core informational needs. Personalization had the weakest and most inconsistent results, failing to support relationships with enjoyment (β = −0.093, p = 0.114) and playfulness (β = 0.063, p = 0.215), and surprisingly showing a negative, though significant, link with gratification (β = −0.158, p = 0.007). This counterintuitive finding suggests that poorly executed or intrusive personalization might hinder the sense of needs being met, perhaps by raising privacy concerns or feeling irrelevant.

Crucially, all three emotional and hedonic outcomes - enjoyment, gratification, and playfulness - were found to be highly significant and positive predictors of intended use. Playfulness (β = 0.426, p = 0.000) and enjoyment (β = 0.404, p = 0.000) were the strongest drivers of intention, surpassing the impact of gratification (β = 0.198, p = 0.000). This robust final stage confirms the theory that for mHealth apps, intrinsic motivation (fun, curiosity, pleasure) is a more potent predictor of long-term behavioral intention than mere gratification with utility.

In essence, users choose to stick with apps that are fast, feel alive, and are genuinely fun to use.

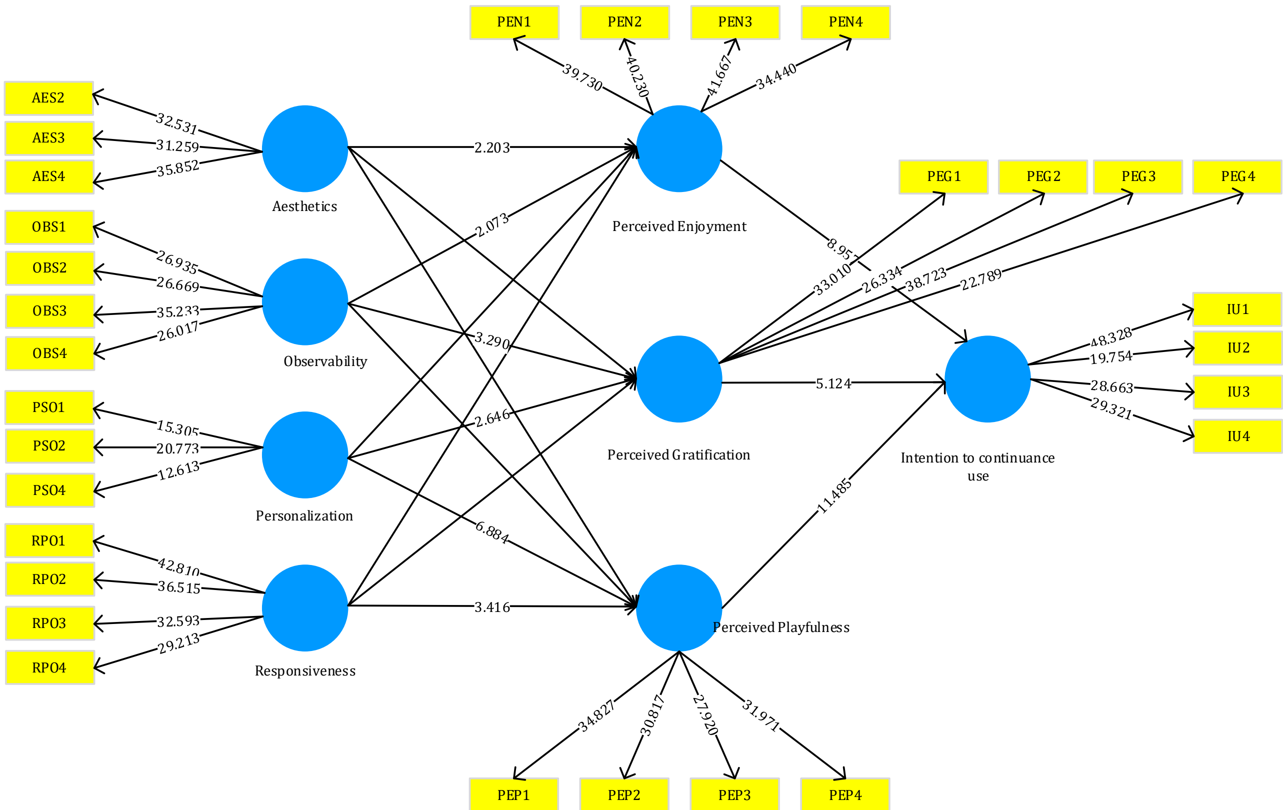

Fig. 2: Structural equation modeling results

The model demonstrates strong explanatory and predictive power across the key constructs of mHealth app usage. The R-squared Adjusted (R^2) values indicate the percentage of variance in a construct that is explained by its predictors. Intended Use showed the highest explanatory power, with an R^2 of 0.573, meaning that the model's predictors - enjoyment, gratification, and playfulness - account for over 57% of the variance in a user's intention to continue using the mHealth app. This confirms that the model is highly effective in capturing the factors that drive long-term user behavior.

The emotional and hedonic variables also exhibited meaningful explanatory power. Playfulness had the highest R^2 among the three, at 0.303, indicating that over 30% of the variation in the feeling of playfulness is explained by mobile app characteristics. This was closely followed by enjoyment (R^2 = 0.292) and gratification (R^2 = 0.262). These figures confirm that the chosen mobile characteristics are significant, though not exhaustive, drivers of the user's emotional experience.

While the standardized impact coefficient of each path indicates the level of impact of each factor on a variable, to evaluate the effectiveness of the impact of each relationship, the study uses the f^2 coefficient. The results of the f^2 index assessment (Table 3) show that perceived playfulness has a strong impact on the intention to use ($0.35 \leq f^2$). Meanwhile, the impact of responsiveness on perceived enjoyment and gratification, perceived enjoyment on the intention to use, is moderate ($0.15 \leq f^2 < 0.35$). In addition, all the remaining impacts are small and very small in magnitude ($f^2 < 0.15$).

Furthermore, the Q^2 values (Stone-Geisser's test) confirm the model's predictive relevance, with all values being greater than zero, a necessary condition for established predictive power. Intended Use again had the highest predictive relevance at 0.359, confirming that the model is robust and can predict future user intentions in a relevant manner. The Q^2 values for enjoyment (0.195), playfulness (0.190), and gratification (0.165) all exceeded the minimal threshold, indicating that the emotional states are also well-predicted by the technical features (Table 4). Overall, the model is highly satisfactory, demonstrating a strong ability to both explain and predict key psychological and behavioral outcomes in mHealth app adoption.

Table 4: Model explanatory and predictive ability

Code	Endogenous variables	R^2	R^2 adjustment	Q^2 index
PEN	Perceived enjoyment	0.302	0.292	0.195
PEG	Perceived gratification	0.271	0.262	0.165
PEP	Perceived playfulness	0.312	0.303	0.190
IU	Intention to continue use	0.578	0.573	0.359

5. Discussion

The structural equation modeling results offer robust and detailed insights into the process through which mobile application characteristics influence user intentions within the context of mHealth adoption in Vietnam. This study utilized a comprehensive theoretical framework that explicitly integrates four technological design features - aesthetics, observability, personalization, and responsiveness - with three intrinsic psychological states - playfulness, enjoyment, and gratification - to predict a sustained intended use of the platform (Alanzi, 2022; Schomakers et al., 2022).

The formal research model has demonstrated strong consistency in capturing the complex, multi-layered determinants of mobile app adoption in the healthcare domain (Hair et al., 2022). The core findings of this study confirm that mobile app adoption is significantly and strongly influenced by the quality of users' experiences, over and above utilitarian perceptions of their use. All three proposed cognitive factors - playfulness, enjoyment, and gratification - were confirmed to be positive and significant drivers of users' future intention to continue using mHealth apps (Huang et al., 2024; Kim and Yum, 2024). A key finding in this construct is that the hedonic component (playfulness, enjoyment) has a significantly greater influence on future intention than the utilitarian component (gratification). This finding is consistent with the current literature on long-term technology adoption, which suggests that psychological rewards, intrinsic engagement, and positive affect from experiences are more important for maintaining long-term engagement than mere perceptions of efficacy or goal attainment (Jo, 2023; Wang et al., 2021). Emphasizing intrinsic motivation is increasingly important as mHealth platforms become not only tools but also experiential services (Wang et al., 2022). Examination of the technological antecedents confirmed that certain design features are far more salient than others in shaping these crucial emotional and hedonic responses. Responsiveness, which captures the platform's speed, reliability, and real-time feedback, emerged as a critically powerful technological determinant (Kim et al., 2026). Its strong influence on both the positive enjoyment of the platform and the sense of efficient gratification indicates that the core technical stability and perceived performance of the mHealth application are not simply passive requirements. Instead, they function as active enhancers that cultivate both pleasure and a sense of fulfilled utility, suggesting that seamless functionality is a precursor to a positive emotional state.

Similarly, observability, defined by the visibility of system activities and subtle social cues, consistently fostered positive user experiences across all three mediators, demonstrating a particularly strong link to playfulness (Park and Kim, 2021). This suggests that design features promoting transparency and a mild sense of social presence - such as seeing one's progress or other users' general activity - encourage a more engaged and exploratory form of interaction, consistent with findings in social commerce and gamified environments (Shen et al., 2022). The perceived "liveliness" or interactivity provided by observability appears to resonate deeply with the user's need for engagement and novelty, significantly fostering the sense of fun and playfulness.

In contrast, the roles of aesthetics and personalization were found to be more nuanced and context-dependent. Aesthetics successfully enhanced the hedonic factors of playfulness and enjoyment, a finding consistent with research linking visual appeal to positive user experiences and exploration (Bazi et al., 2023; Perrig et al., 2023). However, the evidence did not support a connection between aesthetics and the utilitarian factor of gratification. This structural distinction suggests that users tend to compartmentalize visual appeal as a source of pleasure separate from the successful fulfilment of their practical health needs (Sulikowski et al., 2022). That is, a beautiful interface is enjoyable, but it does not intrinsically contribute to the feeling that one's health goals are being met efficiently. The most complex and notable result involves personalization. Personalization did not significantly contribute to either playfulness or enjoyment. Moreover, contrary to expectations based on literature from general e-commerce (Lambillotte et al., 2022; Yi et al., 2022), it registered an unexpected negative relationship with gratification (Balan and Mathew, 2022). This finding strongly suggests that attempts at personalization in a health-sensitive context, such as mHealth, may be interpreted negatively. Overly intrusive or poorly executed personalization might introduce unwanted complexity, raise user concerns regarding data privacy, or lead to content perceived as irrelevant, consequently undermining the user's sense of efficient goal attainment (Mo et al., 2023). This outcome signals the need for context-specific theorization when implementing features imported from non-sensitive domains. The initial qualitative phase, which employed a focus group discussion, was instrumental in ensuring the cultural and domain-specific relevance of the measurement scales, confirming the appropriateness of the constructs for this specific mHealth environment.

The discussion section confirms that sustained mHealth application adoption is driven primarily by intrinsic psychological rewards rather than purely functional benefits, aligning with contemporary technology acceptance theories. All three mediators - playfulness, enjoyment, and gratification - significantly predict intended use, but the hedonic factors (playfulness and enjoyment) were found to exert a substantially greater influence than the utilitarian factor (gratification), validating the critical need to prioritize engagement for long-term user retention. Regarding the technological features, responsiveness emerged as the most critical determinant, actively fostering both enjoyment and gratification, which confirms that core technical stability and speed are necessary foundations for a positive emotional state. Similarly, observability consistently enhances playfulness by providing a dynamic, engaged environment through visible social and system cues. In contrast, aesthetics only supported hedonic factors but failed to enhance gratification, suggesting visual appeal is separated from perceived utility.

Despite the common assumption that personalization enhances users' gratification, the present study uncovered a negative relationship between personalization and gratification, a result that becomes more understandable when interpreted through Privacy Calculus Theory (Culnan and Armstrong, 1999). In the mHealth domain, personalization requires intensive data collection and inference based on highly sensitive health information, which amplifies users' perceptions of intrusiveness and privacy risk. Prior research shows that mHealth users are particularly sensitive to the visibility, storage, and potential misuse of their personal health data (Honglin et al., 2024). When personalization is perceived as overly precise or effortful, users may infer greater surveillance or hidden data-processing activities, which diminishes psychological comfort and weakens the emotional payoff normally associated with gratification. This aligns with findings from digital environments suggesting that users engage in a mental trade-off between the benefits of tailored content and the perceived risks of data disclosure (Bawack et al., 2023; Mo et al., 2023). In health contexts - where trust, sensitivity, and accuracy are paramount - the perceived costs often outweigh the benefits, leading users to experience personalization as a threat rather than support. Consequently, rather than enhancing satisfaction, intrusive or complex personalization may undermine users' sense of efficient goal fulfillment, thereby reducing gratification.

6. Conclusions

This study successfully developed and empirically tested a comprehensive structural model elucidating the factors that govern the continued intention to use mHealth applications, particularly within the nascent Vietnamese market. The findings robustly confirm the critical role of psychological states in mediating the effects of technological design features on sustained user behavior. The model achieved high explanatory power for Intended Use, affirming its strong ability to capture the complex drivers of user retention in this domain. The core conclusion is the decisive evidence that sustained mHealth adoption is driven primarily by intrinsic psychological rewards - namely, playfulness and enjoyment - which were found to exert a greater influence on future intentions than purely utilitarian gratification. This outcome underscores a fundamental shift in technology acceptance: for discretionary and habit-forming applications like mHealth, the user's continuous experience of fun and pleasure is a more potent predictor of long-term engagement than the mere efficiency of goal achievement.

Furthermore, the research provides a detailed classification of the effectiveness of technological antecedents. Responsiveness emerged as the single most critical technical feature, simultaneously enhancing both the hedonic state of enjoyment and the utilitarian state of gratification. This confirms that seamless, low-latency performance is a fundamental and active enhancer of the entire user experience. Similarly, observability consistently fostered playfulness, validating its role in creating a dynamic, engaging environment through transparent systems and social cues. Crucially, the inconsistent effects of aesthetics and the counter-intuitive negative relationship between personalization and gratification issue a significant caution, suggesting that complex features imported from non-sensitive e-commerce domains may be poorly received in the health context. In sum, this study provides a validated framework where technical stability (responsiveness) and social design (observability) are the most effective levers for generating the powerful intrinsic states that compel continued mHealth usage. This study makes three significant contributions to the theoretical discourse on technology adoption. First, it empirically establishes the dominance of hedonic factors (playfulness and enjoyment) over utilitarian factors (gratification) in predicting mHealth continuance intention. While prior models often treat intrinsic motivation broadly, this research successfully differentiates these concepts structurally, confirming that generating curiosity and pleasure is paramount for long-term retention in health-related technology use. Second, the study provides a context-specific validation of technological antecedents for mHealth. By confirming the preeminence of responsiveness and observability, the research refines the technology-to-intention path, offering specific design dimensions relevant to real-time, personalized, and sometimes social, health monitoring platforms. Third, the study introduces a crucial boundary condition for the traditionally accepted positive role of personalization. The negative link between personalization and gratification suggests that personalization may become a psychological cost (e.g., perceived intrusion, complexity, or privacy threat) that outweighs its benefit in a sensitive domain like mHealth, necessitating a re-evaluation of this construct in future models of health technology acceptance.

The findings offer specific, actionable guidance for mHealth application developers and product managers. To maximize user retention, product development should prioritize system speed and technical performance (responsiveness) above all else, recognizing that stability is the foundation for generating positive emotions and perceived utility. Second, developers should focus on integrating transparent, engaging social cues (observability) - such as progress visibility or non-intrusive activity feeds - to foster a sense of dynamism and playfulness. Third, the results issue a clear warning against aggressive or generalized personalization. Resources should be reallocated from complex, data-heavy personalization features toward perfecting core utility and technical integrity. If personalization is implemented, it must be highly transparent, user-controlled, and strictly relevant to demonstrated health goals to avoid undermining the user's sense of efficiency.

Despite the robustness of the statistical model, this study is subject to several methodological limitations that must be considered within Vietnam's broader socio-geographical context. First, the exclusive reliance on convenience sampling in Ho Chi Minh City introduces a clear urban bias. The city's high levels of digital literacy, economic dynamism, and frequent exposure to technology-based services differentiate its residents from those in smaller cities and rural regions. As a result, participants may vary substantially in technology adoption readiness, privacy attitudes, and mHealth usage behaviors, thereby limiting the study's external validity. Second, the analysis revealed an unexpected negative association between personalization and perceived gratification. This counterintuitive result may reflect user discomfort with overly tailored features or stem from measurement limitations or contextual influences inherent to the sample. Further investigation is required to validate and better understand this pattern. Third, the study assessed intended use rather than actual, logged user behavior. Although intention is widely recognized as a reliable predictor of behavior, it may inadequately represent real-world continuance, particularly in the mHealth domain, where app fatigue, fluctuating motivation, and inconsistent engagement are common. Future research should therefore examine whether the psychological and perceptual mechanisms identified here persist and translate into sustained adoption over time.

Building on these findings, several avenues for future research merit consideration. First, adopting a multi-regional, stratified sampling strategy that includes respondents from secondary cities, peri-urban areas, and rural provinces across Vietnam would help address the limitations of an urban-focused sample. Such an approach would better capture variations in digital literacy, healthcare accessibility, socio- economic conditions, and technology adoption patterns that are not reflected in data drawn solely from Ho Chi Minh City. Techniques such as regional weighting or multi-group analysis could further enhance external validity by enabling systematic comparisons between urban and non-urban populations. Broadening data collection beyond major metropolitan centers would therefore meaningfully reduce urban bias and facilitate more generalizable insights into nationwide mHealth adoption. Second, the unexpected negative effect of personalization warrants deeper investigation through moderation analysis. A promising direction is to examine perceived privacy as a moderator of the relationship between personalization and perceived gratification. Although personalization is typically expected to enhance user gratification by delivering tailored content, this effect may diminish when users experience heightened privacy concerns. In such cases, personalized features may be interpreted as intrusive rather than beneficial, thereby reducing the psychological rewards associated with app use. Thus, personalization may increase gratification under low privacy concerns but yield inconsistent or limited effects when privacy concerns are elevated. Third, future research should move beyond initial intended use to explicitly examine continuance intention, which offers a more accurate reflection of long-term commitment to mHealth applications. Longitudinal study designs would enable researchers to track how user perceptions, motivations, and barriers evolve after initial adoption. Integrating constructs such as satisfaction, habit formation, app fatigue, and perceived usefulness over time would enrich understanding of the drivers of sustained engagement. Comparing early intentions with subsequent continuance intention may also reveal intention-behavior gaps, thereby clarifying whether the psychological mechanisms identified in this study persist as users transition from initial adoption to long-term usage.

List of abbreviations

AES	Aesthetics
AI	Artificial intelligence
ANN	Artificial neural network
AVE	Average variance extracted
CA	Cronbach's alpha coefficient
CR	Composite reliability coefficient
ECM-ISC	Expectation-confirmation model of information system continuance
FGD	Focus group discussion
HTMT	Heterotrait-Monotrait correlation index
IU	Intended continuance use
mHealth	Mobile healthcare application
OBS	Observability
PEG	Gratification
PEN	Enjoyment
PEP	Playfulness
PLS-SEM	Partial least squares structural equation modeling
PSO	Personalization
Q^2	Stone–Geisser predictive relevance index
R^2	Coefficient of determination
RPO	Responsiveness
S-O-R	Stimulus–organism–response model
UGT	Uses and gratifications theory
UI	User interface
UTAUT	Unified theory of adoption and use of technology
UX	User experience
USD	United States dollar
VIF	Variance inflation factor

Compliance with ethical standards

Ethical considerations

This study involved the voluntary participation of adults aged 18 and above. Informed consent was obtained from all respondents prior to participation. The questionnaire was anonymous, and no personally identifiable information was collected. All data were kept confidential and used strictly for academic purposes.

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Alanzi TM (2022). Users' satisfaction levels about mHealth applications in post-COVID-19 times in Saudi Arabia. PLOS ONE, 17(5): e0267002. https://doi.org/10.1371/journal.pone.0267002 **PMid:35507590 PMCid:PMC9067643**

Alkhwaldi AF and Abdulmuhsin AA (2022). Understanding user acceptance of IoT based healthcare in Jordan: Integration of the TTF and TAM. In: Yaseen SG (Ed.), Digital economy, business analytics, and big data analytics applications: 191-213. Springer, Cham, Switzerland. https://doi.org/10.1007/978-3-031-05258-3_17

Balan M and Mathew SK (2022). The persuasive nature of web personalization on online users' product perception: A mental accounting perspective. AIS Transactions on Human-Computer Interaction, 14(1): 78-106. https://doi.org/10.17705/1thci.00162

Bawack RE, Bonhoure E, Kamdjoug JRK, and Giannakis M (2023). How social media live streams affect online buyers: A uses and gratifications perspective. International Journal of Information Management, 70: 102621. https://doi.org/10.1016/j.ijinfomgt.2023.102621 **PMCid:PMC12530530**

Bazi S, Filieri R, and Gorton M (2023). Social media content aesthetic quality and customer engagement: The mediating role of entertainment and impacts on brand love and loyalty. Journal of Business Research, 160: 113778. https://doi.org/10.1016/j.jbusres.2023.113778

Chakraborty D and Paul J (2023). Healthcare apps' purchase intention: A consumption values perspective. Technovation, 120: 102481. https://doi.org/10.1016/j.technovation.2022.102481

Culnan MJ and Armstrong PK (1999). Information privacy concerns, procedural fairness, and impersonal trust: An empirical investigation. Organization Science, 10(1): 104-115. https://doi.org/10.1287/orsc.10.1.104

Gosetto L, Falquet G, and Ehrler F (2025). Personalizing mobile applications for health based on user profiles: A preference matrix from a scoping review. PLOS Digital Health, 4(8): e0000978. https://doi.org/10.1371/journal.pdig.0000978 **PMid:40828800 PMCid:PMC12364320**

Gosetto L, Pittavino M, Falquet G, and Ehrler F (2023). Personalization of mobile apps for health behavior change: Protocol for a cross-sectional study. JMIR Research Protocols, 12(1): e38603. https://doi.org/10.2196/38603 **PMid:36602850 PMCid:PMC9853334**

Hair JF, Hult GTM, Ringle CM, and Sarstedt M (2022). A primer on partial least squares structural equation modeling (PLS-SEM). 3rd Edition, SAGE, Thousand Oaks, USA.

Haley JA, Rhind DJ, and Maidment DW (2025). Assessing the usability of accessercise to increase physical activity in adults with physical disabilities: A qualitative think-aloud study. PLOS ONE, 20(4): e0321109. https://doi.org/10.1371/journal.pone.0321109 **PMid:40168349 PMCid:PMC11960980**

Honglin D, Jianghua Z, and Hui C (2024). Quality factors affecting the continued use of mobile health apps in ethnic minority regions of Southwest China using PLS-SEM and ANN. Scientific Reports, 14: 25469. https://doi.org/10.1038/s41598-024-75410-4 **PMid:39462035 PMCid:PMC11513151**

Huang W, Ong WC, Wong MK, Ng EY, Koh T, Chandramouli C, Ng CT, Hummel Y, Huang F, Lam CS, and Tromp J (2024). Applying the UTAUT2 framework to patients' attitudes toward healthcare task shifting with artificial intelligence. BMC Health Services Research, 24: 455. https://doi.org/10.1186/s12913-024-10861-z **PMid:38605373 PMCid:PMC11007870**

Jia Y, Liu L, and Lowry PB (2024). How do consumers make behavioural decisions on social commerce platforms? The interaction effect between behaviour visibility and social needs. Information Systems Journal, 34(5): 1703-1736. https://doi.org/10.1111/isj.12508

Jiang Q, Sun J, Yang C, and Gu C (2022). The impact of perceived interactivity and intrinsic value on users' continuance intention in using mobile augmented reality virtual shoe-try-on function. Systems, 10(1): 3. https://doi.org/10.3390/systems10010003

Jiang Y and Lau AK (2023). Understanding post-adoption behavioral intentions of mobile health service users: an empirical study during COVID-19. International Journal of Environmental Research and Public Health, 20(5): 3907. https://doi.org/10.3390/ijerph20053907 **PMid:36900918 PMCid:PMC10001414**

Jo H (2023). Understanding the key antecedents of users' continuance intention in the context of smart factory. Technology Analysis & Strategic Management, 35(2): 153-166. https://doi.org/10.1080/09537325.2021.1970130

Katz E, Blumler JG, and Gurevitch M (1973). Uses and gratifications research. The Public Opinion Quarterly, 37(4): 509-523. https://doi.org/10.1086/268109

Kim J and Yum K (2024). Enhancing continuous usage intention in e-commerce marketplace platforms: The effects of service quality, customer satisfaction, and trust. Applied Sciences, 14(17): 7617. https://doi.org/10.3390/app14177617

Kim K, Shams G, and Kim K (2026). From seconds to sentiments: Differential effects of chatbot response latency on customer evaluations. International Journal of Human–Computer Interaction, 42(1): 597-612. https://doi.org/10.1080/10447318.2025.2508915

Kim TB and Ho CTB (2021). Validating the moderating role of age in multi-perspective acceptance model of wearable healthcare technology. Telematics and Informatics, 61: 101603. https://doi.org/10.1016/j.tele.2021.101603

Lambillotte L, Magrofuoco N, Poncin I, and Vanderdonckt J (2022). Enhancing playful customer experience with personalization. Journal of Retailing and Consumer Services, 68: 103017. https://doi.org/10.1016/j.jretconser.2022.103017

Li G, Jiang Y, and Chang L (2022). The influence mechanism of interaction quality in live streaming shopping on consumers' impulsive purchase intention. Frontiers in Psychology, 13: 918196. https://doi.org/10.3389/fpsyg.2022.918196 **PMid:35874389 PMCid:PMC9306557**

Liu C, Wang J, Chen R, and Zhou W (2024). Exploring the influence of Chinese online patient trust on telemedicine behavior: insights into perceived risk and behavior intention. Frontiers in Public Health, 12: 1415889. https://doi.org/10.3389/fpubh.2024.1415889 **PMid:39247232 PMCid:PMC11377225**

Liu JYW, Sorwar G, Rahman MS, and Hoque MR (2023). The role of trust and habit in the adoption of mHealth by older adults in Hong Kong: A healthcare technology service acceptance (HTSA) model. BMC Geriatrics, 23: 73. https://doi.org/10.1186/s12877-023-03779-4 **PMid:36737712 PMCid:PMC9898708**

Mo L, Zhang X, Lin Y, Yuan Z, and Peng Z (2023). Consumers' attitudes towards online advertising: A model of personalization, informativeness, privacy concern and flow experience. Sustainability, 15(5): 4090. https://doi.org/10.3390/su15054090

Mustafa AS, Ali NA, Dhillon JS, Alkawsi G, and Baashar Y (2022). User engagement and abandonment of mHealth: A cross-sectional survey. Healthcare, 10(2): 221. https://doi.org/10.3390/healthcare10020221 **PMid:35206837 PMCid:PMC8872344**

Olivar CM, Pineiro M, Quintero JSG, Avendaño-Vásquez CJ, Ormeño-Arriagada P, Rivadeneira SP, and Toro CT (2025). Education and symptom reporting in an mHealth app for patients with cancer: Mixed methods development and validation study. JMIR Human Factors, 12(1): e60169. https://doi.org/10.2196/60169 **PMid:40294430 PMCid:PMC12052293**

Palas JU, Sorwar G, Hoque MR, and Sivabalan A (2022). Factors influencing the elderly's adoption of mHealth: An empirical study using extended UTAUT2 model. BMC Medical Informatics and Decision Making, 22: 191. https://doi.org/10.1186/s12911-022-01917-3 **PMid:35871682 PMCid:PMC9308955**

Pan Z, Xie Z, Liu T, and Xia T (2024). Exploring the key factors influencing college students' willingness to use AI coding assistant tools: An expanded technology acceptance model. Systems, 12(5): 176. https://doi.org/10.3390/systems12050176

Park S and Kim S (2021). Leaderboard design principles to enhance learning and motivation in a gamified educational environment: Development study. JMIR Serious Games, 9(2): e14746. https://doi.org/10.2196/14746 **PMid:33877049 PMCid:PMC8097522**

Perrig SA, Ueffing D, Opwis K, and Brühlmann F (2023). Smartphone app aesthetics influence users' experience and performance. Frontiers in Psychology, 14: 1113842. https://doi.org/10.3389/fpsyg.2023.1113842 **PMid:37388645 PMCid:PMC10306164**

Pigera S, Van Schaik P, Renaud K, Campbell M, Manley P, and Esser P (2025). Privacy and security in digital health contact-tracing: A narrative review. Applied Sciences, 15(2): 865. https://doi.org/10.3390/app15020865

Schomakers EM, Lidynia C, Vervier LS, Calero Valdez A, and Ziefle M (2022). Applying an extended UTAUT2 model to explain user acceptance of lifestyle and therapy mobile health apps: Survey study. JMIR Mhealth and Uhealth, 10(1): e27095. https://doi.org/10.2196/27095 **PMid:35040801 PMCid:PMC8808343**

Schwarz A, Winkens LH, de Vet E, Ossendrijver D, Bouwsema K, and Simons M (2023). Design features associated with engagement in mobile health physical activity interventions among youth: Systematic review of qualitative and quantitative studies. JMIR Mhealth and Uhealth, 11: e40898. https://doi.org/10.2196/40898 **PMid:36877551 PMCid:PMC10028523**

Shaver J (2022). The state of telehealth before and after the COVID-19 pandemic. Primary Care, 49(4): 517. https://doi.org/10.1016/j.pop.2022.04.002 **PMid:36357058 PMCid:PMC9035352**

Shen L, Zhang Y, Fan Y, Chen Y, and Zhao Y (2022). Improving consumer stickiness in livestream e-commerce: A mixed-methods study. Frontiers in Psychology, 13: 962786. https://doi.org/10.3389/fpsyg.2022.962786 **PMid:36118462 PMCid:PMC9473288**

Sulikowski P, Kucznerowicz M, Bąk I, Romanowski A, and Zdziebko T (2022). Online store aesthetics impact efficacy of product recommendations and highlighting. Sensors, 22(23): 9186. https://doi.org/10.3390/s22239186 **PMid:36501888 PMCid:PMC9741377**

Tanantong T and Wongras P (2024). A UTAUT-based framework for analyzing users' intention to adopt artificial intelligence in human resource recruitment: A case study of Thailand. Systems, 12(1): 28. https://doi.org/10.3390/systems12010028

Tian XF and Wu RZ (2022). Determinants of the mobile health continuance intention of elders with chronic diseases: An integrated framework of ECM-ISC and UTAUT. International Journal of Environmental Research and Public Health, 19(16): 9980. https://doi.org/10.3390/ijerph19169980 **PMid:36011615 PMCid:PMC9408135**

Tran L, Cucé F, An NT, Dila KA, Nam NH, Cat DL, Jun LW, Ansar F, Abdallh F, Vo A, and Huy NT (2025). A content review of COVID-19-related apps used in Vietnam. The Journal of Infection in Developing Countries, 19(2): 208-220. https://doi.org/10.3855/jidc.19329 **PMid:40063748**

Uncovska M, Freitag B, Meister S, and Fehring L (2023). Patient acceptance of prescribed and fully reimbursed mHealth apps in Germany: An UTAUT2-based online survey study. Journal of

Medical Systems, 47: 14.
https://doi.org/10.1007/s10916-023-01910-x
PMid:36705853 PMCid:PMC9880914

Wang T, Fan L, Zheng X, Wang W, Liang J, An K, Ju M, Lei J (2021). The impact of gamification-induced users' feelings on the continued use of mHealth apps: A structural equation model with the self-determination theory approach. Journal of Medical Internet Research, 23(8): e24546.
https://doi.org/10.2196/24546
PMid:34387550 PMCid:PMC8391751

Wang T, Wang W, Liang J, Nuo M, Wen Q, Wei W, Han H, and Lei J (2022). Identifying major impact factors affecting the continuance intention of mHealth: A systematic review and multi-subgroup meta-analysis. npj Digital Medicine, 5: 145.
https://doi.org/10.1038/s41746-022-00692-9
PMid:36109594 PMCid:PMC9476418

Wang X, Lee CF, Jiang J, and Zhu X (2023). Factors influencing the aged in the use of mobile healthcare applications: An empirical study in China. Healthcare, 11(3): 396.
https://doi.org/10.3390/healthcare11030396
PMid:36766970 PMCid:PMC9914473

Yadegari M, Mohammadi S, and Masoumi AH (2024). Technology adoption: An analysis of the major models and theories. Technology Analysis & Strategic Management, 36(6): 1096-1110. https://doi.org/10.1080/09537325.2022.2071255

Yang M, Al Mamun A, Gao J, Rahman MK, Salameh AA, and Alam SS (2024). Predicting m-health acceptance from the perspective of unified theory of acceptance and use of technology. Scientific Reports, 14: 339.
https://doi.org/10.1038/s41598-023-50436-2
PMid:38172184 PMCid:PMC10764358

Yi M, Huang Z, and Yu Y (2022). Creating a sustainable e-commerce environment: The impact of product configurator interaction design on consumer personalized customization experience. Sustainability, 14(23): 15903.
https://doi.org/10.3390/su142315903

Zhang R, Jun M, and Palacios S (2023). M-shopping service quality dimensions and their effects on customer trust and loyalty: An empirical study. International Journal of Quality & Reliability Management, 40(1): 169-191.
https://doi.org/10.1108/IJQRM-11-2020-0374

Zhu Y, Zhao Z, Guo J, Wang Y, Zhang C, Zheng J, Zou Z, and Liu W (2023). Understanding use intention of mHealth applications based on the unified theory of acceptance and use of technology 2 (UTAUT-2) model in China. International Journal of Environmental Research and Public Health, 20(4): 3139.
https://doi.org/10.3390/ijerph20043139
PMid:36833830 PMCid:PMC9960455