mHealth Apps on the Rise: Exploring the Influence of App and Individual Characteristics on Adoption

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Abstract The usage of mobile health (mHealth) applications is rising steadily in India in recent years. Examining factors that influence users' intention to continue using mHealth apps is vital for increasing the adoption rate. This research adopts the basic TAM model and extends it by incorporating user characteristics and app characteristics to predict continuance intention toward mHealth apps. A questionnaire was administered with a sample of 537 respondents. The proposed model was tested with structural equation modeling (SEM). The empirical evidence confirms the influence of mHealth app characteristics (data access, data storage, interactivity, integration of artificial intelligence, and playfulness), individual characteristics of mHealth app users (self-efficacy, technological anxiety, health consciousness, perceived vulnerability, and personal innovativeness), as well as perceived ease of use and perceived usefulness on users' intention to continue with mHealth apps. The study offers insights for mHealth app developers, policymakers, and healthcare providers seeking to optimize mHealth interventions and ensure their effectiveness in addressing the healthcare needs of developing nations.

Keywords mHealth · Technology acceptance model · Artificial intelligence · Continuance use intention · India

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1 Introduction

Mobile health (mHealth), a key component of electronic health, is essential for managing and communicating disease and health situations using mobile devices [19]. According to Pai and Alathur, 'mHealth' is "the use of mobile phones to provide healthcare services to people living in particular locations or for self-care purposes" [47]. The market for mHealth applications in India was worth INR 43.41 billion in 2020 and by 2026, it is projected to grow up to INR 337.89 billion, according to research by Research and Markets titled "India Healthcare Apps Market Report 2021" [50]. In India, downloads of mHealth apps reached a total of seventy-six million in the year 2021 [59]. In India, there are more than 670 health apps available on Google Play store, and this number is steadily increasing [59]. Though the usage of mHealth apps is increasing in India, the research exploring determinants of users' intentions to use these apps in future is scant. Existing research on mHealth app adoption and usage intentions primarily comes from Western countries and China, and little is known about the Indian context. India's unique sociocultural, economic, and technological landscape calls for research specifically examining the adoption of mHealth apps.

This research investigates user characteristics and the app's characteristics that determine users' continuance intentions in the mHealth app context going forward. Our analysis will focus on the impact of key mHealth app attributes, such as data access, data storage, interactivity, integration of artificial intelligence (AI integration), and playfulness, as well as perceived ease of use and perceived usefulness on users' intention to continue with them. Aside from that, we will look into how traits like self-efficacy, technological anxiety, health consciousness, perceived vulnerability, and personal innovativeness affect users' plans for future use of mHealth apps. User acceptance and adoption of mHealth apps are influenced by their perceived ease of use and perceived usefulness. The perceived ease of use of the app refers to how easy it is to use and navigate [66], and the perceived usefulness refers to how beneficial it is to improving health outcomes [20]. Additionally, the characteristics of the mHealth app influence user engagement [52]. This research seeks to get insights on what drives the engagement of mHealth app users and the sustained use of these apps. Developing strategies and interventions based on these findings can improve user satisfaction and long-term engagement, ultimately enhancing the effectiveness of mHealth interventions.

Research in this area holds significant importance for several reasons. The effective utilization of mHealth apps results in enhanced health outcomes and overall well-being for the users. If users discontinue app usage shortly after adopting it, the potential benefits of the mHealth app may remain unrealized. By studying users' continuance intentions, practitioners and researchers can identify strategies to maximize the health impact of app usage.

Following are the research questions the study seeks to answer:

RQ1: Is there a significant impact of mHealth app characteristics (such as data access, data storage, interactivity, AI integration, and playfulness) on users' intention to continue using them?
RQ2: Is there a significant impact of individual characteristics (such as self-efficacy, health consciousness, technology anxiety, perceived innovativeness, and perceived vulnerability) on users' intention to continue using mHealth apps?
RQ3: Does user perception about ease of use and usefulness has a significant impact on users' intention to continue using mHealth apps?

2 Literature Review

This section presents arguments for the relationships hypothesized in the conceptual model based on the existing literature. It narrates the relationships adopted from Technology Acceptance Model (TAM) [20], the mHealth app characteristics affecting users' behavior, and users' characteristics affecting the mHealth app users' behavior.

2.1 TAM Model

Technology Acceptance Model (TAM) [20] is a generic model applicable to study the users' adoption of any new technology. The model has been applied to a variety of technologies and applications [46]. It considers behavioral intention to use technology as a proxy for user adoption and identifies two constructs as predictors of users' intention to use technology: perceived ease of use and perceived usefulness. The current study adopts the basic TAM model and extends it by incorporating user characteristics and app characteristics to predict the continuance intention of users toward the mHealth apps.

Perceived Ease of Use and mHealth App: Perceived ease of use refers to "how easily people believe they can use technology without facing any difficulties or struggles" [20]. Users of the mHealth app are more likely to establish the intention to use the app consistently over time if they believe it to be user-friendly [12]. Users of mHealth apps who find the app to be simple to use can pick up the app's features and functionalities rapidly [48]. mHealth apps are perceived as more useful when they are perceived as easy to use. Apps that are easy to use encourage users to explore their features, navigate the interface effortlessly, and get the most out of their functionalities [5]. A positive user experience makes users more likely to perceive the app as useful [54]. While an app may have valuable features, users may perceive it as less useful if it is complicated or requires a steep learning curve. We hypothesize the following based on the above discussion:

H1: Perceived usefulness of the mHealth app is positively influenced by its perceived ease of use.

H2: Intention to continue with the mHealth app is positively influenced by perceived ease of use.

Perceived Usefulness and mHealth App: Perceived usefulness refers to "the degree to which a person believes that using a particular system would enhance his or her job performance" [20]. The perceived usefulness of mHealth features can motivate users to stay continue with mHealth apps [2, 44]. If individuals perceive that the mHealth app supports them in efficiently managing their health, such as predicting their health, monitoring their vital signs, or providing personalized health information and recommendations, they are more likely to continue using the mHealth app [33, 58]. We hypothesize the following based on the above discussion:

H3: Intention to continue with the mHealth app is influenced by perceived usefulness.

2.2 Key Characteristics of mHealth Apps Users

Five user characteristics—self-efficacy [37], technology anxiety [43], health consciousness [13], perceived vulnerability [3], and personal innovativeness [66], were found relevant to mHealth app usage. Self-efficacy is the term used to describe an individual's confidence level or belief in their ability to accomplish a specific task [9]. Extensive research established that self-efficacy affects an individual's health status and health behavior [27]. Self-efficacy significantly influences the intention to continue with mHealth apps in various ways. It is associated with increased confidence in utilizing mHealth apps [45], a positive perception of the effectiveness of mHealth apps [8], the ability to overcome challenges encountered during mHealth app usage [65], and effective self-regulation and goal-setting practices with mHealth app [60, 61]. Higher levels of self-efficacy can lead to increased confidence in using the mHealth app. Health consciousness refers to an individual's awareness and concern for their health and well-being. Those who are health-conscious sacrifice a lot for their health and are ready to take action for their health [16]. The mindset and thought process of health-conscious individuals align with mHealth apps because they provide access to personalized health information, enable health and physical activity tracking, and offer reminders for medication, nutrition, or exercise [13]. A mHealth app can play a crucial role in supporting health-conscious individuals, enhancing their motivation, and reinforcing their commitment to continue it [16]. The ability to immediately obtain health tips, utilize symptom checkers, or access telemedicine services through a mHealth app significantly impacts their intention to continue using such apps. Technology anxiety refers to the unease and fear experienced while interacting with technology. Technology anxiety can impact individuals' behaviors, beliefs, and attitudes toward using and continuing to use the mHealth app [64]. Individuals with technology anxiety may feel resistant to using mHealth apps due to their concerns about fear of making mistakes or the ability to navigate the technology, and this creates barriers to adopting and continuing to use the app [31, 43]. Personal innovativeness refers to an individual's willingness and ability to adopt and use new technologies or innovations [1]. Early adopters and innovators, with higher personal innovativeness, are more likely to use new technologies and be among the first to use mHealth apps [66]. Personal innovativeness determines the degree to which one learns and explores the functionalities and features of mHealth apps. Highly innovative people are ready to experiment with various features and functions of mHealth apps. Perceived vulnerability refers to "an individual's perception or belief of their susceptibility to a specific health condition or risk". This perception or belief influences the intention to continue with the mHealth app [40]. Perceived vulnerability influences the intention to continue with mHealth app because it is associated with motivation to use the mHealth app, sense of urgency, personal relevance of health information, control over one's health, and perceived benefits of the mHealth app [5, 40]. People with high perceived vulnerability may be more motivated to continue using a mHealth app as a tool for monitoring and improving their health [7]. We hypothesize the following based on the above discussion:

H4a,b,d,e: The intention to continue with the mHealth app is positively influenced by self-efficacy, health consciousness, personal innovativeness, and perceived vulnerability.
H4c: The intention to continue with the mHealth app is negatively influenced by technology anxiety.

2.3 Key Characteristics of mHealth Apps

Five mHealth app characteristics affecting user behavior toward mHealth apps, namely AI integration [24], data access [41], data storage [57], interactivity [30], and playfulness [36], were identified from the literature. AI integration in mHealth app provide numerous benefits to the users of mHealth app like Personalized health monitoring [39], Health data analysis [52], Early detection and prevention [18], Health risk assessment [51], Virtual health assistants [17, 26], etc. This positively impacts users' intention to use the app regularly [48] and engage in proactive health management. Data access features in mHealth apps refer to the ability of users to access and manage their health data. It helps in getting comprehensive medical information [56, 63], supporting networks and informed decision-making, timely and informed care [25], etc. The inclusion of data access features in a mHealth app has a significant influence on the adoption, usage, and overall satisfaction of its users [38]. The data stored in mHealth apps include health activity tracker data, physical activity tracker data, personal data, medical data, and other health-related documents [6, 28]. By providing secure and reliable data storage features to mHealth app users, mHealth app providers can enhance the trust and confidence of app users. Users can be more likely to use and continue using a mHealth app that gives easy access to their health-related data and securely store their data [53]. The interactivity feature

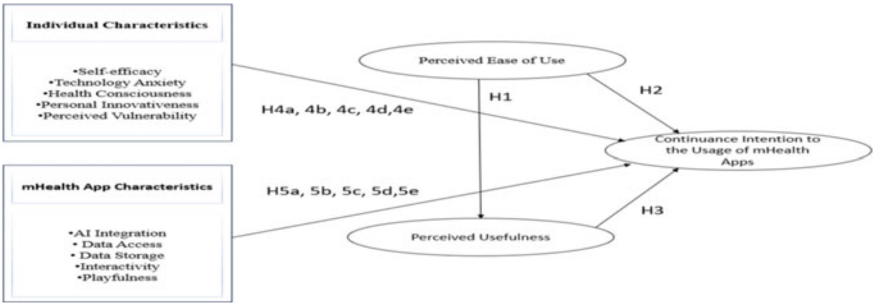

Fig. 1 Conceptual model

of a health app is of utmost importance as it enables direct interaction with caregivers [42], provides integration with social media platforms [42], and enhances adherence with automatic reminders and alerts [11]. This type of interacting facility reduces administrative burden, saves time, and facilitates efficient communication between mHealth app users and healthcare providers. A playful mHealth app incorporates interactive elements like games, challenges, quests, online rewards, etc. to make the user experience more enjoyable and engaging. The playfulness feature of the mHealth app is of utmost importance as it significantly increases users' engagement, motivates users, encourages behavioral change, facilitates enhanced learning, and fosters social support [55]. A positive and enjoyable experience increases user satisfaction and intention to reuse it. We hypothesize the following based on the above discussion:

H5a,b,c,d,e: The intention to continue with the mHealth app is positively influenced by AI integration, data access, data storage, interactivity, and playfulness.

The conceptual model is shown in Fig. 1.

3 Research Design

3.1 Measures

The study used scales from existing literature to gauge the variables involved in the study. The responses for a total of 52 statements measuring the latent constructs were collected on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). For mHealth self-efficacy, the three-item scale was adapted from Fox and Connolly [23]. The scale for perceived vulnerability was adapted from Luo et al. [40]. The health consciousness scale was based on Chen [15] and Halvadia et al. [29]. The scale for technology anxiety was adopted from Xue et al. [64]. The scale for personal innovativeness was based on Bhatt [10]. The scale for app characteristics such as data access, data storage, and AI integration was adapted from Kharrazi et al. [35] and Gimpel et al. [25]. The interactivity scale was based on Davis et al. [21] and the playfulness scale was adapted from Proyer [49] and Kang and Hwang [34], respectively. The scales for TAM variables—perceived usefulness, perceived ease of use, and intention to continue were adapted from Wu et al. [62] and Bhatt [10].

3.2 Data Collection

The mHealth apps users were contacted using a convenience sampling method for data collection. The questionnaires were administered in physical form and electronically also. From a total of 550 responses received through the survey, 537 were usable in terms of completeness and validity. The sample consists of 43% female and 57% male respondents. 32% of respondents were from the age group of 16 to 25 and 49% were from 26 to 40. 45% of all were salaried and 29% were self-employed. 48% were graduates and 31% were post-graduates. From the sample, 39% had a family monthly income of INR 50 thousand to 1 lakh and 35% had a monthly family income of INR thirty thousand to fifty thousand.

4 Results

4.1 Measurement Model Results

Before testing the hypothesis, data were analyzed for reliability and validity of the scales used for assessing the latent constructs. Confirmatory Factor Analysis was performed for this purpose. The results indicated reasonably good model fit (Model fit indices values met the cut-off limits prescribed by Hu and Bentler [32]: χ^2/df = 2.510, CFI = 0.932, GFI = 0.902, RMSEA = 0.054, RMR = 0.048). Further, the factor loading values were > 0.5 for all measured items, and all measured items loaded well on their respective constructs. The criteria recommended by Fornell and Larcker [22] were applied to appraise whether the scales used for the study are reliable and valid. The reliability of the scales was examined based on the Composite Reliability (CR) values. The CR values were greater than the minimum cut-off value (0.7) required to confirm the reliability [22]. Furthermore, the Average Variance Extracted (AVE) values were above the minimum value (0.5) indicating convergent validity. Lastly, the square root of the AVE of each construct was compared with its correlation with all other constructs to establish the discriminant validity. The correlation values are lower than the square root of AVEs. Thus, discriminant validity was confirmed.

4.2 Hypothesis Testing

Having checked the scale for validity and reliability, the next step was to test the proposed conceptual model. We applied structural equation modeling (SEM) for the same. The values of the model fit indices were found acceptable based on the prescribed values by Hu and Bentler [32] (χ^2/df = 2.205, CFI = 0.935, GFI = 0.907, RMSEA = 0.053, RMR = 0.047). The results of hypothesis testing are shown in Table 1. The results supported the hypothesis based on the core TAM model as H1, H2, and H3 were accepted. Perceived usefulness (β = 0.670, $p < 0.05$) and perceived ease of use (β = 0.689, $p < 0.05$) were found to have a significant effect on users' intention to continue using the mHealth apps. The results also confirmed the relationship between personal characteristics and users' behavioral intentions. Self-efficacy was found to have a significant effect on behavioral intentions and H4a was accepted (β = 0.545, $p < 0.05$). H4b was also found to be statistically acceptable as the effect of health consciousness on intention to continue was significant (β = 0.572, $p < 0.05$). The results also evidenced the negative effect of technology anxiety on users' intention (β = − 0.448, $p < 0.05$) and H4c was supported. H4d and H4e were also held up as personal innovativeness (β = 0.393, $p < 0.05$) and vulnerability (β = 0.229, $p < 0.05$) had a significant impact on users' intention to continue using the mHealth apps. Further, the results also confirmed the impact of app characteristics on user behavior. Data access and data storage showed a strong positive impact on intention to continue and therefore, H5a (β = 0.535, $p < 0.05$) and H5b (β = 0.474, $p < 0.05$) were confirmed. The effect of interactivity (β = 0.385, $p < 0.05$) and AI integration (β = 0.335, $p < 0.05$) on behavioral intention were affirmed providing evidence for H5c and H5d. Lastly, playfulness was also found to significantly influence intention to continue (β = 0.247, $p < 0.05$) and H5e was supported.

5 Discussion

The study tested a comprehensive model by incorporating personal characteristics and app characteristics into the core TAM model for predicting users' intention to continue usage of mHealth applications. The results supported all the hypothesized relationships. The core TAM variables—perceived usefulness and perceived ease of use were found to have a significant impact on users' intention to use mHealth apps in the future. These findings were consistent with earlier studies [4, 49]. It can be deduced that designing the mHealth app for user-friendliness and ease of operation induces users to continue the use of the app. The results also established that users with more confidence in their abilities will find it less difficult to learn the app and its various features and therefore, are more likely to keep using the apps. The results indicated that consumers with higher personal innovativeness tend to show less resistance to new products and technologies and therefore are more

Table 1 Results of hypothesis testing

Path	Estimate	*P*
PEOU → PU (H1)	0.786	***
PU → IU (H2)	0.670	***
PEOU → IU (H3)	0.689	***
SE → IU (H4a)	0.545	***
HC → IU (H4b)	0.572	***
TA → IU (H4c)	– 0.448	***
PINO → IU (H4d)	0.393	***
VUL → IU (H4e)	0.229	***
DA → IU (H5a)	0.535	***
DS → IU (H5b)	0.474	***
IN → IU (H5c)	0.385	***
AI → IU (H5d)	0.335	***
PLY → IU (H5e)	0.247	***

PEOU Perceived Ease of Use; *PU* Perceived Usefulness; *TA* Technology Anxiety; *SE* Self-Efficacy; *VUL* Vulnerability; *HC* Health Consciousness; *PINO* Personal Innovativeness; *DA* Data Access; *DS* Data Storage; *IN* Interaction; *AI* Artificial Intelligence; *PLY* Playfulness; *IU* Intention to Continue
*** $p < 0.001$

likely to adopt new technology-based services easily compared to those with low innovativeness is consistence with the findings of Ciftci et al. [18]. Further, the study confirmed that users with higher perceived vulnerability to future health risks are more likely to take actions to mitigate such risks and therefore find mHealth apps effective in better monitoring and timely diagnosis [40].

The study also confirmed the importance of app characteristics in determining the mHealth apps adoption. The capability of the app in terms of improved data storage, management, and access facilitates planning and decision-making concerning one's health. By maintaining and tracking personal health data, health-related documents, and personal history securely the mHealth apps lend convenience, assurance, and reliability to users when it comes to personal health management. Furthermore, apps that provide features for connecting to peers and caregivers, communication, information sharing, and discussion enhance user experience and are more likely to be used repeatedly. The results also evidenced the positive influence of AI integration on behavioral intention. The users having received augmented service experience from AI-enabled mHealth apps are more likely to use these apps regularly [48]. Lastly, the study affirmed influence of playfulness on users' acceptance of mHealth apps. The apps that integrate learning, behavior modification, and joyfulness along with primary health care benefits lead to greater satisfaction and thus are more likely to be adopted [14].

6 Implications

The study makes an important contribution by extending the basic TAM model for the adoption of mHealth apps with user characteristics and app characteristics in emerging economies like India. This study identifies relevant personality traits from extant literature and examines how they influence the continuance intention of users toward mHealth apps.

There are important practical implications of the study also. The study implies that a user-friendly interface and easy-to-use features are prerequisites for user acceptance of mHealth apps. The manufacturers of mHealth apps should communicate to users about the critical role the apps can play in personal health management. Furthermore, it is important to assess user characteristics for greater acceptance of the mHealth apps. User segments with higher confidence in using the apps, lesser apprehension toward new technology, more concern and awareness for one's health, a tendency to try new things, and wary of developing major health issues soon are the most likely to use mHealth apps repeatedly. Marketers should devise strategies focusing on this segment of users to gain better results from their marketing activities. Organizing free camps or events to familiarize and train the users with apps can improve their confidence and reduce their anxiety in using these apps. Further, people participating in personal healthcare activities regularly, like going to gymnasiums and wellness centers, having periodic health check-ups, consuming preventive medicines and treatments, etc. are highly expected to use mHealth apps due to their inherent concern and pro-activeness for their health. The apps that provide for storage, access, and sharing of users' health-related data stand a better chance of being used regularly. The apps should have features to track health-related information and to share data on a real-time basis with concerned decision makers. The study indicates a need to develop mHealth apps to facilitate interaction with doctors, peers, and experts for sharing experiences, concerns, and information. Integrating AI-based elements can be another vital step to enhance the effectiveness of these apps. By forecasting health conditions and detecting serious issues in advance the mHealth apps can take healthcare services a step forward. Lastly, app managers should also include gaming and learning elements in their apps to strongly engage users with the apps.

7 Limitations

One of the major limitations of the study is that it did not measure the actual usage of the mHealth app. Instead, it collected data on users' intentions. Future studies may incorporate variables to study actual usage in the model. Future studies may investigate the moderating role of individual differences in the adoption of mHealth apps. Lastly, future studies may apply a segmentation approach to identify homogeneous segments based on consumer traits to devise targeted marketing strategies.

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