Continued intention of mHealth care applications among the elderly: An enabler and inhibitor perspective

Urvashi Tandon
Chitkara University
Punjab, India
Email: urvashiguptav@gmail.com

Myriam Ertz
Université du Québec à Chicoutimi
Chicoutimi (Québec)
Email: Myriam_Ertz@uqac.ca

Shashi
Indian Institute of Management
Sirmaur, HP, India
Email: shashikashav37@gmail.com

Abstract

Optimal healthcare provision for the elderly is increasingly possible via real-time health indicators data generated via mHealth care applications. Yet, these apps require continuous utilization, which remains problematic. This research examines gamification, usability, as well as empathetic cooperation and social interaction (ESCI) as enablers whereas inertia, sunk cost, transition cost, perceived risk, and technological anxiety are validated as inhibitors of mHealth care applications continued usage intention. Drawing on self-determination theory (SDT) and the Health IT Usability Evaluation Model (Health- ITUEM), the study also validates engagement as an influencer of continued intention. The sample comprised 643 older adults using mHealth care applications and residing in North Indian states. Structural Equation Modelling (SEM) was applied to assess and validate the hypothesized relationships. The results confirmed that usability strongly impacted engagement, followed by gamification, ESCI). Conversely, perceived risk emerged as the strongest inhibitor, followed by sunk cost, technological anxiety, and transition cost. Interestingly, Inertia had a positive and significant impact on engagement. This research is an initial endeavor to understand enablers and inhibitors of mHealth care apps concerning older adults. The model that emerged from this study would provide valuable insights by validating an all-inclusive model covering various significant issues to generate engagement of the elderly towards mHealth care apps.

Keywords: Gamification, Usability, Empathetic cooperation and social interaction, mHealth application, Inertia, Sunk cost, Transition cost, Perceived risk, Health-ITUEM, Self-determination theory.

JEL Classification: I11

1 Introduction

The rapid diffusion of health-related Information and communication technology (ICT) has substituted traditional machines with smart health monitoring products dominated by ICT (Shareef et al., 2021; Talukder et al., 2021; Papa et al., 2020; Chudhery et al., 2022). These smart products have facilitated the usage of intelligent and smart applications which are dynamic and customized as per human needs (Acampora et al., 2013). The healthcare segment has further witnessed a significant shift due to the outbreak of the COVID-19 pandemic, that made healthcare more sustainable and affordable for the masses. Users' rapid adoption of mobile and connected devices to access healthcare opens new avenues for patients to understand their own healthcare needs and be more conscious about their health (Papa et al., 2020). The strength of any innovation depends upon its design which further leads to ease of understanding. A good design satisfies users' needs and leads to a positive attitude towards innovation (Shareef et al., 2021; Tandon et al., 2021). Mobile health applications (mHealth care apps), due to the amalgamation of mobile phones and the healthcare segment, have revolutionized the entire healthcare system (Parker et al., 2013). According to the World Health Organization (WHO) Global Observatory for eHealth (GOE), mHealth is defined as "medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices" (WHO, 2011, p. 6). mHealth care apps refer to the programs that use smartphone's inbuilt tools such as a microphone, speaker, and camera to automatically detect and measure health-related behaviors (Shachak et al., 2017), applications transfer and link their health-related data with the concerned services and thus give users advice about their health condition (Shareef et al., 2021; Papa et al., 2020). mHealth care apps provide numerous health benefits and solutions to the elderly, such as reducing hospital visits and leading a healthier lifestyle (Schnall et al., 2016). These apps also provide adequate support to doctors by refining doctor-patient interactions, giving them real-time longitudinal data, which is more accurate and truthful. This, in turn, lessens the frequency of required hospital visits (Guo et al., 2012; Shareef et al., 2021; Chudhery et al., 2022). Thus, the mHealth care app may be an appropriate solution for the health-related issues of the elderly, leading to an improvement in their lifestyle as well as addressing the sustainability of current healthcare systems.

The mHealth care app market was estimated at USD 40.05 billion in 2020 and is expected to develop at a compound annual growth rate (CAGR) of 17.7% from 2021 to 2028. There has been a significant improvement in the age of the elderly due to the declining mortality. This increase in the population of elderly has led governments across the world to consider the health of the elderly as a priority and design applications for their betterment. Previous studies have also emphasized the significance of health services and support for the elderly (Schnall et al.,2016; Talukder et al., 2021; Hoque and Sorwar, 2017). mHealth care apps can keep track of one's health by comparing the previous readings with the latest ones. Additionally, the usage of these apps may improve the experience as well as the engagement of the elderly. The elderly may monitor day-to-day health-related issues like blood sugar levels, record their weight, and document symptoms of chronic diseases.

Although several mHealth care applications have recently been developed swiftly in India, and many early adopters have tried to use these applications, the adoption rate remains slow, especially among the elderly (Pai and Alathur, 2019; Chudhery et al., 2022). Most of the Indian population still has not adopted these apps to resolve their health-related issues (Sampat et al., 2020; Pai and Alathur, 2019; Iyanna et al., 2022). mHealth care apps for the elderly, if designed adequately, may lead to significant improvements in their health, which is now particularly precautious in a post-Covid era. An effective, usable mHealth care app may decrease reliance on human support and provide essential health services to the secluded elderly (Rashidi and Mihailidis, 2013). Usability has been validated as a stand-alone construct in various studies, but in this research, we have attempted to analyze the significance of usability compared to other constructs like gamification or empathetic cooperation and social interaction (ECSI). For this, the Health-ITUEM has been preferred as a rigorous theoretical framework comprising constructs necessary to understand app utility for this particular cohort. Further, the model, though validated extensively for usability-related concerns, has not been validated in the sample of the elderly, as highlighted in the study. Similarly, gamification apps motivate patients to be more concerned about their treatment (Deterding et al., 2011; Xu, 2012; Johnson et al., 2016). This, in turn, improves engagement and leads to more self-awareness and reduced apprehension towards the mHealth apps. The study by Seaborn and Fels (2015) highlighted that besides substantial studies explaining the merits and demerits of gamification, fewer empirical studies had validated gamification and its role in motivating and engaging users in non-entertainment environments. Therefore, this study validates gamification and usability along with empathetic cooperation and social interaction as enablers of engagement with mHealth care apps by focusing on the elderly.

Further, users evaluate various costs and risks associated with adopting technology. For example, as the elderly are less tech-savvy, they show resistance while switching over to new technology. Therefore, this study evaluates perceived risk (Deng et al., 2018; Klaver et al., 2021), technological anxiety (Ahmad and Khalid, 2017), inertia (Polites and Karahanna, 2012; Rahman et al., 2021), sunk and transition cost (Talukder et al., 2021) as dominant inhibitors in the adoption of mHealth care apps.

Most of the previous studies have focussed on a single aspect (enablers or inhibitors) using Davis's Technology Adoption Model (TAM) (1989). Previous researchers have also tried to understand the health behavior of older adults by validating either enablers (Moudud-Ul-Huq et al., 2021) or inhibitors (Dupuis and Tsotsos, 2018) related to various technologies. But engagement and continued intention are equally important as these are related to cognition and measure perception in general (Shareef et al., 2021). and have not been validated in-depth by researchers. This is a critical research gap concerned with the behavioral aspect of the elderly concerning mHealth care app adoption. However, it is crucial to understand that the widespread utilization of these applications depends upon users' ease of accessibility and usability. Subsequently, this research develops a model for elderly people to adopt mHealth care apps and provides practical implications to practitioners and developers to overcome the inhibitors. Due to the prevalent technology and penetration of smartphones, users devote considerable time to their smartphones and apps (Dey et al., 2019). Previous researchers also support that this high use of mobile applications may be an adequate tool leading to change in behavior of users of diverse age groups, which in turn may help address health concerns (Jacquez et al., 2016; Flaherty et al., 2016). However, a significant challenge that still prevails and needs to be addressed is inspiring the elderly the continued use of mHealth care apps (Michie et al., 2017). There is limited research on factors that simultaneously encourage the elderly to use mHealth care apps or inhibit their continued usage. Such knowledge is required not only to improve the design of apps but also for related interventions to sustain a healthier lifestyle. The sparse literature in this area motivated us for an in-depth quantitative study aimed at exploring both inhibitors and enablers simultaneously. This research validates the relationship between engagement and continued intention, which previous studies have ignored. Based on these gaps, this research develops a model for elderly people to adopt mHealth care apps and provides practical implications to practitioners and developers to overcome the inhibitors.

Therefore, the study contributes theoretically to the mHealth care ecosystem in the context of developing countries. It goes beyond what previous studies have highlighted by either validating enablers or inhibitors. Practitioners will gain an understanding of factors that inhibit the continued use of mHealth care apps. This research will also empower professionals in designing sophisticated applications with additional functions (e.g., chatbots) for the elderly so that the latter can use such apps in their daily routine for monitoring routine health check-ups. The research questions are thus as follows:

> RQ1) What is the role of gamification as well as empathetic cooperation and social interaction (ESCI) in improving the engagement of the elderly towards mHealth care apps?
>
> RQ2) What is the impact of usability on customer engagement concerning mHealth care apps among the elderly?
>
> RQ3) What are various inhibitors which hinder the usage of mHealth care apps among the elderly?

In order to cover all the broader themes related to mHealth care apps, we extracted relevant literature about the topic. The search strategy was carried out using the major academic databases, including Google Scholar, ScienceDirect, Emerald, Springer, Taylor & Francis, SAGE, and PubMed. These databases are preferred search engines for conducting research in ICT and health sciences. We focused on scientific articles, book chapters, and conference proceedings, as well as publications written in English. Only papers published between January 1st, 1985, and June 30th, 2022, were included. Besides, we used the following specific keywords and searched items to extract topical publications: “e-health,” “eHealth,” “Gamification,” “mHealth app,” “mHealth care apps,” “digital care,” “Health IT usability evaluation model,” and “Health-ITUEM.”

The remainder of the manuscript is structured as follows: the next section discusses various theories employed to validate the objectives of the present study. This is followed by hypotheses development and research methodology, including scale development, sample selection, and data collection. Statistical analysis is presented, followed by a discussion section and implications (both managerial and theoretical). The article ends with the limitations section.

2 Theoretical framework

2.1 The dual-factor model of technology adoption

The continuing execution and implementation of any technology depend upon a wide array of factors where enablers and inhibitors play a significant role in continued intention (Cenfetelli, 2004; Guo et al., 2012; Talukder et al., 2021). This research, in order to explore deep insights into the factors influencing the adoption of mHealth care apps, validates both enablers and inhibitors and arrives at an all-inclusive, comprehensive model. The enablers may be defined as "factors which enhance usage when they are present, but at the same time, do not necessarily hurt usage when they are not available; in contrast, the inhibitors refer to the factors that hurt usage when they are present, but do not necessarily enhance usage when they are not available" (Cenfetelli 2004, p.16). Yet, both enablers and inhibitors play a significant role in the adoption of any technology (Tsai et al., 2019). While interacting with innovations and technologies, the elderly may get perplexed and thus hesitate to adopt them. More specifically, when the product is related to health and fitness, users are apprehensive about trying novel apps (Tsai et al., 2019). Unfortunately, there is a dearth of research studies addressing the adoption of mHealth care apps by considering the elderly in India. The population of elderly in India has increased, and further, the migration of their children to foreign countries has made them isolated and socially insecure. Secluded living after the demise of one partner has further added stress, and there is thus a crucial need to improve upon the adoption and penetration of the latest technological gadgets so that the elderly can perform their routine health check-ups without any hassle.

2.2 The Health-ITUEM

The usability of any technology includes the extent to which any application can accomplish a task through interaction and exchange of information (Nielsen, 1994). The efficient usability of any application improves interaction with it, which further enhances its performance. Brown et al. (2013) validated the appropriateness of Health-ITUEM for evaluating mobile health technology. Health-ITUEM was derived by taking support from the technology acceptance model (TAM) (Davis, 1989) and ISO 9241-11. Health-ITUEM examines usability by Error prevention, Completeness, Memorability, Information needs, Flexibility/Customizability, Learnability, Performance speed, Competency, and Other outcomes. This study also adopted the Health-ITUEM model based on the work of Brown et al. (2013). Previous researchers have validated Health-ITUEM to understand HIV (Schnall et al., 2015), obstructive sleep apnea (OSA) (Al-Mardini et al., 2014), and various complex chronic diseases (Hamine et al., 2015).

Health-ITUEM provides a rigorous theoretical framework comprising constructs necessary to understand app utility for a particular cohort. This model is expedient in understanding app-related concepts and thus has been taken as a theoretical underpinning in this research. Further, the model, though validated extensively for usability-related concerns, has not been validated in the sample of the elderly. Therefore, it is of utmost significance to validate the available usability frameworks for elders because of their inhibitions regarding the usage of mHealth care apps.

2.3 Self-determination theory

Self-determination theory (SDT) (Deci and Ryan, 1985), is very useful to understand the adoption of any technology as it emphasizes those motivating factors leading to the adoption of technology. SDT explains how individuals control their psychological needs to indulge in a particular behavior. SDT is based upon three psychological needs, i.e., competence, autonomy, and relatedness (Gagné & Deci, 2005). The fulfillment of these needs leads to contentment and satisfaction. These three needs are termed intrinsic motivators (Deci and Ryan, 1985). Intrinsic motivation is described as "the natural inclination towards assimilation, mastery, spontaneous interest, and exploration, which are essential to cognitive and social development. It represents a principal source of enjoyment and vitality throughout life" (Deci and Ryan, 2000, p. 70). Extrinsic motivation may be defined as "the performance of an activity to attain some separable outcome" (Deci & Ryan, 2000, p. 71). Extrinsic motivation focuses upon “instrumentality” where some external mechanism controls behavior. These extrinsic and intrinsic motivators stimulate individuals to perform specific actions. An in-depth analysis of various extrinsic and intrinsic motivators reveals that mHealth care apps boost users' concern for their health, which may help them engage with those apps. Understanding users’ motivation to stay healthy can be instrumental in predicting the mHealth care app's continued intention. Thus, SDT can be a useful framework for this study. An intrinsically motivated consumer has more self-control over his behavior and is more self-determined. Though examined in diverse arenas, the theory has not been explored extensively to understand users’ engagement with mobile apps. mHealth care apps provide notably countless motivating features to create utilitarian health-related experiences and enhance engagement leading to continued intention.

SDT has been applied in the literature to comprehend the significance of *gamification* in appealing to the customer. Previous research (e.g., Högberg et al., 2019; Garett and Young, 2019) highlighted that obtaining points, badges, or other virtual rewards strengthens users’ to get themselves involved in gamifying activities. A few researchers suggested that these rewards may get converted into intrinsic motivators (Seaborn and Fels, 2015; Hofacker et al., 2016; Kim and Ahn, 2017; Shi and Cristea, 2016). Olsson et al. (2016) and Kim and Ahn (2017) suggested that gamification improves engagement with an application, which could impact intrinsic motivation. Gamified health apps tend to involve users to get engaged in their well-being. This makes them cognizant of their condition, especially when they are old. The unending feedback the gamified content provides is similar to that provided by the physician or healthcare practitioner, which may strengthen the healthy choice. Gamified activities also allow users to compare their health progress against benchmarks (Garett and Young, 2019).

Similarly, older adults often appraise the usage of any particular technology concerning cost and time (Thibaut and Kelley, 2008). The versatility of mobile apps motivates the elderly to adopt this innovation. Previous scholarly research covering man-machine interactions admits that internal and external motivations significantly improve continued intention (Shareef et al., 2011; Tandon et al., 2021). Interactions with applications provide a persuasive environment leading to affection, friendliness, and motivation (Heerink et al., 2010; Dwivedi et al., 2019). In addition, previous research studies (Shareef et al., 2019; Dwivedi et al., 2019) acknowledged that the elderly, to some extent, feel emotionally disconnected from society and thus strongly desire to interact with someone (Korber et al., 2018). Therefore, we argue that the desire for empathetic and social interaction is a strong motivator, as suggested by SDT, and could be a strong predictor of customer engagement leading to continued intention.

3 Hypotheses Development

3.1 Usability

A few previous studies have empirically analyzed the mHealth care apps (Schnall et al., 2016; Brown et al., 2013), but the usability assessment of mHealth care technology has been under-explored so far. Low-resolution screens and the inability to operate without a keyboard pose severe challenges to the elderly to use mHealth care apps. Furthermore, difficult interfaces, complicated operating procedures, and incomplete information suspend workflow, which delays the procedure leading to errors (Kossman et al., 2008; Brown et al., 2013). This may further dissatisfy the elderly, and they may quit using the app. Therefore, mHealth care apps should be powerful and capable of providing health-related advice outside the clinics. The existing body of literature validates usability as a key construct to comprehend HIV (Schnall et al., 2015), obstructive sleep apnea (OSA) (Al-Mardini et al., 2014), and various complex chronic diseases (Hamine et al., 2015). In an attempt to capture the facets of usability, Brown et al. (2013) conducted focus group discussions and showed that usability is a multidimensional construct encompassing error prevention, completeness, memorability, information needs, flexibility, learnability, performance speed, and competency. This study considered error prevention, completeness, memorability, learnability, and customization to capture usability (Appendix 1). These sub-constructs were selected based on their inter-rater reliability (ranging from 90-100 percent) (Brown et al., 2013). Therefore:

H1: Usability is a multi-dimensional construct significantly predicted by error prevention, completeness, learnability, memorability, and customization.

H2: Usability has a positive impact on mHealth care app engagement.

3.2 Gamification

Gamification is "a process of enhancing services with affordances to invoke gameful experiences and further behavioral outcomes" (Hamari et al., 2014). Gamification is also considered as the use of game design elements in non-game contexts (Deterding et al., 2011a). Game design, mechanics, and feedback are considered vital aspects of gamification. Furthermore, Werbach and Hunter (2012) suggested various gamification applications like "avatars," "badges," "content unlocking," "gifting," "leader boards," "points," and so on. Past literature has shown the potential of gamification in the context of health behavior change (Deterding et al., 2011b; Xu, 2012; Seaborn and Fels, 2015). Nacke and Deterding (2017) emphasized that such gamification features needs to be harnessed for improving user experience and engagement across diverse industries. In the specific area of healthcare, Johnson et al. (2016) validated the significant impact of gamification on health and well-being. Von Bargen et al. (2014) suggested that gamified content may be incorporated within medical education programs to improve customer engagement. Gamified applications may thus instigate older adults to engage with the applications, feel concerned about their treatment, and report symptoms to their health practitioners on time. Therefore, it may be concluded that the gamified applications improve self-introspection, abridge apprehensions towards treatment, and thus increase engagement with mHealth care apps. Therefore:

H3: Gamification has a positive impact on mHealth care app engagement.

3.3 Empathetic cooperation and social interaction

Shareef et al. (2021) validated empathetic cooperation and social interaction, which may be defined as "the level of scope and availability of sympathetically and socially interactive service that develops the perception of esteemed social involvement" (p. 162). Elderly people evaluate any application regarding time spent, social value, utilitarian, and hedonic benefits. To continue their usage, the elderly expect higher rewards and satisfaction from technological applications (Shareef et al., 2019). An environment of social interaction and hedonic motivation that helps engage users toward a particular application has also been highlighted in previous studies (Dwivedi et al., 2019; Acampora et al., 2013; Heerink et al., 2010). Researchers have stressed that older adults, who are emotionally disconnected from active society, indicate a strong desire to interact with caretakers (Korber et al., 2018; Schaefer et al., 2016). This desire for psychological affection may be a strong predictor of customer engagement and thus if apps demonstrate desirable properties pertaining to emphathetic cooperation and social interaction, they may be valued by the elderly who will thus be more prone to engage with them. Therefore:

H4: Empathetic cooperation and social interaction positively impact mHealth care app engagement.

3.4 Technological anxiety

Technological anxiety signifies consumers' ability to use any technological application (Shareef et al., 2021). As the elderly own fewer technical skills, the anxiety of learning and using a novel application may lessen their interest and lead to change resistance. Thus, mHealth care apps specially designed for older adults need to reduce technical content as these people may have limited understanding of any technological application and thus behave with great caution (Ahmad and Khalid, 2017). Talukder et al. (2021) and Shareef et al. (2021) emphasized that technological anxiety may negatively impact the use of technological applications. Tsai et al. (2019) specifically confirmed the negative impact of anxiety on customer engagement. Therefore, we argue that if older adults are scared or apprehensive of mHealth care apps, it may negatively influence their continued usage. Therefore:

H5: Technological anxiety has a negative impact on mHealth care app engagement.

3.5 Perceived risk

Perceived risk has been considered a significant factor inhibiting the usage of any technology, in general, and of healthcare-specific technology, in particular, due to maximum online transactions (Dwivedi et al., 2019; Shareef et al., 2021). Perceived risk may be explained as the ambiguity associated with using any application beyond the information manager's control associated with e-health service (Schnall et al., 2015). mHealth care app users consider the app security important and feel at risk when their personal health information is not verified. After reviewing scholarly literature on perceived risk (Featherman and Pavlou, 2003; Deng et al., 2018; Klaver et al., 2021), it could be articulated that perceived risks hinder the acceptance and adoption of any application, especially by older adults. The elderly fear the risks of being exposed to incorrect health recommendations and of revealing sensitive information, which refrains them from using mHealth care apps. Termination of perceived risk accompanying usage of mHealth care apps may increase the elderly’s trust in these applications. Hence, perceived risks lead to an antagonistic attitude, thereby discouraging the elderly to use any technological innovation. Therefore:

H6: Perceived risk has a negative impact on mHealth care apps engagement

3.6 Inertia

Older adults frequently evaluate any application's costs and benefits before actually switching to it. Samuelson and Zeckhauser (1988) insisted that users are more concerned about losses than gains and termed it loss aversion. Thus, users tend to display a status quo bias (SQB) in a particular decision (Kahneman et al., 1991). Users tend to avoid making a decision, and this aversion is called inertia (Samuelson and Zeckhauser, 1988). Past studies have established inertia as the combination of resistance and maintaining the status quo (Polites and Karahanna, 2012; Rahman et al., 2021) and considered it as s dominant factor for avoiding a decision. Lucia-Palacios et al. (2016) described inertia as abandoning a situation regardless of the substitutes and benefits of a particular technology. To be precise, Inertia is a firm belief and continuation of the status suo and leads to avoiding new technological applications (Tsai et al., 2019). Inertia could thus be an inhibitor in the usage of mHealth care apps, especially among older adults, because the elderly circumvent innovation due to inertia (Talukder et al., 2021). Indeed, the elderly might fail to understand the advantages of mHealth care apps and may prefer visiting physicians rather than relying upon these applications. Therefore:

H7: Inertia has a negative impact on mHealth care app engagement.

3.7 Sunk Cost

Another leading notion associated with the status quo bias is sunk cost, which means users’ mitigated perception of application use due to the previous obligation to use another system (Hsieh, 2016). Hsieh (2016) suggested that sunk cost happens when the users give up and recede from the ideal decision because they are entirely under the influence of sub-optimal ways of doing. This is manifest when users justify the use of existing applications or current ways of doing because of the perceived investment required to purchase and adopt the new application (Tsei et al., 2019). Past studies insisted that sunk costs delay decision-making as adopting new technology altogether may entail some investiment through learning (Talukder et al., 2021; Tsei et al., 2019; Cunha & Caldieraro, 2009; Kim and Kakkanhalli, 2009). Yet, the higher the investment, the stronger the resistance from the eldery so that they resist the continued usage of mHealth care apps.. Therefore,:

H8: Sunk costs have a negative impact on mHealth care app engagement.

3.8 Transition Cost

Correspondingly, transition costs also have a vital effect on adopting mHealth care apps. Transition costs are defined as the "perceived disutility a user would incur in switching from SQB [status quo bias] to a new IS [information system]. These costs include transient expenses and permanent losses associated with change" (Kim and Kankanhalli, 2009, p. 568). The study by Hsieh (2016) argued that transition costs have a negative impact on users' attitudes toward healthcare applications. The elderly may indicate strong resistance if they feel that learning an application is both time-consuming and requires lots of effort. As a result, the elderly may prefer to stick to their previous system (Tsai et al., 2019). Talukder et al. (2021) emphasized that transition costs hinder the adoption of any technology, especially among the elderly, as this cohort has spent a major part of their life without these technological applications. Therefore, transition costs may be a vital hindrance factor with regard to mHealth care apps among this generation. Therefore:

H9: Transition costs have a negative impact on customer engagement.

3.9 Engagement and Continued Intention

Most elderly prefer visiting a health care practitioner rather than relying on mHealth care apps (Chib et al., 2015). However, motivating the elderly may facilitate their emotional and spiritual outcomes, leading to engagement with a particular behavior (Bitrián et al., 2021). Kim and Baek (2018) insisted that highly engaged users with mobile apps continue using them frequently and perform day-to-day activities. The results of past studies also indicated a significant association between engagement and continued use intention (Kim and Baek, 2018). A past study by Wu et al. (2018) also empirically validated that engagement results in greater intention to use a particular technology. Therefore:

H10: Engagement with the mHealth care apps has a positive impact on continued intention.

The resulting conceptual framework is shown in Figure 1.

[Insert Figure 1 here]

4 Research methods

4.1 Participants

This study was carried out on the population of elderly residing in North Indian states. The number of elderly has increased in recent decades, with around 34 million elderly persons recorded in 2021 over the population census of 2011.

4.2 Sampling Strategy

The proper sample size selection is very important when performing Structural Equation Modeling (SEM). Specifically, Kline (2015) recommended that the N:Q ratio should be 20 to 1 or 20 observations (participants) for each estimated parameter in the model. The total number of variables also determines the sample size for the proposed study while a larger sample size reflects the generalizability and reliability of the results. Thus, to improve the generalizability of the sample, we collected a sample of 643 older adults.

We used a non-random sampling approach in the study because this method is appropriate in the India's specific social and cultural context. In fact, in India, personal relationships are preferred over professional ones (Dubey et al., 2019). Further, non-probability sampling techniques have been adequately applied by previous studies on the elderly (Talukder et al., 2021; Lázaro-Pérez et al., 2020). The elderly we approached possessed at least a bachelor's degree and had experience using mHealth care apps. We further requested them to suggest a few of their peers, relatives, and friends who had experience with mHealth care apps.

4.3 Instrument Development

Scale items of various constructs used in the study were derived from previous studies. The scale items of usability were extracted from Yen (2010) and Nielsen (1994). These items were modified and improved to address the specific tasks performed by the elderly by using mHealth care apps. The items of gamification were extracted from Soni et al. (2021), while the study of Shareef et al. (2021) lent support for developing the scale items of the construct "Empathetic cooperation and sympathetic interaction." The customer engagement and repurchase intention scale items were taken from previous technology adoption studies (i.e., Soni et al., 2021; Dwivedi et al., 2019). Again, these scale items were revised and reframed for comprehensive theoretical explanations to fit the mHealth care app adoption context. The initial questionnaire was drafted following a pilot study consisting of a focus group with three professors having technical knowledge of virtual mediums - and preferably using mHealth care apps - and six older adults between the age group of 65-70 using mHealth care apps. A pretest was also conducted among fifty older people to maintain clarity and consistency. The pretest ensured that the questionnaire is logically consistent and that the proposed meaning of scale items is clear to the elderly. Appendix 2 displays the scale items of the constructs. Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) was preferred as it is easy to comprehend for the elderly (Shareef et al., 2021). The survey was initially developed in English but was later translated into the native language of the respondents. The questionnaire was again revised to certify that the translated scale items corresponded with the original ones.

4.4 Data Collection

As the study is based on the elderly, respondents above 60 years old were considered for this study. Only those elderly respondents who had used mHealth care apps at least once in their lifetime were eligible. The invitation assured privacy protection, and that responses would be used only for academic purposes. To control social desirability bias, respondents were requested to respond naturally and honestly (De Leeuw, 2008). To moderate the bias caused by non-probability sampling techniques, we made participation in the survey voluntary, and no personal information was sought, thereby confirming the anonymity of responses. Data were collected with a mixed-method approach consisting of a web-based survey and face-to-face interviews during field visits. Due to the effective data collection and the ability to preserve respondent privacy, a web-based survey was undertaken. This approach aids in lowering (Andrews et al., 2003). Another benefit of an online survey is that respondents complete it thoroughly, giving the researcher complete responses and lowering the amount of missing data (Andrews et al., 2003). Additionally, an online survey saves results into a data file, limiting potential transcription problems. North Indian states were selected due to the socioeconomic condition of these states. Further, these states are considered safe for the elderly (NCRB Report, 2018).

4.5 Preliminary quality checks and Common method bias

Several preliminary checks were carried out to determine the data quality before analyzing the data. Initially, we checked for the missing values and found that missing values were not an issue in the study as these were less than 3 percent (Vesin et al., 2013). Therefore, the missing data were replaced by the arithmetic mean in accordance with the simple imputation method (Byrne, 2010).

Non-response bias: Non-response bias was mitigated by contacting more respondents through personal contacts, as suggested by Dillman (2007). Furthermore, the respondents were assured of confidentiality and use of their responses for academic purposes only. This motivated them to respond spontaneously and openly. This procedure also helped us to mitigate social desirability bias (de Leeuw, 2008). Importantly, respondents were classified as early (who replied within three weeks) and late respondents (who responded after three weeks). A three weeks cut-off was preferred as the response rate was reduced after three weeks. The previous study by Chen et al. (2003) also categorized early respondents as those who returned the survey questionnaire within 3-4 weeks. Further, early and late responses were compared using means and standard deviation, and the results indicated almost similar values, indicating the absence of non-response bias (Table 1).

Common method bias: Harman's one-factor test was also conducted to assess CMB (Harman,1976). This procedure involves "constraining all the scale items into a single unrotated factor in exploratory factor analysis, with the assumption that the presence of CMB is indicated by the emergence of either a single factor or a general factor accounting for the majority of covariance among measures" (Podsakoff et al. 2003, p. 889). The results indicated a 39.46% variance below the recommended value.

Table 1: Non-response bias

Variables	Early Respondents		Late Respondents	
	M	SD	M	SD
Continued Intention	2.950	1.040	3.013	1.084
Engagement	3.207	0.987	3.218	1.047
Technological Anxiety	3.316	0.698	3.324	0.711
Perceived Risk	3.321	0.849	3.290	0.912
Sunk Cost	2.901	0.861	2.896	0.886
Transition Cost	3.154	0.970	3.134	1.053
Inertia	2.995	1.048	3.076	1.066
Completeness	3.241	0.971	3.234	0.998
Learnability	3.145	0.985	3.338	0.898
Memorability	3.430	0.886	3.703	0.795
Customization	3.013	1.015	3.068	1.045
Gamification	3.311	0.840	3.454	0.816
Empathetic Cooperation and Sympathetic Interaction	3.188	0.881	3.226	0.898

M: Mean, SD: Standard Deviation

4.6 Demographic details

A total of 643 respondents participated in this survey. Of the total respondents, 61 percent were males, and 39 percent were females. Most of the respondents were post-graduates (43.22 percent), and 66.71 percent of them have used the mHealth care apps for 1-3 years. Details of the respondents are given in Table 2.

Table 2: Demographic Profile

Demographic Characteristic N=643	**Response**	**Percentage**
Gender		
Male	392	61
Female	251	39
Education Qualification		
Bachelor Degree	130	20.28
Master Degree	278	43.22
Doctorate Degree	235	36.50
Age		
61-65	285	44.32
66-70	205	31.89
Above 70	153	23.79
mHealth care apps usage		
Less than 1 year	125	19.44
1-3 years	429	66.71
More than 3 years	89	13.84
Preferred mHealth care apps use		
For up-to-date information	70	10.89
For calling the doctor	203	31.57
For weight and diet management	214	33.28
For meditation and stress relief	156	24.26

5 Data analysis

5.1 Reliability and Validity

To evaluate the reliability and validity of the measurement model, a confirmatory factor analysis (CFA) was carried out with all the scale items of dependent and independent variables. A few items, such as error prevention (ERR1, ERR2, and ERR3), GAM1 (Gamification), and TEC4 of Technology barriers, were rejected due to poor factor loadings. The CFA (Table 3) designated that the standardized loadings of all the included variables are significant. The constructs further demonstrate evidence of validity (i.e., significant and high standardized loadings as well as average variance extracted > 0.50 on all occasions), internal consistency (i.e., all composite reliability values > 0.70 on all occasions), and discriminant validity (i.e., the AVE estimate of each construct is larger than the squared correlations of this construct to any other construct) (Fornell and Larcker, 1981) (see Table 4).

Table 3: Measurement Model

Variables	Items	Std. Estimate	S.E.	C.R.	Average Variance Extracted	Composite Reliability
Completeness	COM1	0.78				
	COM2	0.817	0.063	18.032	0.643	0.878
	COM3	0.827	0.058	18.306		
	COM4	0.783	0.057	17.102		
Learnability	LRN1	0.848				
	LRN2	0.654	0.04	14.837	0.667	0.888
	LRN3	0.893	0.042	23.911		
	LRN4	0.85	0.044	21.953		
Memorability	MEM1	0.776				
	MEM2	0.675	0.066	12.915	0.551	0.786
	MEM3	0.771	0.067	14.632		
Customization	CTM1	0.835				
	CTM2	0.821	0.047	20.683	0.711	0.908
	CTM3	0.87	0.048	22.768		
	CTM4	0.847	0.048	21.746		
Gamification	GAM2	0.638				
	GAM3	0.594	0.091	10.773		
	GAM4	0.845	0.114	14.299	0.572	0.868
	GAM5	0.849	0.104	14.341		
	GAM6	0.817	0.104	13.943		
Empathetic Cooperation and Social Interaction	ECS1	0.797				
	ECS2	0.716	0.059	15.893		
	ECS3	0.784	0.043	21.806	0.584	0.906
	ECS4	0.876	0.068	20.869		
	ECS5	0.814	0.061	18.832		
	ECS6	0.819	0.062	18.989		
	ECS7	0.477	0.052	9.884		
Engagement	ENG1	0.855				
	ENG2	0.946	0.038	27.425	0.808	0.927
	ENG3	0.894	0.039	24.773		
Continued Intention	CII1	0.893				
	CII2	0.949	0.032	31.214	0.835	0.938

	CII3	0.899	0.034	27.695		
Technological Anxiety	TEC1	0.784				
	TEC2	0.718	0.058	11.507	0.577	0.804
	TEC3	0.776	0.069	11.24		
Perceived Risk	PRI1	0.797				
	PRI2	0.783	0.063	16.914	0.598	0.856
	PRI3	0.732	0.062	15.599		
	PRI4	0.78	0.062	16.851		
Sunk Cost	SUN1	0.624				
	SUN2	0.806	0.106	12.56	0.532	0.771
	SUN3	0.746	0.104	11.958		
Transition Cost	TRA1	0.853				
	TRA2	0.819	0.05	20.138	0.677	0.863
	TRA3	0.795	0.052	19.229		
Inertia	INR1	0.862				
	INR2	0.839	0.043	21.964	0.771	0.91
	INR3	0.93	0.044	26.125		

Table 4: Correlation Matrix

	ENG	COM	LRN	MEM	CTM	GAM	ECS	CII	TEC	PRI	SUN	TRA	INR
ENG	***0.898***												
COM	.620**	***0.801***											
LRN	.616**	.687**	***0.816***										
MEM	.459**	.591**	.502**	***0.742***									
CTM	.662**	.524**	.594**	.544**	***0.843***								
GAM	.619**	.626**	.642**	.558**	.643**	***0.756***							
ECS	.584**	.574**	.569**	.569**	.533**	.534**	***0.764***						
CII	.548**	.686**	.680**	.432**	.622**	.676**	.643**	***0.913***					
TEC	-.282**	-.264**	-.247**	-.197**	-.279**	-.272**	-.255**	-.300**	***0.759***				
PRI	-.463**	-.527**	-.522**	-.366**	-.555**	-.460**	-.507**	-.485**	.534**	***0.773***			
SUN	-.448**	-.490**	-.507**	-.356**	-.518**	-.486**	-.515**	-.466**	.375**	.680**	***0.729***		
TRA	-.528**	-.593**	-.541**	-.372**	-.619**	-.515**	-.573**	-.550**	.466**	.667**	.671**	***0.822***	
INR	.572**	.597**	.557**	.324**	.637**	.461**	.552**	.605**	.037	-.281**	-.249**	-.346**	***0.878***

**. Correlation is significant at the 0.01 level (2-tailed). ENG: Engagement, COM: Completeness, LRN: Learnability, MEM: Memorability, CTM: Customization, GAM: Gamification, ECS: Empathetic Cooperation and Social Interaction, CII: Continued Intention, A TEC: Technological anxiety, PRI: Perceived Risk, SUN: Sunk Cost, INR: Inertia TRA: Transition Cost

Table 5: Structural Model

			Std. Estimate	S.E.	C.R.	P	Result
Completeness	→	Usability	0.89				Supported
Learnability	→	Usability	0.872	0.038	25.454	***	Supported
Memorability	→	Usability	0.638	0.043	14.698	***	Supported
Customization	→	Usability	0.924	0.038	28.927	***	Supported
Usability	→	Engagement	0.56	0.091	7.359	***	Supported
Gamification	→	Engagement	0.129	0.06	2.703	0.01	Supported
Empathetic cooperation and social interaction	→	Engagement	0.169	0.077	2.568	0.01	Supported
Sunk cost	→	Engagement	-0.345	0.053	-6.189	***	Supported
Transition cost	→	Engagement	-0.203	0.049	-3.63	***	Supported
Technological anxiety	→	Engagement	-0.225	0.036	-6.339	***	Supported
Inertia	→	Engagement	0.4	0.029	11.262	***	Not-Supported
Perceived Risk	→	Engagement	-0.581	0.04	-14.476	***	Supported
Engagement	→	Continued Intention	0.696	0.038	19.689	***	Supported
CMIN/df=3.126, GFI=0.945, AGFI= 0.923. NFI=0.958, RFI=0.936, IFI=0.918, TLI=0.982, CFI=0.932, RMSEA= 0.065							

5.2 Structural Model

After achieving adequate results from the measurement model, the theorized model was evaluated with all the independent and dependent variables (Table 5 and Figure 2). The satisfactory fit indices suggest that the theorized model is a good representation of the structure underlying the observed data (CMIN/df=3.126, GFI=0.945, AGFI= 0.923. NFI=0.958, RFI=0.936, IFI=0.918, TLI=0.982, CFI=0.932, RMSEA= 0.065), as suggested by Hair et al. (2010). All four sub-constructs of usability emerged significantly, thereby supporting H1. Customization emerged as the strongest predictor of usability (β= 0.924, P=0.000), followed by completeness (β= 0.89, P=0.000) and learnability (β= 0.872, P=0.000). Memorability had a lower loading compared to the other constructs (β= 0.638, P=0.000). Further, usability had the highest impact on engagement, thus supporting H2. Although less impactful, gamification (β= 0.129, P=0.010) and empathetic cooperation and social interaction (β= 0.169, P=0.000) were also significantly related to engagement, thus supporting H3 and H4.

Among the inhibitors, perceived risk emerged as the strongest inhibitor (β= -0.581, P=0.010), followed by sunk cost (β= -0.345, P=0.000), thereby lending support to H6 and H8. In addition, technological anxiety (β= -0.225, P=0.000) and transition cost (β= -0.203, P=0.010) were directional and significant, thus validating H5 and H9. Surprisingly, Inertia exerted a positive and significant impact. Therefore, H7 is rejected. Lastly, the results highlighted the significant contribution of engagement (β= 0.696, P=0.000) in improving continued intention towards mHealth care apps, thus supporting H10.

6 Discussion

This study validates the enablers and inhibitors of mHealth care apps among older adults. The study also analyses the impact of enablers and inhibitors on engagement, which further influences continued intention.

In answer to the first RQ, all four sub-constructs of usability emerged significantly, namely customization, memorability, learnability, and completeness. However, customization and completeness contributed significantly and depicted a stronger impact than learnability and memorability. These findings align with previous studies (Schnall et al., 2016; Brown et al., 2013). Compared to gamification and ESCI, Usability indicated a strong positive impact on engagement. This analysis revealed that mHealth care apps exclusively for the elderly need to give substantial attention to their needs and requirements. In addition, these apps must be easy to use, learn and understand. As the healthcare system is laden with suboptimal outcomes and raised costs (Schnall et al., 2016; Iyanna et al., 2022), therefore, adoption of untested apps may lead to confusion and limit the usage of mHealth care apps among the elderly, further leading to antagonistic consequences.

Further, the results indicated that gamification and ESCI also improved engagement toward mHealth care apps. These results demonstrate that those applications which are interactive and motivating help in generating frequent interactions with the system. Previous studies have also emphasized the significance of gamified content in increasing the usage of mHealth care apps (Deterding et al., 2011; Xu, 2012; Johnson et al., 2016; Clark et al., 2016). However, the elderly may not use apps at the preliminary stage due to perceived risk and technological anxiety.

The elderly and disabled people are more reliant on personal ability and are enthusiastic about committing to those people that reveal a caring attitude towards them which fills their secluded life with some care and entertainment (Korber et al., 2018; Schaefer et al., 2016; Shareef et al., 2021). Therefore, it could be concluded that the caring feelings of the machines may also promote the ability to use any application frequently. Adequate focus on these would help app developers design effective and engaging mobile applications as well as the finest health intercession procedures (Eldredge et al., 2016; Talukder et al., 2020).

Some interesting findings were noticed while analyzing inhibitors of mHealth care app adoption among the elderly. Perceived risk emerged as the strongest inhibitor of the adoption of mHealth care apps, and this finding is consistent with recent studies (Shareef et al., 2021; Talukder et al., 2021; Deng et al., 2018; Klaver et al., 2021).

Further, sunk and transition costs also emerged as significant deterrents to adopting mHealth care apps. This finding also aligns with previous studies (Talukder et al.,2021; Tsai et al., 2019; Cunha and Caldieraro, 2009). It may be inferred that inconvenient and complicated systems discourage the elderly from switching to any novel application. Thus, they prefer to use existing applications instead of novel applications. Surprisingly, inertia had a positive relationship with engagement. The results of this research thereby provide limited support to the existing literature where inertia aligns with resistance (Nel and Boshoff. 2021; Rahman et al., 2021; Polites and Karahanna, 2012). The intuition behind the positive and significant relationship emerging between Inertia and engagement can be considered by observing that the elderly though they understand the utility of health apps, still feel apprehensive about using th these apps. Another probable reason could be that the elderly may be more concerned about the risk related to security instead of SQB. This may indicate because of the Covid-19 pandemic, the elderly changed their status quo bias and became ready to switch to mHealth care apps but still show confidence in conventional health check-up methods. They may use mHealth care apps but still prefer conventional doctor check-ups to verify the information and interact.

7 Implications of the Study

7.1 Theoretical Implications

This research provides clear and vital implications for academicians trying to get further insights on the behavior of the elderly towards continued intention towards mHealth care applications. The findings help us conclude that mHealth care apps may be logically described by integrating usability, gamification, and ESCI. The model provides useful insights by validating enablers as well as inhibitors, thereby validating an all-inclusive model covering various significant issues to generate engagement of the elderly towards mHealth apps. The validation of the enabler-inhibitor approach, SDT, and Health-ITUEM-based model adds to the existing domain of knowledge, where most of the previous studies are based on the TAM (Davis, 1989). This conceptual framework is supported by previous research related to technology adoption (Bagozzi, 2017; Tandon et al., 2021).

The elderly living in solitary houses, especially after their life partner's death, need to understand the functioning of apps without human support. Therefore, applications must be easy to understand, navigate, and function. Apps need to be compassionate and generous with an additional level of attachment and interaction. Apps encourage people to engage enthusiastically in a particular application. Gamified apps provide an additional benefit in measuring progress against various health benchmarks, thus improving the quality of life.

Users search for comparative benefits while adopting any new technology (Rashidi and Mihailidis, 2013) and are equally concerned about the risk of adopting new technology. This study, in addition to enablers, also validates inhibitors providing a holistic view of the research. Perceived risk emerged as the strongest inhibitor, and thus, it may be determined that the elderly in our sample were more worried about their well-being and the security of their personal information (Cenfetelli, 2004; Guo et al., 2012; Heish, 2016). Therefore, it may be concluded that though the elderly have gained a lot of information regarding mHealth care apps due to COVID-19, they still need human intervention due to the presence of risk factors like perceived risk, sunk cost, and transition costs that emerged significantly in this study also. These risks must be validated further to understand overarching issues in adopting mHealth care apps by the elderly. Additionally, these risks may be of significance for academicians and warrant further research.

7.2 Practical implications

This research also provides significant practical implications for app developers and marketing managers designing mHealth care apps - especially those targeted to the elderly - by identifying enablers and inhibitors that lead to engagement. mHealth care app designers must prioritize usability issues like customization, completeness, learnability, and memorability. The study highlights how critical it is to have an intuitive design approach where features and services are easier to discover and use and have satisfaction related to app quality. The visual characteristics of the mHealth care applications are the most important aspect of this ecosystem. Thus, these characteristics can further aid the makers of these devices and applications in considering critical features like usability as the most important user need. The elderly, especially those with some specific disability, must interact with these applications with limited information. Therefore, designers must use language which is easy to comprehend. As unaccompanied and disabled elderly use these applications single-headedly, they need full operational knowledge of the system. Ease of navigation, interaction, and customization of their health experience may help them to use an app frequently. Further, the significance of game elements in designing the applications can not be ignored. Adding games to the application makes it more engaging and enjoyable. Customized game elements catering to the needs of the elderly may require social interaction, motivating them to use mHealth care apps more frequently. Therefore, designing an effective system to overcome these challenges is paramount. To improve engagement and continuous intention to use the application, both technological aspects in the form of usability, social benevolence, and thought process of the elderly need to be unified while designing an acceptable mHealth care app.

Additionally, the need for kindness, generosity, and societal interactions may not be overlooked while designing any application for the elderly. A sense of affinity, association, and attachment in a secluded life are all significant issues among the elderly. Therefore, designing an effective system to overcome these challenges is paramount. To improve engagement and continuous intention to use the application, both technological aspects in the form of usability, social benevolence, and thought process of the elderly need to be unified while designing an acceptable mHealth care app.

This research, in addition to enablers, validates inhibitors, providing thought-provoking and stimulating implications for app designers. Perceived risk, sunk costs, and transition costs emerged as significant inhibitors. Therefore, mHealth care apps must include those features that are in sync with the lives of the elderly. The apps should not put an emotional and cognitive burden on the elderly, which may reduce transition and sunk costs. These findings are also significant for other stakeholders like health practitioners and the government concerned about engaging and promoting digital health applications for the elderly. The design of the mHealth care apps must provide specialized features, including regular physical and interactive social support.

The responsibility lies on the shoulders of practitioners as well as academicians to recognize these bottlenecks and prioritize these issues while conducting future research and designing an application for this cohort.

8 Limitations of the Study

This research explores the engagement of the elderly concerning mHealth care apps. Therefore, it has certain limitations. First, these enablers and inhibitors need to be validated among the elderly with specific ailments requiring a diverse magnitude of service from these apps to confirm a generalized concept. Second, this research was conducted among the elderly staying in India. But there may be differences in the insights and perceptions of the elderly living in developed countries. Future studies may compare these variables among the elderly in developing and developed countries as infrastructure, culture, and service support vary across these countries. Another limitation of the study is that we considered only those elderly with at least a Bachelor's degree. As this is one of the initial studies on this theme, future researchers may bridge this gap by validating less educated elderly. Future researchers may also compare the perception of the elderly residing in urban and rural areas with education as a moderating variable. Future studies may also consider other variables such as trust, technology readiness, and satisfaction, which may be validated as mediators. This study didn't consider the impact of moderating variables like demographic variables, technology readiness, and so on, which could be an interesting avenue for further studies. Surprisingly, while all the costs related negatively to engagement, inertia was positively associated with it, and this finding needs additional validation.

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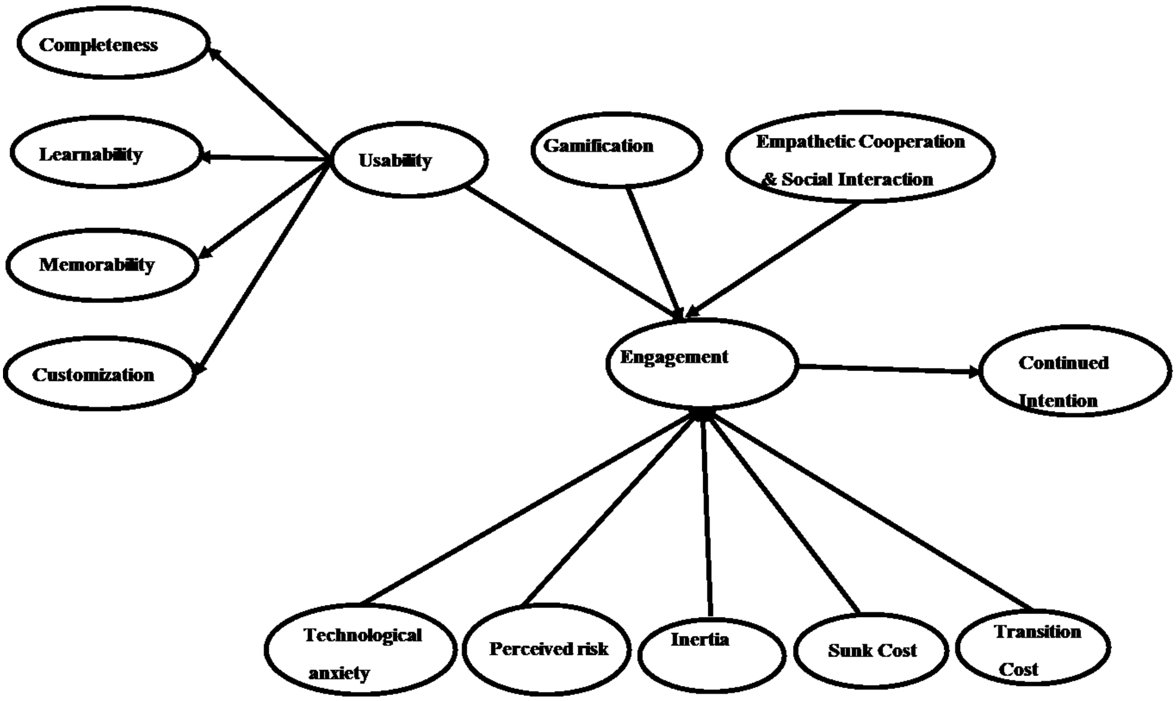

Figure 1: Proposed Model

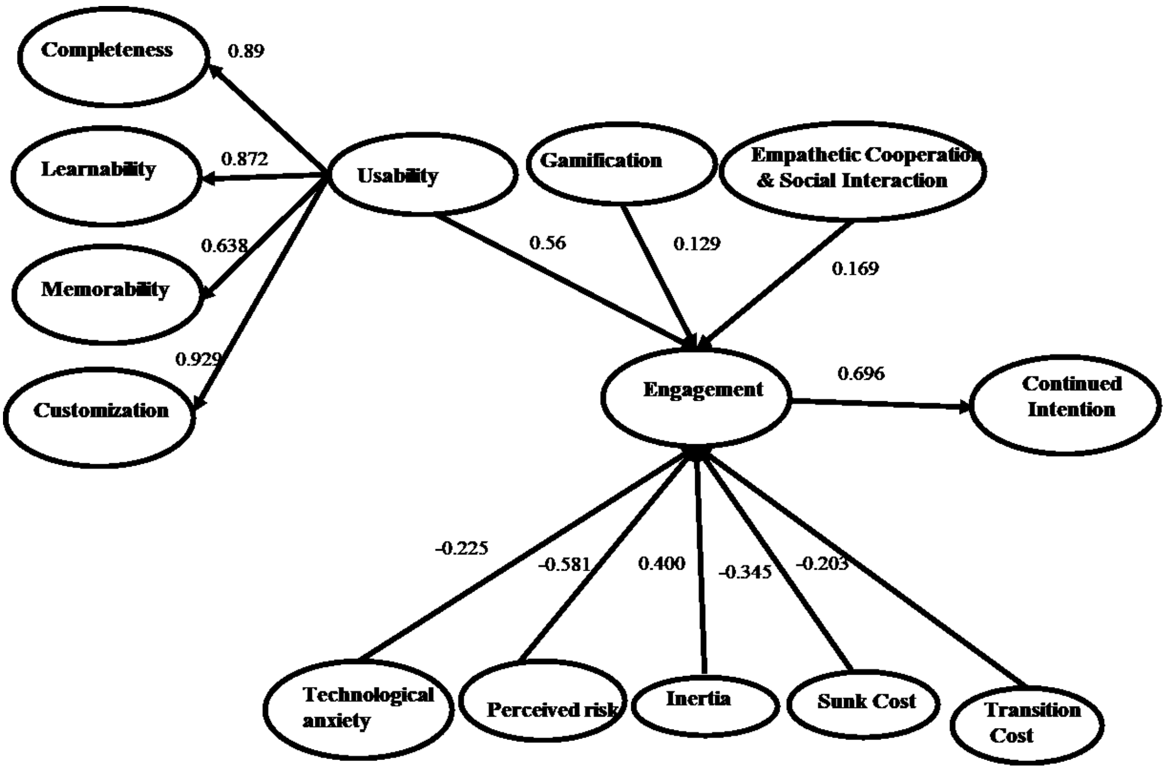

Figure 2: Path Relationships

Appendix 1. Definition of Usability Concepts

Concept	Definition	Source
Error Prevention	Error prevention System offers error management, such as error messages as feedback, error correction through undo function, or error prevention, such as instructions or reminders, to assist users performing tasks.	**Brown et al. (2013, p. 1083)**
Completeness	The system can assist users in successfully completing tasks. This is usually measured objectively by system log files for completion rate.	
Memorability	Users can easily remember how to perform tasks through the system.	
Learnability	Users are able to easily learn how to operate the system.	
Customization	System provides more than one way to accomplish tasks, which allows users to operate system as preferred.	

Appendix 2. Scale items per construct

Scale items	
Engagement	
When using mHealth care apps:	
I am usually absorbed intensely in the activity	ENG1
I am deeply engrossed in the activity	ENG2
I concentrate fully on the activity	ENG3
Continued Intention	
I intend to continue using the health app	CII1
I want to continue using the health app rather than discontinue it	CII2
I predict I will continue using the health app	CII3
I plan to continue using the health app	CII4
Perceived Risk	
mHealth app may steal my information	PRI1
mHealth app may make me psychologically uncomfortable	PRI2
Using mHealth app is dangerous because of privacy and safety issues	PRI3
I feel that mHealth app may have detrimental implications	PRI4
Technology Anxiety	
I feel afraid to use mHealth app	TEC1
I feel nervous about mHealth care app	TEC2
I feel uncomfortable with mHealth app	TEC3
Sunk Cost	
I feel I need to put so much time to learn how to use mHealth care app	SUN1
I expended a lot of resources studying how to use mHealth care app	SUN2
The time and money spent on the mHealth care app that cannot be used with conventional healthcare practices	SUN3
Transition Cost	
I am not interested in using mHealth app as downloading and running the latest technologies would be challenge	TRA1
It takes me a lot of time and commitment to change to the mHealth care application	TRA2
In general, switching to mHealth care technology is challenging	TRA3
Inertia	
I will prefer conventional medical channels as they are a part of my life	INR1
Even though conventional medical channels do not have effectiveness, I will still use them	INR2
I am already used to these conventional medical channels	INR3
Empathetic cooperation and social interaction	
Using mHealth app is a fun	ECS1
Using mHealth app is enjoyable	ECS2
Using mHealth app cannot decrease my scope to be attached with society	ECS3
Using mHealth app cannot decrease my scope to interact socially	ECS4
Service of mHealth app gives me feelings of caring	ECS5
I find good feelings while seeking service from mHealth app to accomplish routine medical check-ups	ECS6
Company of mHealth app while accomplishing my daily monitoring is entertaining	ECS7
Usability	
Error Prevention (Dropped items)	
mHealth app offers error management by giving accurate feedback	ERR1
mHealth app has an undo function to correct any error	ERR2
mHealth app provides instructions to assist me in performing tasks	ERR3
Completeness	
Provides me with complete information related to symptom self-management	COM1

Adequate user support helps me to complete my tasks easily	COM2
mHealth app	COM3
Timely and comprehensive notifications provided by mHealth app update me about my health status	COM4
Memorability	
I can easily remember how to perform tasks using mHealth app	MEM1
The messages provided by mHealth app are easy to memorize	MEM2
It assists me in remembering the symptoms whenever I go to the doctor, which I tend to forget	MEM3
Learnability	
I can easily learn how to use mHealth app	LRN1
It is easy to operate mHealth app	LRN2
I am able to manage my health check-ups using the mHealth app	LRN3
It is easy to become skillful using mHealth app	LRN4
Customization	
mHealth app provides more than one way to accomplish tasks	CTM1
I can always log on and use by using multiple tabs	CTM2
I can generate reports regarding my health issues (e.g., BP monitoring) through multiple means	CTM3
Navigational structure is simple, and related information is in place together	CTM4
Gamification	
I express feelings of connectedness when thinking of myself in relation to the mHealth app	GAM1
Thinking of myself in relation to the mHealth app, I feel an emotional attachment to the device	GAM2
Thinking of myself in relation to the mHealth app, I feel enduring enthusiasm about the device	GAM3
Thinking of myself in relation to the mHealth app, I feel an emotional attachment to the device	GAM4
Thinking of myself in relation to the mHealth app, I feel a sense of dependence upon the device to manage my healthcare	GAM5
I think that the mHealth+A28 app tells me what I have accomplished lately through feedback	GAM6

Annexure 3

Abbreviations Used

SEM	Structural Equation Modelling
ICT	Information and communication technology
WHO	World Health Organization
GOE	Global Observatory for eHealth
ESCI	Empathetic cooperation, and social interaction
SDT	Self-determination Theory
CAGR	Compound Annual Growth Rate
TAM	Technology acceptance model
CMB	Common Method Bias
CFA	Confirmatory Factor Analysis
AVE	Average Variance Extracted
C.R.	Critical Ratio
S.E,	Standard Error