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Article

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A comprehensive examination of factors influencing intention to continue usage of health and fitness apps: a two-stage hybrid SEM-ML analysis

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ABSTRACT

This research developed a theoretical framework based on the uses and gratification theory to investigate the intention to continue usage of Health and Fitness Apps (HFAs). In addition, this study explored how health valuation moderates the relationship between determinants and users' intention to continue usage. A total of 447 HFA users' data was collected from Delhi NCR, India through a purposive sampling technique. Partial least square-structure equation modeling was used to test the role of potential predictors influencing users' behavioral intention to continue. The machine learning algorithms were employed to identify the features of importance. The results revealed that system quality, networkability, recordability, and task technology fit have a positive influence on hedonic motivation and utilitarian motivation. While information quality influences hedonic motivation but does not affect utilitarian motivation. Health valuation positively moderates the relationship between information quality, system quality, and networkability to intention to continue usage. We also observed that hedonic motivation emerged as a key predictor of users' intention to continue usage of HFAs. The results would possibly offer useful recommendations for HFA developers, marketers, and health policymakers. The quality of fitness apps should be the primary concern of app developers. Furthermore, gamification can be incorporated into HFAs as it may influence the users' hedonic motivations. The research contributes by developing a uses and gratification theory tailored for the HFAs. Additionally, this research incorporates hedonic and utilitarian motivation as mediating variables and health valuation as a moderator.

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1. Introduction

Ever since the outbreak of the COVID-19 pandemic that wreaked global havoc, Health and Fitness Apps (HFA) have been extensively used (Yang & Koenigstorfer, 2020; Wu et al., 2022). Several studies have indicated a whopping increase in adoption (i.e. 330%) over the past few years (Ceci, 2022; Sensor Tower, 2023; Yan et al., 2021). The valuation of HFAs is projected to reach \$2983 million by 2029, with India alone expected to contribute about \$364.5 million within the same period (Digital Fitness & Well-Being, 2024). This growth is mirrored by increasing user penetration, projected to rise from 7.91% in 2024 to 9.24% by 2029, indicating a growing interest in fitness apps among the Indian population. Additionally, the average revenue per user (ARPU) is anticipated to be INR 13.05 (US\$13.05), signifying substantial revenue generation per user (Digital Fitness & Well-Being, 2024).

However, despite the significant growth rate, India is losing its position in the global market. Currently holding the fifth position, India is projected to drop to the seventh position by 2029 (Digital Fitness & Well-Being, 2024; Gough, 2024). This shift underscores the necessity of understanding and addressing

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user behavior to enhance retention and sustained engagement. The HFA market in India, driven by a surge in demand for personalized workout plans and virtual fitness classes, aligns with the global trend, making it a critical area for research on health and fitness technologies. Given its growing relevance, this study aims to analyze the factors contributing to intention to continue usage of HFA among Indian consumers.

These numbers are quite encouraging but at the same time, studies have also found that many users abandon HFAs after early acceptance (Alam et al., 2020; Liao et al., 2021; Peng et al., 2005). Pellegrini et al. (2018) found that user retention of HFAs plummeted within the first six months of installation. Similarly, one of the survey reports confirms that there are as many as 25% of users abandoned the HFAs after a single use and only 32% of users chose to use the app even after 10 sessions (Localytics, 2019; Sensor Tower, 2023). This has led some recent scholars to believe that it's a behavioral issue, owing to which, a few recent studies (Bouton, 2014; Cai et al., 2022; Damberg, 2022; Santos-Vijande et al., 2022; Sensor Tower, 2023) observed that changing unhealthy behaviors is tough, while on the other hand, maintaining a healthy behavior over time is much more difficult. As a result, this raises a crucial question: what could be done to alter the way HFA users behave? The question becomes all the more imperative to address given the fact that attracting new users, retaining existing users over time, and facilitating intention to continue usage of these health applications is critical to their long-term success, including that of the parent organizations. Thus, this study undertakes to explore dimensions of intention to continue the usage of HFAs for the long-term sustenance of the organization.

This research employs the Uses and Gratification Theory (UGT) (Katz et al., 1973) to answer the underlying questions of why people use HFA, and what they use it for. The rationale for using UGT is in contrast to other theoretical perspectives, it assumes that users are active participants, who are responsible enough to choose their media to satisfy their desires and needs (Calder et al., 2009; Gao & Feng, 2016; Menon, 2022b; Muntinga et al., 2011). We included gratification-related components, such as Information Quality (IQ), System Quality (SQ), Task Technology Fit (TTF), Recordability (Rec), and Networkability (Net). Besides, we also incorporated Utilitarian Motivation (UM), Hedonic Motivation (HM), and Health Valuation (HV).

Specifically, we integrated (HM) into the conceptual framework to investigate ICU for HFA. HM in the context of HFA refers to the motivation that arises from the pursuit of pleasure and enjoyment in engaging in health and fitness-related activities (Baabdullah, 2018; Pellegrini et al., 2018). Hedonic motivation focuses on individuals' satisfaction and positive experiences from participating in these activities (Direito et al., 2017). Moreover, it may be noted that HM has never been explored in terms of its integration into the HFA framework, albeit as a mediator. However, this is surprising, because HM vis a vis HFA may foster long-term engagement and adherence to healthy behaviors, whereby it could look to tap into the inherent pleasure and enjoyment individuals derive from participating in these activities (Baabdullah, 2018). However, the influence of hedonic motivation on ICU for HFA has not been studied previously.

We also examine the influence of health valuation (HV) on the ICU of HFA which refers to incorporating health concerns into daily activities (Jayanti & Burns, 1998; Yan et al., 2021). Notably, although previous studies have explored various factors that affect HFA usage, HV's role has not been investigated. Therefore, this study seeks to fill this gap and explore how health valuation influences the ICU for HFA, particularly among health-conscious consumers who prioritize fitness.

The primary objective of this study is to pinpoint the factors that influence ICU for HFA, while simultaneously affirming the suggested theoretical model, using actual data from Indian HFA users. Second, the paper takes into account HM, a factor of great importance to HFA developers, for engaging users in depicting healthy behavior. Third, we examine the extent to which, users' HV moderate ICU for HFA. In the process of meeting our stated objective, we make use of both structure equation modeling (SEM) and machine learning (ML) algorithms. The main rationale for us to use ML, along with SEM, is because the latter (i.e. SEM) is only able to predict the linear relationship among the variables, whereas it is equally important to identify the non-linear (Akgül, 2018; Leong et al., 2020). We believe this would help developers in the future to create efficient HFAs, as they could take into account factors that are most likely to be significant to users. In terms of our primary theoretical contribution, we believe that our incorporation of HM and HV into UGT is something that would help future studies.

The following section describes the theoretical foundations of our research. Subsequently, we present the methodology employed, followed by a detailed explanation of the findings. In the final section, these findings are discussed concerning earlier work, along with the theoretical and practical implications, and limitations of the present research.

2. Literature review

2.1. Theoretical framework

The UGT propounds that each user has unique wants and motivations that determine how each one uses a particular medium or piece of technology to achieve his/her goals (Bracken & Lombard, 2001; Katz et al., 1973; Pantano et al., 2023). This theory argues that people actively seek out media and content for specific uses and to achieve gratifications (or results). If those gratifications are met, the user is expected to continue using the media at hand. Katz et al. (1973) developed five categories of cognitive needs: affective, personal, social, and tension-release needs that motivate people to use media and seek gratification. McQuail (1985) found that information, identity, integration, social interaction, and entertainment as common reasons for media use. Moreover, marketing literature has extensively used UGT to investigate the relationship between technology adoption of cutting-edge technology (Menon, 2022b, 2022a), and to understand users' privacy concerns for technology adoption (Quinn, 2016). Besides, it has also been used to understand the factors that influence consumer adoption and use of new technologies (Dindar & Dulkadir Yaman, 2018; Huang & Zhou, 2018; Marjerison et al., 2022; Nanda & Banerjee, 2020; Ray et al., 2019). In fact, UGT is one of the most extensively employed theories in the study of consumers' post-adoptive behaviors, customers' intention to continue usage, and consumers' repurchase of products/services. This goes to show the criticality and the appropriateness of the theory, whereby it enables us to understand the reasons why a certain group of users continue using a particular HFAs, while another set of users abandon them (Bracken & Lombard, 2001; Gao & Feng, 2016; Katz et al., 1973; Muntinga et al., 2011) hence, this study adopts UGT to build the conceptual framework of the study and formulate the hypotheses. Figure 1 presents the hypothetical framework used in the study.

In the process of reviewing the literature, we observed that extant literature tried to determine the variables that affect adoption or establish some form of relationship with technology adoption. In our study, we look to analyze the factors that influence continuous usage of Health and Fitness Apps (HFAs) using UGT as our base. The summary of the recent literature is given in Table 1.

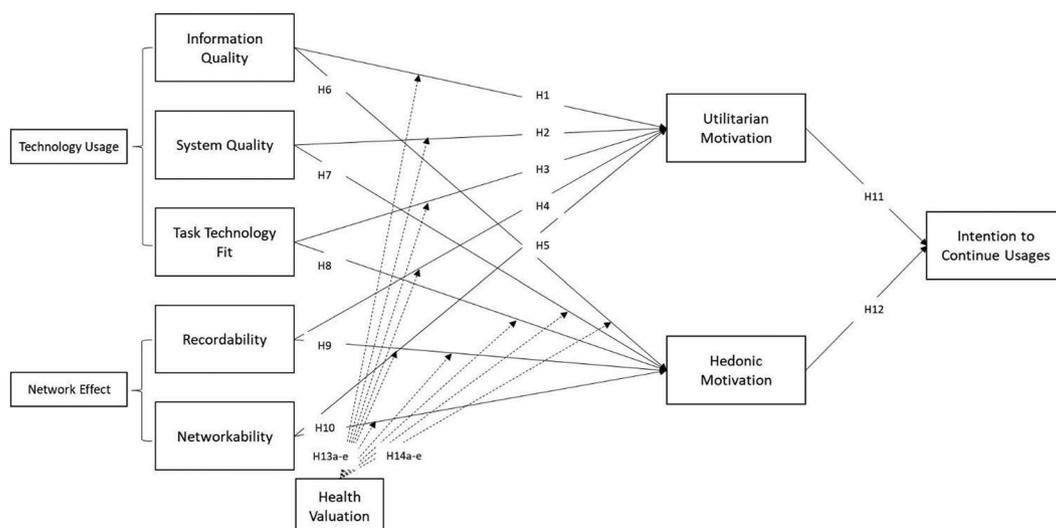


Figure 1. Proposed conceptual framework.

Table 1. Summary of the recent literature.

Research	DV	IV	Theory	Analysis	Findings
Neves et al. (2021)	Health and fitness app usage	Education, digital literacy and depression	–	Multivariate logistic regression	Education and digital literacy were associated with health and fitness app usage Depression patients has lower probability of using HFA Gamification elements can lead to continue intention to use health and fitness apps, and increase users' tendency for information sharing through the apps Perceived performance, perceived performance, habit, health consciousness impact future use intention
Esmaelzadeh, (2021)	Continue usage of HFA	Gamification, information technology identity	Identity theory	PLS SEM (Smart PLS)	
Damberg Damberg (2022)	Future Use Intention	Perceived performance, social influence, price value, perceived performance, habit, health consciousness	UTUAT2		
Wei et al. (2021)	Adoption intention	Self-efficacy perceived benefits, barriers, and threats of weight loss, risk perception	UTAUT, health belief model (HBM), theory of self-control	SEM(AMOS21)	Self-efficacy as well as the perceived benefits, barriers, and threats of weight loss significantly influence a fitness apps' performance expectancy, which, in turn, predicts users' intention to adopt it.
Yan et al., (2021)	Continuous intention	Psychological and social factors	ECT, TAM, Flow theory	PLS SEM (SMART PLS)	Perceived usefulness, Perceived Ease of use, Behavioural control technique impacted continue intention
Cho and Lee (2020)	Continues intention	Perceived ease of use, perceived usefulness, investment size, quality of alternatives	TAM, IM		Perceived ease of use influences perceived usefulness, which further influences users' continuance intention.
Yousaf et al. (2021)	Continue usage	Performance expectancy, effort expectancy, trust, social influence, perceived usefulness, privacy, interface quality, self-efficacy	UTUAT, ECM	PLS SEM	Technology self-efficacy, user-interface quality and perceived privacy determine the continual usage for fitness applications
Cai et al., (2022)	App use, App continue use		TAM, ECT, PAM-JSC	SEM	Expectation confirmation, satisfaction, perceived ease of use, perceived usefulness, and trust impact continue use.
Santos-Vijande et al. Santos-Vijande et al. (2022)	Long term behaviour towards app	Enjoyment, hedonic motivations, social value, effort, performance, trust	Customer value theory, UTUAT, customer engagement theory,	PLS SEM	Performance enhances networkability, while effort impacts enjoyment and brand trust impact social image. The hedonic and social value enhances user engagement, leading to user loyalty and advocacy

2.2. Hypotheses development

2.2.1. Information quality

The term information quality (IQ) refers to the caliber of information that an application provides, encompassing dimensions such as personalization, usefulness, completeness, ease of understanding, timeliness, and relevance (Bardus et al., 2016; Elsotouhy et al., 2022; Stoyanov et al., 2015; Urbach & Müller, 2012; Zhou, 2011). High IQ ensures that users receive accurate, timely, and relevant information tailored to their needs, which enhances their overall experience and satisfaction with the application. For instance, personalization ensures that the information is tailored to individual preferences, while timeliness guarantees that users receive current and pertinent data.

Numerous studies have shown that IQ significantly impacts the behavioral intention of users to continue engaging with information systems, including e-commerce websites, banking apps, and health and fitness apps (Chen & Chang, 2018; Chen & Tsai, 2019; Leon, 2018; Won et al., 2023). When users perceive the information provided by an app as high quality, they are more likely to use the app regularly and remain engaged over time (Chen & Tsai, 2019). However, there is some contention in the literature, as Park et al. (2018) found that information quality had no significant impact on the intention to continue using health and fitness apps (HFAs). This discrepancy suggests that the relationship between IQ and user retention in HFAs may be influenced by other factors or contexts, highlighting the need for further investigation into this area. Therefore, we posit:

H₀₁: Information quality significantly impacts the users' utilitarian motivation to intention to continue usage of HFAs.

H₀₆: Information quality significantly impacts the users' hedonic motivation to intention to continue usage of HFAs.

2.2.2. System quality

System Quality is a crucial measure of the performance of an information system, encompassing characteristics such as accuracy, speed, navigation, and response time (Delone & McLean, 2003). These attributes are fundamental in determining how effectively an information system functions, directly impacting user satisfaction and engagement. High system quality ensures that users experience minimal errors, efficient loading times, intuitive navigation, and prompt responses, all of which contribute to a seamless user experience (Elsotouhy et al., 2022).

Studies have consistently demonstrated that system quality significantly influences users' behavioral intentions to continue using any information system, including mobile apps. For example, (Chen & Tsai, 2019) found that users are more likely to develop a positive perception and show greater intention to reuse a system when it performs reliably and efficiently. Similarly, Leon (2018) highlighted that enhanced system quality leads to increased user satisfaction, which in turn fosters continued use and loyalty. This relationship indicates that the better the system quality, the more likely users are to perceive the app positively, thereby enhancing their intention to continue its usage (Won et al., 2023). Good system quality can thus be seen as a key determinant in retaining users and encouraging ongoing engagement with the app. Therefore, we posit:

H₀₂: System quality significantly impacts the users' utilitarian motivation to intention to continue usage of HFAs.

H₀₇: System quality significantly impacts the users' hedonic motivation to intention to continue usage of HFAs.

2.2.3. Task technology fit

Goodhue and Thompson (1995); defined the 'fit between task and technology (task-technology fit) as the degree to which a technology assists a user in performing his or her tasks'. Task-Technology Fit (TTF) was one of the earliest theories that attempted to identify the post-adoption component of technology use (Goodhue & Thompson, 1995). In this regard, it may be noted that users only embrace and utilize technology when it helps them to perform their tasks better. TTF has been used in various contexts; for instance, to study users' ICU emerging internet services (Shang et al., 2007) and mobile

technologies (Lee & Cho, 2017); interestingly, (Aljukhadar et al., 2014) found that TTF does not positively impact ICU technology. Further, Lin and Huang (2008) posited that if TTF is high, it would increase the users' intention to continue usage of technology, while Valaei et al. (2019) found a positive relationship between TTF and behavioral intention to continue usage. Besides, the authors also found that TTF positively influences the use of mobile apps for online banking transactions (Valaei et al., 2019). Zhao and Bacao (2020) reported that TTF positively impacts the users' intention to continue usage for food delivery apps. TTF is therefore a crucial variable that is either missing or implicit in most studies relating to technology usage. Hence it is important to study TTF's impact on ICU to adopt fitness apps. Therefore, the study posits:

H₀₃: Task Technology Fit significantly impacts the utilitarian motivation to intention to continue usage of HFAs.

H₀₈: Task Technology Fit significantly impacts the hedonic motivation to intention to continue usage of HFAs.

2.2.4. Recordability

Recordability refers to the management of users' physical fitness through prompt and regular recording of their activities (Kerr et al., 2016). This feature is fundamental to most fitness apps, which track and log users' daily activities, enabling them to monitor their fitness routines comprehensively. For instance, fitness apps commonly record the number of steps taken, calories consumed, and other workout and meal schedule details. This capability allows users to maintain an accurate and detailed record of their fitness journey, providing valuable insights into their progress and areas for improvement.

Previous research highlights that self-monitoring of fitness-related activities is a core attribute offered by fitness apps (Ahn et al., 2020; Goldstein et al., 2019; Hu et al., 2015, 2020). This self-monitoring aspect is critical as it empowers users to take control of their fitness goals by providing continuous feedback and motivation. For example, König et al. (2018) found that recordability has a strong positive effect on users' intentions to continue using fitness apps. This finding underscores the importance of recordability in enhancing user engagement and retention. By allowing users to track their progress and adjust their routines accordingly, fitness apps with robust recordability features foster long-term adherence to fitness activities, making them an essential tool for achieving sustained health and fitness goals. Based on the discussion thus far, we posit:

H₀₄: Recordability significantly impacts the utilitarian motivation to intention to continue usage of HFAs.

H₀₉: Recordability significantly impacts the hedonic motivation to intention to continue usage of HFAs.

2.2.5. Networkability

Networkability refers to the extent to which a user believes that s/he can share information about fitness activities with other users through a fitness app (Lee & Cho, 2017). This is possible due to the convergence between apps and social networking platforms. Several studies have found that networkability integrated with fitness apps promotes physical activities, routines, and behaviors among users. In fact, through these fitness apps, the 'networkability' function can promote user engagement through competition, social comparison, and cooperation (Almutari & Orji, 2019; Hamamatsu et al., 2020; Kim, 2022; Zhang & Xu, 2020). Tong et al. (2019) conducted a pre-post quasi-experimental study, in which, the participants were observed for six months. The authors found that networkability integrated with fitness apps promotes physical activities, routines, and behaviors among users. Petersen et al. (2019) compared fitness apps with and without networkability function integration, and found that apps with networkability features were more effective in promoting physical activity among users. Teng and Bao (2022) noted that the human-to-human interaction supported by social networking features intends to enhance the users' post-adoption behavior. Based on the understanding thus far, we posit:

H₀₅: Networkability significantly impacts the utilitarian motivation to intention to continue usage of HFAs.

H₁₀: Networkability significantly impacts the hedonic motivation to intention to continue usage of HFAs.

2.2.6. Utilitarian motivation

According to the Unified Theory of Acceptance and Use of Technology (UTAUT), utilitarian value refers to the practical benefits and advantages that individuals expect from using a specific technology (Ashraf et al., 2022). It primarily encompasses two key components: performance expectancy, which is the belief that using the technology will help achieve gains in job performance (Venkatesh et al., 2012), and the functional and task-oriented features of the technology (Ashraf et al., 2022). These aspects underscore the technology's capacity to provide effective solutions and meet user needs efficiently.

This study places significant emphasis on utilitarian motivation due to its close relationship with the tangible benefits users perceive from downloading and using Health and Fitness Apps (HFAs). Users are more likely to adopt and continue using HFAs when they believe these apps offer high utilitarian value, such as improving their fitness, tracking their progress, or managing their health more effectively (Luarn et al., 2023). The practical benefits, including accurate tracking of physical activity, personalized fitness plans, and detailed health analytics, play a crucial role in influencing user adoption and sustained engagement. Hence, understanding and enhancing the utilitarian value of HFAs is critical for developers aiming to increase user satisfaction and retention. Given this understanding, we posit:

H₁₁: Utilitarian motivations significantly impact the user intention to continue usage of HFAs.

2.2.7. Hedonic motivation

Hedonic Motivation refers to when users drive fun and pleasure using technology (Venkatesh et al., 2012). The main purpose of HFA is to record the physical activities and routines of the user. Some fitness apps also include entertainment and gamification features to keep the users interested and engaged which results in habit-forming usage, such as curiosity, relaxation, passing time, and entertainment (Lowry et al., 2013; Ryan, 2022). Many studies found that 'hedonic motivation' is the main factor for users to adopt, use, and intend to continue using the latest technologies like mobile technology and apps, online learning, online banking, online shopping, location-based services, etc. (Alalwan et al., 2017; Cho et al., 2015; Ryan, 2022). Chiu and Cho (2020) found that hedonic motivation positively impacts the user's intention to continue usage of fitness apps and in contrast, Dhiman et al. (2019) reported that it does not impact the user's intention.

There is conflict on the role of hedonic motivation in continued usage. Therefore, it becomes important to subject the relationship between hedonic motivation and users' intention toward fitness apps for further investigation. Therefore, the study posits that:

H₁₂: Hedonic motivations significantly impact the users' intention to continue usage of HFAs.

2.2.8. The moderating role of health valuation

Health Valuation (HV) refers to the degree of importance given by individuals to their health and wellness (McGloin et al., 2017). Joo et al. (2021) for instance, found that individuals who value their health are more likely to pay attention to their health and engage in behaviors/activities/routines that can keep them healthy through fitness, wellness, and health-related apps. Additionally, they seem more inclined towards maintaining or improving their health and quality of life. HV thereby significantly affects the users' intention to adopt, use, and continue using fitness apps (Chen & Lin, 2018; Damberg, 2022; Yan et al., 2021). Higher HV individuals tend to make better decisions about a health app's IQ, SQ, Net, Rec, TTF, and HM, since they are well-informed, and have clearly defined health goals. The influence of IQ, SQ, Net, Rec, TTF, and HM on intention to continue usages is therefore expected to be amplified in the case of people with greater HV. Therefore, we posit:

H_{13a}: Health valuation significantly moderates the impact of information quality on utilitarian motivation to intention to continue usage of HFAs.

H_{13b}: Health valuation significantly moderates the impact of system quality on utilitarian motivation to intention to continue usage of HFAs.

H_{013c}: Health valuation significantly moderates the impact of task-technology fit on utilitarian motivation to intention to continue usage of HFAs.

H_{13d}: Health valuation significantly moderates the impact of recordability on utilitarian motivation to intention to continue usage of HFAs.

H_{13e}: Health valuation significantly moderates the impact of networkability on utilitarian motivation to intention to continue usage of HFAs.

H_{14a}: Health valuation significantly moderates the impact of information quality on hedonic motivation to intention to continue usage of HFAs.

H_{14b}: Health valuation significantly moderates the impact of system quality on hedonic motivation to intention to continue usage of HFAs.

H_{014c}: Health valuation significantly moderates the impact of task-technology fit on hedonic motivation to intention to continue usage of HFAs.

H_{14d}: Health valuation significantly moderates the impact of recordability on hedonic motivation to intention to continue usage of HFAs.

H_{14e}: Health valuation significantly moderates the impact of networkability on hedonic motivation to intention to continue usage of HFAs.

3. Research methodology

3.1. Data collection

We used a survey approach, which was administered by a team of five skilled interviewers over three months at various major public places, metro stations, workplaces, and both private and public university campuses in Delhi-NCR, India. The team personally distributed the questionnaire, which had been approved by the Academic Integrity Committee of Symbiosis Centre for Management and Human Resource Development, Symbiosis International (Deemed University), India. To ensure participants' willingness, both verbal and written consent were obtained. The interviewers began by clearly explaining the study's purpose, the nature of the questions, and how the collected data would be used. Participants were then asked if they consented to take part in the study, emphasizing the voluntary nature of their participation.

To obtain written consent, the participants were asked to sign the questionnaire and submit it back to the team after completing it, which indicated their agreement to participate. Additionally, the team ensured that no personal information, such as names, email addresses, or contact numbers, was collected within the questionnaire. Participants were encouraged to ask any questions they had before signing the consent form and were informed that the data would be used exclusively for research purposes with no commercial application. This comprehensive consent process aimed to foster trust and transparency, ensuring participants felt comfortable and informed throughout their involvement in the study.

We employed purposive sampling due to the lack of a reliable list of HFA users, necessitating data collection from existing HFA users. Purposive sampling allowed us to intentionally select participants who meet specific criteria relevant to our study, ensuring that the data gathered is highly pertinent and accurate. This method is particularly useful when targeting a specific population segment, as it enables researchers to focus on individuals who have direct experience with the subject matter (Hair et al., 2019). To enhance the response rate and expand our sample, we incorporated the snowball sampling technique, as suggested by Chiu et al. (2021). Snowball sampling involves initial participants referring other potential participants, thereby increasing the sample size through a network of contacts.

We established minimum eligibility criteria for our respondents to ensure the reliability and relevance of the collected data. Specifically, all respondents were required to have used HFAs for at least six months. This criterion was critical to ensure that participants had sufficient experience and familiarity with the apps, allowing them to provide detailed, insightful, and accurate responses based on comprehensive usage. Participants with extended usage are more likely to draw on a wider range of experiences, improving the quality and depth of the data collected.

Additionally, setting a minimum usage period eliminates bias from new users who may not have fully explored all the features of the HFA or might still be in the initial stages of adoption. Their feedback might be skewed by initial impressions or lack of comprehensive usage, potentially leading to biased or

incomplete data. Establishing this criterion creates a more homogeneous sample group, enhancing the comparability of responses and ensuring that the data collected is consistent and reliable for the study's objectives. Participants were assured that their privacy would be strictly safeguarded and that only aggregate results would be published. After discarding incomplete and unengaged responses, 447 usable surveys were received, which, with an effect size of 0.3, an alpha level of 0.05, and a power of 0.95, exceeded the suggested minimum sample size as determined by G*Power (Faul et al., 2009; Kang, 2021).

3.2. Measurement scales

The measurement scale was borrowed from the literature and then it was applied to the context of HFA to ensure the validity of the construct (Shareef et al., 2016). The review helped in identifying information quality, system quality, networkability, recordability, task technology fit, hedonic motivation, utilitarian motivation, and health valuation to assess the intention to continue the usage of HFAs. The scales of information quality and system quality were adapted from Zhou (2011), networkability and recordability scales were adopted from (Lee & Cho, 2017), the scale to measure task technology fit was adopted from (Lin & Huang, 2008), and hedonic motivation and utilitarian motivation scales were adopted from (Cenfetelli et al., 2008; Yuan et al., 2015). Similarly, the scale of health valuation was taken from (Michaelidou & Hassan, 2008), and the scale of ICU was adopted from (Bhattacharjee, 2001). The instrument consisted of 28 items. Table 2 presents all the measurement items considered in the study.

We measured both gender and marital status through nominal scales; while a 4-point ordinal scale was used to capture the respondents' age and income were assessed via 5-point interval scale. Moreover, attitudinal variables of HFA were examined on a 5-point Likert scale based on an earlier recommendation (Pai & Huang, 2011). The authors opted for this scale design, as it minimizes the respondents' annoyance level, and increases the response rate when we compare with 7 & 9-point Likert scales. Notably, the advantage of using different points of the scale as it reduces the common method bias (Teck Soon & Syed A. Kadir, 2017).

Table 2. Measurement scales.

Factor	Item code	Items	Reference
Information Quality (IQ)	IQ1	Information provided by fitness app is up to date	Zhou Zhou, (2011)
	IQ2	Information provided by fitness app is accurate	
	IQ3	Information provided by fitness app is comprehensive	
System Quality (SQ)	SQ1	It is easy to navigate the health and fitness app	Lin et al. Lin and Huang (2008)
	SQ2	The layout of the health and fitness app is clear	
Networkability (Net)	SQ3	The health and fitness app quickly loads the text and graphics.	Zhou Zhou, (2011)
	Net1	Through the HFA, I am currently using, I can share health and fitness information with other users.	Lee & Cho Lee and Cho, (2017)
	Net2	The HFA, I am currently using support the service of sharing information with other users	
Net3	Through the health and fitness app I am currently using, I can access health and fitness of other users.		
Recordability (Rec)	Rec1	Through using HFA, I can record my health and fitness information.	Lee & Cho Lee and Cho, (2017)
	Rec2	Keeping record of the health and fitness is helpful for managing my health and fitness	
	Rec3	Keeping record of the health and fitness is a necessary function of the health and fitness app I am currently using.	
Task Technology Fit (TTF)	TTF1	In my fitness Management, functions of fitness apps are enough	Lin & Huang Lin and Huang (2008)
	TTF2	In my fitness Management, functions of fitness apps are appropriate	
	TTF3	In general, functions of fitness apps meet my needs.	
Hedonic Motivation (HM)	HM1	Using fitness app is fun	Yuan et al., (2015)
	HM2	Using fitness app is enjoyable	
	HM3	Using fitness app is entertaining	
Utilitarian Motivation (UM)	UM1	I am delighted with the functionalities offered by the application	Cenfetelli et al. (2008)
	UM2	I am satisfied with the esthetic properties by the application	
Health Valuation (HV)	HV1	I reflect about my health a lot	Michaelidou & Hassan Michaelidou and Hassan, (2008)
	HV2	I am very self-conscious about my health	
	HV3	I am usually aware of my health	
	HV4	I take responsibility for the state of my health	
	HV5	I am aware of the state of my health as I go through the day	
Intention to Continue Usages (ICU)	ICU1	I find using to be worthwhile	Bhattacharjee Bhattacharjee, (2001)
	ICU2	I will frequently use in the future.	
	ICU3	I intend to keep using HFA.	

Table 3. Validity and reliability analysis.

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)	Square root of AVE	CIU	HM	IQ	Net	Rec	SQ	TTF	UM
CIU	0.845	0.847	0.846	0.733	0.8559	1.000	0.958	0.740	0.616	0.550	0.781	0.795	0.795
HM	0.887	0.890	0.888	0.665	0.8156	0.958	1.000	0.699	0.680	0.612	0.720	0.805	0.746
IQ	0.874	0.875	0.874	0.635	0.7967	0.740	0.699	1.000	0.589	0.493	0.753	0.711	0.655
Net	0.920	0.922	0.921	0.795	0.8914	0.616	0.680	0.589	1.000	0.521	0.603	0.711	0.577
Rec	0.936	0.936	0.936	0.829	0.9104	0.550	0.612	0.493	0.521	1.000	0.520	0.569	0.570
SQ	0.927	0.929	0.928	0.762	0.8731	0.781	0.720	0.753	0.603	0.520	1.000	0.725	0.875
TTF	0.898	0.903	0.901	0.694	0.8333	0.795	0.805	0.711	0.711	0.569	0.725	1.000	0.709
UM	0.883	0.885	0.883	0.791	0.8895	0.795	0.746	0.655	0.577	0.570	0.875	0.709	1.000

3.3. Pilot study

Then we assessed both the face and content validity of the instrument by conducting interviews with five professors from information science research. Considering their recommendation, we rectified some of the ambiguities in the wording of a few statements. This approach was similar to what some of the earlier authors had used (e.g. Kim et al., 2009; Yang et al., 2022). Furthermore, we conducted a pilot study with 15 participants, including HFA developers, academicians, and people using HFA for at least six months to obtain a higher degree of reliability and validity. It is evident from previous research that a sample size of 12 is sufficient to conduct a pilot study (Julious, 2005). Notably, a similar method was recommended by Dwivedi et al. (2013) too. Cronbach's alpha value of each construct was obtained greater than 0.70, which indicates good construct reliability (Nunnally, 1978). Table 3 displays all the items and their sources.

4. Data analysis

SPSS version 25, Smart PLS version 4, and R-Studio were utilized for analyzing the data through machine learning techniques. Table 4 contains demographic details, while Figure 2 illustrates the data analysis process employed in this study.

4.1. Common method bias (CMB)

Common method bias arises in research methodologies, particularly in studies using Structural Equation Modeling (SEM). This is primarily owed to the measurement method used rather than the inherent causal relationships in the model. This study employs three methods to measure the CMB in the data. First, it measures through principal axis factoring with Harman's Single-factor test, using SPSS Version 25 to analyze CMB. According to Herrmann and Kim (2017) and Harman and Chomsky (1967) if the value of a single construct is less than 40% of the variance observed, confirms the absence of the CMB. The results showed a 23.12% variance of a single factor and thus it confirms no CMB. Second, CMB was examined using the variance inflation factor (VIF). Kock and Lynn (2012) suggested that if VIF exceeding 3.3 indicates the presence of CMB. Results confirmed that VIF is less than 3 for each construct, thus there is no CMB in the data. Third, the latent factors' correlation below 0.90 suggests the absence of CMB (Podsakoff et al., 2013) and thus we confirm the absence of CMB in the data.

4.2. Measurement model

The validity and reliability of the constructs were measured by using the output of Smart-PLS Version 4. Table 3 presents the values of Cronbach's Alpha and Composite Reliability (CR) which is greater than 0.70, indicating that the measurement model has a high level of construct reliability (Hair et al., 2019). Convergent validity has also been confirmed as the Average Variance Extracted (AVE) is greater than 0.50, reflecting thereby that the items do converge to the pertinent constructs (Hair et al., 2019; Leong et al., 2020).

Table 4. Demographic profile of the respondents.

	N (447)	%
Gender		
Male	248	55
Female	199	45
Age		
21–30 Years	107	24
31–40 Years	158	35
41–50 Years	127	28
Above 50 years	55	12
Marital status		
Single	197	44
Married	230	51
Other	20	4
Annual income		
Below 5 Lk	35	8
5–10 Lk	62	14
10–15 Lk	110	25
15–20 Lk	102	23
Above 20 Lk	138	31
How long you have been using this application		
<6 Months	106	24
6–12 Months	139	31
1–2 Years	133	30
>2 Years	69	15

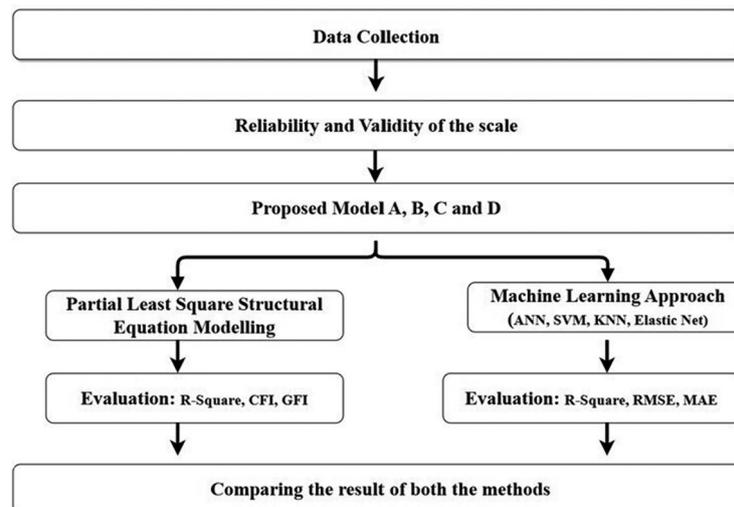
**Figure 2.** Illustrates the methodology adopted for the study.

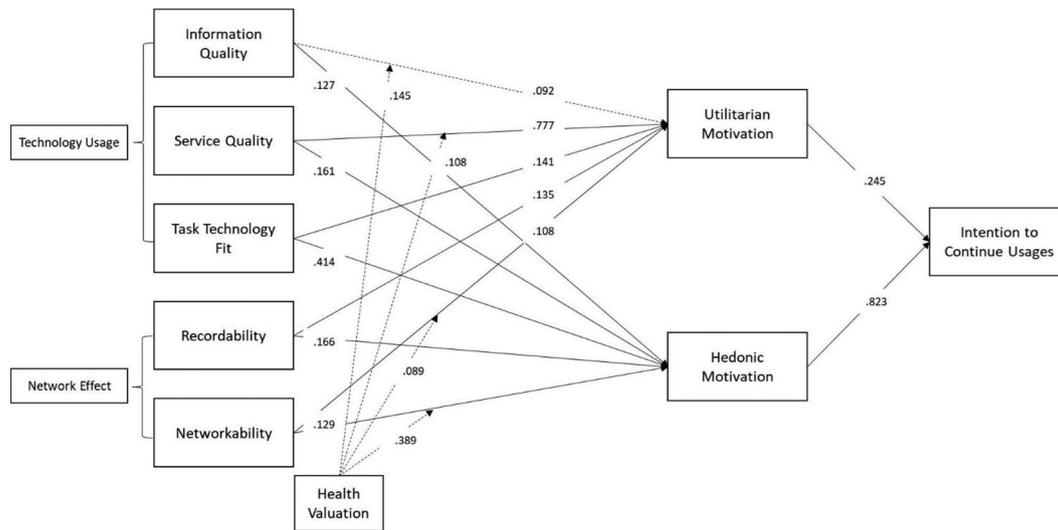
Table 5 presents the output of the Fornell-Larcker Criterion, where we observed that the square roots of Average Variance Extracted (AVEs) surpass the inter-correlation coefficients (Fornell & Larcker, 1981; Chin, 1998; Chin et al., 2003). Thus, confirms discriminant validity within the model. Furthermore, the discriminant validity was also assessed through the Heterotrait-Monotrait (HTMT) criterion where the upper limit of the HTMT confidence interval for the HTMT ratio, determined that all values remained below 0.90. Thus, it indicates robust discriminant validity, as all HTMT ratios noted were less than 0.9.

4.3. Structure model

The hypotheses were tested using Smart PLS-SEM version 4. The model fitness was measured using the Normalized Fit Index (NFI) and Standardized Root Mean Square Residual (SRMR). NFI values close to 1 (within the range of 0 to 1) suggest a good match and SRMR values less than 0.08 are considered acceptable (Hair et al., 2019). The results confirmed the model fits as the obtained value of NFI was 0.908 and SRMR was 0.038. This strengthens confidence in the suggested associations and assures the validity of the structural framework. Please see Figure 3 for the structured model tested using Smart PLS-SEM.

Table 5. HTMT and Fornell-Larcker criterion.

Constructs	HTMT-ratio						Fornell-Larcker criterion								
	CIU	HM	IQ	Net	Rec	SQ	CIU	HM	IQ	Net	Rec	SQ	TTF	UM	CIU
CIU							0.856								
HM	0.886						0.958	0.816							
IQ	0.741	0.699					0.740	0.699	0.797						
Net	0.617	0.681	0.588				0.616	0.680	0.589	0.891					
Rec	0.549	0.614	0.493	0.522			0.550	0.612	0.493	0.521	0.910				
SQ	0.783	0.721	0.755	0.604	0.521		0.781	0.720	0.753	0.603	0.520	0.873			
TTF	0.798	0.812	0.712	0.716	0.575	0.727	0.795	0.805	0.711	0.711	0.569	0.725	0.833		
UM	0.797	0.749	0.655	0.578	0.570	0.876	0.712	0.795	0.746	0.655	0.577	0.570	0.875	0.709	0.890

**Figure 3.** Structured model.

Furthermore, the five exogenous components (i.e. IQ, SQ, TTF, REC, and NET) have R^2 and adjusted R^2 values that account for 79.2 and 79% of the variability in UM. In this section of the model, the predictive relevance (Q^2) is 0.649; this suggests a high level of predictive relevance (Hair et al., 2019). Similarly, IQ, SQ, TTF, REC, and NET have an impact on HM; their combined effects account for 72.6% of the variance (R^2) and 72.3% (Adjusted R^2). The model's predictive relevance (Q^2) for this section is 0.479; this does indicate a high level of predictive relevance.

In Model 3, with UM and HM as independent variables and CIU as the dependent variable, the model elucidates 93.2% (R^2) and 93.2% (Adjusted R^2) of the variance. The Q^2 for this model is 0.583, indicating thereby significant predictive relevance across all three models. For detailed results, refer to Table 6.

Using resampling methods like Bootstrap, the statistical significance of partial least squares was ascertained. All path coefficients' t -test results are obtained by this process. The link between the independent and dependent variables was assessed using t -statistics and the model's path coefficients (β). Once the quality of fit of the model was determined, we computed the significance of the coefficient.

As shown in Table 7, both HM and UM have positive and significant impacts on ICU ($\beta=0.823$, $p<0.05$) and ($\beta=0.245$, $p<0.05$) respectively. Our results do confirm that components of technology usage, such as SQ ($\beta=0.777$, $p<0.05$), TTF ($\beta=0.141$, $p<0.05$), and components of network effect, such as Rec ($\beta=0.135$, $p<0.05$) and Net ($\beta=0.108$, $p<0.05$) have positive and significant impact on UM; therefore, H2–H5 are supported. Interestingly, IQ ($\beta=0.092$, $p>0.05$) which is a component of technology usage has no significant impact on UM; therefore, H1 is not supported.

4.4. Mediating effect

Similarly, findings corroborate that component of technology usage, such as IQ ($\beta=0.127$, $p<0.05$), SQ ($\beta=0.161$, $p<0.05$), TTF ($\beta=0.414$, $p<0.05$), and component of network effect, such as Rec ($\beta=0.166$, $p<0.05$) and Net ($\beta=0.129$, $p<0.05$) have positive and significant impact on HM; therefore, H6–H10 are supported.

Table 6. Model fitness indicators.

Relation	F-square	R-square	R-square adjusted	Q-square predict	RMSE	MAE
HM -> CIU	4.431	0.932	0.932	0.583	0.648	0.508
UM -> CIU	0.212					
IQ -> HM	0.022	0.726	0.723	0.612	0.625	0.479
Net -> HM	0.028					
Rec -> HM	0.061					
SQ -> HM	0.033					
TTF -> HM	0.198					
IQ -> UM	0.015	0.792	0.790	0.649	0.595	0.432
Net -> UM	0.000					
Rec -> UM	0.055					
SQ -> UM	1.019					
TTF -> UM	0.030					

Table 7. Path coefficient- direct effect.

Hypotheses	Relation	Path coefficient	Sample mean	Standard deviation	t-Statistics	P-Values
H1	IQ -> UM	0.092	-0.098	0.058	0.135	0.893
H2	SQ -> UM	0.777	0.781	0.082	9.720	0.000
H3	TTF -> UM	0.141	0.142	0.082	2.720	0.046
H4	Rec -> UM	0.135	0.135	0.079	9.866	0.000
H5	Net -> UM	0.108	0.137	0.047	2.852	0.004
H6	IQ -> HM	0.127	0.129	0.075	2.697	0.030
H7	SQ -> HM	0.161	0.160	0.076	5.422	0.034
H8	TTF -> HM	0.414	0.411	0.076	5.422	0.000
H9	Rec -> HM	0.166	0.162	0.065	2.499	0.043
H10	Net -> HM	0.129	0.132	0.067	1.928	0.040
H11	UM -> CIU	0.245	0.177	0.065	3.771	0.006
H12	HM -> CIU	0.823	0.827	0.055	15.025	0.000

Table 8 shows the indirect effect; the findings support the existence of a significant and favorable mediating role of UM between Rec and CIU, and between SQ and CIU. Comparably, HM has a significant mediating role between Rec and CIU, TTF and CIU, Net and CIU, and SQ and CIU.

4.5. Moderating effect

In order to evaluate the moderation of HV interaction between IQ, SQ, TTF, REC, and NET; and UM and also between Q, SQ, TTF, REC, and NET; and HM, using PLS-SEM path coefficients are calculated and tabulated in Table 9. Results confirm that health valuation moderates the relationship between networkability and hedonic motivation. Moreover, it also moderates the relationship between networkability, service quality, information quality, and utilitarian motivation.

4.6. Machine learning approach

We employed both Structural Equation Modeling (SEM) and Machine Learning (ML) approaches to comprehensively analyze both linear and non-linear relationships among variables. Notably, the SEM-ML combination enhances the robustness of our findings, as SEM is proficient in testing linear relationships, while ML effectively captures nonlinearity (Cepeda-Carrion et al., 2019; Henseler et al., 2015; Vinod Sharma et al., 2023). Utilizing R Programming packages for ML, such as nnet (Venables & Ripley, 2002), neuralnet (Fritsch et al., 2019), and caret package (Kuhn, 2021), we assessed the significance of relationships and cross-validated the results against SEM models (Das & Panja, 2022; Tiwari, 2022).

For ML analysis, we considered independent variables (IQ, SQ, TTF, Net, Rec, UM, and HM) and CIU as the dependent variables. We created four models to explore the relationships between different variables; the results in Table 10 present RMSE, R-square, and MAE values, using 10-fold cross-validation to avoid over-fitting issues (Negnevitsky, 2011).

Various ML models, including neural networks, support vector machines, random forests, k-nearest neighbors, boosted generalized linear models, generalized additive models, and elastic net, were employed to enrich the analysis. This integrated SEM-ML approach provides a comprehensive understanding of the complex relationships within the model.

Table 8. Path coefficient- mediation effect.

Relation	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	p Values	Result
Net -> UM -> CIU	0.005	0.011	0.401	0.688	Not Supported
Rec -> UM -> CIU	0.033	0.011	3.143	0.002	Supported
SQ -> UM -> CIU	0.154	0.030	5.173	0.000	Supported
Rec -> HM -> CIU	0.111	0.029	3.865	0.000	Supported
TTF -> HM -> CIU	0.227	0.038	6.005	0.000	Supported
TTF -> UM -> CIU	0.033	0.014	2.378	0.017	Supported
IQ -> UM -> CIU	-0.003	0.013	0.204	0.839	Not Supported
IQ -> HM -> CIU	0.087	0.035	2.489	0.013	Supported
Net -> HM -> CIU	0.101	0.035	2.796	0.005	Supported
SQ -> HM -> CIU	0.120	0.033	3.599	0.000	Supported

Table 9. Path coefficient-moderating effect.

Hypothesis	Relation	Standard deviation (STDEV)	T statistics (O/STDEV)	p Values	Result
H013a	HV x IQ -> UM	0.035	2.270	0.027	Supported
H013b	HV x SQ -> UM	0.032	2.853	0.034	Supported
H013e	HV x Net -> UM	0.027	3.427	0.006	Supported
H014e	HV x Net -> HM	0.033	2.554	0.011	Supported

The algorithms that appear to perform analysis are based on RMSE, R-Square, and MAE. Since the primary objective of the study was to identify the features that influence CIU rather than identifying the best algorithm for the study, we assessed variable importance, which is a measure that indicates the contribution of each predictor variable to the model's performance in terms of reducing error or enhancing accuracy (Breiman, 2001; Friedman, 2001; Hastie et al., 2009; Nicodemus et al., 2010; Strobl et al., 2008). Table 11 presents the computed variable of importance for Model D, encircling all variables.

Ensembling is an ML technique that involves the amalgamation of multiple models to create a robust model (Hare & Kutsuris, 2022; Sagi & Rokach, 2018; Tuv, 2002). This approach involves combining individual models through mechanisms like averaging to derive a collective outcome with enhanced predictive power. This study integrated seven ML models to discern the most crucial features through an ensemble approach over a singular model. As illustrated in Table 8, where the scores from Model-D were averaged across all ML algorithms, the variables identified as most essential were HM, UM, SQ, TTF, IQ, NET, with REC being deemed the least influential. This ensemble technique supports capturing a comprehensive and robust understanding of the significant features that contribute to the model's predictive performance.

5. Discussion and implication

The study provides a noteworthy contribution to the existing literature on user intention to continue using health and fitness mobile apps. To explain the same, we developed a theoretical framework that expands the uses and gratification theory (Katz et al., 1973) by incorporating both hedonic and utilitarian motivation as mediating variables, and health valuation as moderating variables. Our findings corroborated most assumptions regarding how the antecedents result in gratification for ICU health and fitness applications. Additionally, the study established the moderating role of health valuation on IQ, SQ, and Net on UM and Net on HM.

We identified that information quality did not affect utilitarian motivation, whereas it did have an impact on hedonic motivation. This finding differs with (Leon, 2018) and (Chen & Tsai, 2019); they found IQ to positively influence both UM and HM. Secondly, we observed that system quality had a significant impact on both UM and HM; this finding concurs with the findings of Leon (2018); (Leon, 2018) and (Chen & Tsai, 2019). Thirdly, we found that information quality and system quality increase the users' gratification, which ultimately entices him/her to continue with the apps that they were using to gratify individual needs

This study further established that task technology fit significantly impacts both utilitarian and hedonic motivation, resulting in ICU for HFAs. Notably, this finding concurs with (Zhao & Bacao, 2020); those who found that task technology fit significantly impacts the ICU.

Table 10. Model fit parameters for model A, B, C and D of ML algorithms.

ML algorithm	Model A				Model B				Model C				Model D			
	Parameters	RMSE	R-square	MAE												
Neural network	5 Neurons with single hidden layer	2.9773	0.6529	2.700	5 Neurons with single hidden layer	2.3752	0.5532	2.080	2 Neurons with single hidden layer	2.5228	0.6617	2.2155	7 Neurons with single hidden layer	2.5228	0.6622	2.2153
Support vector machine	Linear kernel with C=0.1052	0.5836	0.6596	0.4238	Linear kernel with C=0.1052	0.7163	0.6278	0.5305	Linear kernel with C=1	0.6378	0.72911	0.4784	Linear kernel with C=1	0.6188	0.7415	0.4701
	Radial Kernel with sigma = 0.3009 and C=1	0.6160	0.6208	0.4576	Radial Kernel with sigma = 0.2855 and C=0.25	0.7121	0.6170	0.5359	Radial Kernel with sigma = 1.2285 and C=0.25	0.6568	0.7039	0.5012	Radial Kernel with sigma = 0.1758 and C=0.50	0.6576	0.7132	0.5006
Random forest	mtry (No of variables selected at random) = 3	0.6011	0.6374	0.4448	mtry (No of variables selected at random) = 2	0.7148	0.6204	0.5437	mtry (No of variables selected at random) = 2	0.6802	0.6848	0.5173	mtry (No of variables selected at random) = 2	0.6510	0.7130	0.4979
KNN	K=9	0.6474	0.5765	0.4802	K=9	0.7066	0.6220	0.5297	K=9	0.6758	0.6877	0.5045	K=7	0.6814	0.6870	0.5154
GLM	mstop = 50	0.5813	0.6690	0.4284	mstop = 150	0.7066	0.6236	0.5511	mstop = 150	0.6314	0.7268	0.4772	mstop = 150	0.6145	0.7394	0.4668
boosting	Fraction =1, and lambda = 0.0001	0.5831	0.6635	0.4277	Fraction = 1, and lambda = 0.0001	0.7111	0.6234	0.5533	Fraction = 1, and lambda = 0.0001	0.6321	0.7258	0.4799	Fraction =1, and lambda = 0.0001	0.6157	0.7451	0.4659

Table 11. Variable importance for ML model D.

Machine learning algorithm	Variables	Overall variable importance	Machine learning algorithm	Variables	Overall variable importance
Neural network	UM	57.21	KNN	UM	52.74
	HM	100.0		HM	100.0
	IQ	33.29		IQ	37.04
	SQ	49.12		SQ	53.74
	TTF	40.84		TTF	54.74
	REC	4.967		REC	0.000
SVM linear	NET	0.000	GLM boosting	NET	12.67
	UM	52.64		UM	20.54
	HM	100.0		HM	100.0
	IQ	37.04		IQ	13.12
	SQ	53.74		SQ	16.98
	TTF	54.23		TTF	12.16
SVM radial	REC	0.000	Elastic net	REC	0.000
	NET	12.67		NET	1.859
	UM	52.64		UM	52.64
	HM	100.0		HM	100.0
	IQ	37.04		IQ	37.04
	SQ	53.74		SQ	53.74
RF	TTF	54.23	Overall mean values	TTF	54.23
	REC	0.000		REC	0.000
	NET	12.67		NET	12.67
	UM	33.00		UM	45.92
	HM	100.0		HM	100.0
	IQ	21.13		IQ	30.81
	SQ	34.31	SQ	45.05	
	TTF	37.88	TTF	44.04	
	REC	0.000	REC	0.709	
	NET	11.61	NET	9.164	

Further, we found that recordability significantly impacts both utilitarian and hedonic motivation. This finding concurs with the findings of Al Ayubi et al. (2014), (Rabin & Bock, 2011), along with (Li et al., 2018). These authors had earlier highlighted that if users recorded their fitness activities, it would become easier for them to monitor their health goals, and hence, might be deemed as an important variable affecting ICU of HFA.

Our findings also revealed that networkability significantly impacts both utilitarian and hedonic motivation, concurring in the process with the findings (Anderson et al., 2007); (Tong et al., 2019); (Petersen et al., 2019); (Tu et al., 2019). These authors emphasized that networkability does enhance self-esteem, confidence, and social status; and hence, is an important variable in determining the ICU of HFA.

The findings indicated that both hedonic and utilitarian motivation significantly impact the users' intention to continue HFA usage. Similar results were obtained by Yuan et al. (2015), where they reported that fun and gamification were very important for users' intention to continue using apps. This study first helps in identifying the key influencers of the decision to continue to use HFA. However, it may be noted that prior research did not consider the influence of UM and HM on ICU. Nevertheless, our findings describe the function of both UM and HM from the users' viewpoint, demonstrating thereby how they can effectively boost their overall gratification with HFA, which in turn results in ICU.

Importantly, this is possibly one of the very few researches where the moderating role of health valuation in ICU had been examined within the ambits of HFAs in India. However, incorporating health valuation as a moderating variable in the ICU of HFA does provide personalized recommendations and interventions that are largely customized to a person's needs and objectives. Our results revealed that health valuation significantly moderates the relationship between technology factors, such as information quality, and system quality, as well as the network effect, such as the networkability of the application, coupled with utilitarian motivation. Moreover, it also moderates networkability and hedonic motivation. By and large, this implies that users, who value their health and are serious about it, are sufficiently knowledgeable, and possibly therefore, are most likely to have specific health goals. Therefore, one may assume that a customer, who values his/her health is more likely to continue to use the app, as it helps in achieving personal goals. Furthermore, our results demonstrate that if users do value their health, the effect of information quality and system quality on ICU is augmented. This finding echoes the results of

Vaghefi and Tulu (2019); the authors therein, affirming the influence of the level of commitment of a customer to his/her health goals on his/her ICU of such apps.

As mentioned earlier, we employed ML, using R Programming to counterbalance the SEM findings. Our rationale for adopting both SEM-ML was to complement each other, as SEM is suitable for hypotheses testing of linear relationships, while ML helps in capturing nonlinear relationships in the construct (Cepeda-Carrion et al., 2019; Henseler et al., 2015).

Thus, once the assembling methods that integrate several models or learners to produce a more robust and accurate model were applied (Hare & Kutsuris, 2022; Sagi & Rokach, 2018; Tuv, 2002), They were combined, typically through a voting or averaging mechanism to get the amalgamated result. Notably herein, rather than using a single model to find the most relevant features, we mixed seven ML models, including ANN, SVM Linear, SVM Radial, Random Forest, KNN, and GLM Boosting. The results indicate that HM seems to be the most significant predictor of the intention to continue HFA usage. This finding is in line with (Alam et al., 2020) study. Further, our results revealed that as youths are naturally tech-savvy, they are largely employed for hedonic motivation—that is, entertainment, fun, and fascinating features; and these are also significant to boost the intention to continue usage for HFA.

Interestingly, the statistical findings from the ML algorithms were remarkably similar to those from the SEM model. Hedonic motivation, information quality, system quality, recordability, task technology fit, and networkability were the outcomes of both SEM and ML. Importantly, our adoption of the extended UGT model helped in explaining everything quite well, as all variables turned out to be substantial predictors of intention to continue usage. However, the artificial neural network analysis had a stronger model fit and was able to capture both the linear and non-linear correlations between the predictors and the intention to continue usage of HFA amongst the youth of India.

5.1. Theoretical implications

This study provides a significant theoretical contribution by expanding the uses and gratification theory (UGT) with a novel framework that incorporates hedonic and utilitarian motivations as mediating variables and health valuation as a moderating variable. To our limited knowledge, this is possibly among the first few studies to investigate factors affecting users' continuance intention towards HFA. Findings pinpoint the factors that account for the users' intention to continue usage, specifically for health and fitness apps.

Our findings thereby have various theoretical implications; first, this is possibly among the few studies to extend the use and gratification theory, while incorporating information quality, system quality, recordability, networkability, task technology fit, utilitarian motivation, and hedonic motivation as gratification to ICU of health and fitness apps. In fact, by extending the Use and Gratification model, we explored ICU from the users' perspective of gratifications derived from technology, along with the users' perception of task technology fit. We found that the gratification that the user derives from technology and how suitably the functions required by the user are available in the app impacts whether the user will continue using the app or abandon it.

Second, to the best of our knowledge, this is one of the few studies that has engaged health valuation as a moderator variable in the ICU of HFAs. If a user does value health and wants to focus on his/her health and fitness, s/he would continue using the apps. The users' attribute of '*valuing their health*' would help them absorb the information provided by these apps, leading to an enhanced perception of the information and system quality of the app. Through our results and findings, we believe that we have helped in broadening the horizons of use and gratification theory, and enhanced ICU literature in the process, by validating the results through an innovative methodology of the two-way approach of the PLS-SEM and ML models. The use of machine learning to complement structural equation modeling (SEM) further validates the findings and suggests that incorporating advanced analytics can enhance the prediction and understanding of user behavior, guiding more effective app development and marketing strategies.

5.2. Practical implications

This study has significant practical implications for the health and fitness app (HFA) industry, particularly regarding strategies to enhance users' intention to continue using these apps. To support continued usage, HFA designers, developers, and managers should collaborate with healthcare professionals such as doctors, nurses, dieticians, and certified health and fitness trainers, alongside reputable health organizations. These experts can provide accurate, relevant, and scientifically-based information, which should be regularly updated to reflect the latest health and industry trends. Including disclaimer information advising users to consult healthcare professionals before starting new routines is crucial. Additionally, the app's interface should be clean, consistent, quick to load, and intuitive, enhancing the overall system quality and user experience.

Enhancing the recordability and networkability functions is also essential. Users should be able to record their progress, share it seamlessly with friends, social media, wearable devices, and fitness communities, and participate in health challenges. Incorporating fun elements like leaderboards, points, and badges can motivate users to stay engaged. The app should offer a variety of engaging content, such as videos and articles, and provide access to health and fitness experts to ensure a holistic approach to health. By focusing on high-quality information, system functionality, and features that encourage healthy behaviors and social interaction, HFA designers can enhance health valuation among users, leading to increased loyalty and continued app usage. Marketing efforts should target individuals who prioritize health maintenance, as they are more likely to remain loyal users.

6. Limitations and scope for the future study

Finally, our study has limitations; first, we mainly focused on the users' intention to continue using health and fitness mobile apps within the demographic context of India, owing to which, all the results may not be generalizable to other countries and cultures. Future studies could thereby explore the same/similar constructs/variables within the ambits of other countries. Second, our study primarily has been cross-sectional in its approach; future studies could explore longitudinal research. Finally, the cost to the customer to use such apps may also have to be considered in the future, as most apps so offer certain moderate features for free, and for additional benefits, customers have to pay a premium.

7. Conclusion

HFAs do have the potential to impact the users' health and wellness, as they provide them with appropriate information and tools to record, track, and manage the same. HFAs can also help users to set and achieve their fitness goals. Besides, the social networkability functionality available on these apps can help users stay motivated and inspired.

This study investigated the factors that impact the users' intention to continue using HFAs post the COVID-19 pandemic, using the use and gratification theory. We tested some of the predicted associations, and validated them in the first phase of the investigation, using SEM. In the second phase, the predictors were ranked according to their importance, using ML algorithms, and we found that gratifications obtained from both utilitarian and hedonic motivation may significantly impact the users' intention to continue usage, even post-pandemic. We also studied the impact of 'health valuation' as a moderating variable; we observed that there's a relationship between information quality, system quality, networkability, and utilitarian motivation; interestingly, the relationship between networkability and hedonic motivation is impacted by HV. From these findings, it may be assumed that the users' intention to continue using the app is dependent on two major aspects, such as features within the app itself, coupled with the users' self-attributes. Furthermore, we noted that while task technology fit and user gratification do influence the intention to continue usage, along with the users' belief about the importance of health (i.e. health valuation) it does influence the outcome.

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Author contributions

Vinod Sharma: Introduction, research methodology, data analysis, and final proof. Ruchi Payal: Introduction, literature review, discussion, and final proof. Kirti Dutta: Literature review, discussion, implications and final proof. Jeanne Poulouse: Discussion, implications, conclusion, and final proof. Manohar Kapse: Research methodology, data analysis, interpretation, and final proof.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

Authors agree to make data and materials supporting the results or analyses presented in their paper available upon request from the corresponding author.

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