Adoption of Mobile Health Applications Based On UTAUT2: A Study of North-Indian States

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Abstract:
Mobile technologies are changing the way people across the globe are achieving their day-to-day tasks. Mobile health applications or mHealth apps are an example of these technologies that are used by healthcare professionals (HCPs) as well as users/patients alike. This study aims to analyze the adoption of mHealth apps which provide the facility of consulting online with an HCP among the population of the north-Indian states using the prior validated measurement scale of Unified Theory of Acceptance and Usage of Technology 2 (UTAUT2). Following convenience and snowball sampling, data was collected through an online survey using Google Forms. Using Smart-PLS 4, descriptive analysis and structural equation modeling were conducted. Among the five constructs and three moderators undertaken for the study, only three constructs, i.e., performance expectancy, social influence and price value were found to have a significant effect on the behavioral intention to adopt mHealth apps in users/patients.

Keywords: Adoption, healthcare, UTAUT, mHealth

INTRODUCTION

Revolutionizing the entire healthcare industry, mHealth has changed the way health information and services are delivered across the globe. Combined with an increase in the use of smartphone and mobile applications in turn, the world, including India, has witnessed a boom in the development and adoption of mHealth applications (apps) with the total mHealth apps market predicted to exceed 50 billion U.S. dollars in 2025 (Statista, 2020).

With the HCP-patient ratio standing at 1:834 (The Print, 2022), the lack of medical manpower was further highlighted during the COVID-19 pandemic. Owing to the pandemic, the governments across the world started motivating people to avoid visiting healthcare facilities for routine consultations or appointments that could be managed online by using mHealth applications or even government managened online portals.

With features ranging from record maintenance to medication reminders, from appointment booking to sample collection for testing, from online consultation or sharing of records with HCPs, these applications empower users to actively participate in managing their health, enhance patient outcomes, promote preventative care and remote monitoring so as to bridge the gaps in healthcare access by reaching both rural and urban population, surpassing geographical barriers. However, even with such an incredible USP, users face multiple issues in adopting these apps over the traditional system of consultations.

Numerous studies have been conducted across different developing countries to study the factors influencing the adoption of these apps. However, limited research has been conducted in the context of the Indian population. This paper aims to study the determinants of behavioral intention to adopt mHealth apps among the population of India and record the effects, if any, of age, gender and experience on the same.

RESEARCH/THEORETICAL BACKGROUND

The adoption and perception of mHealth applications is an area of research that has received considerable attention by researchers among developed as well as developing nations across the world, moreso after the COVID-19 pandemic. Most of these studies have followed a theoretical framework to determine factors influencing user intention, like, Diffusion of Innovations Theory, TAM (Technology Acceptance Model), UTAUT ((Unified Theory of Acceptance and Use of Technology), TRP (Theory of Planned Behavior), etc. The determinants of behavioral intention have been studied for both the user groups of these apps, which include Healthcare Professionals (HCPs) and patients/ users by a number of researchers. A comparative review of some studies that have used UTAUT (Venkatesh et al., 2003) and its extension UTAUT2 ((Unified Theory of Acceptance and Use of Technology 2) (Venkatesh et al., 2012) to study the determinants of behavioral intention for users/patients is presented in Table 1**.**

Table 1. Review of Studies Based on UTAUT and UTAUT2

Source	**Methodology**	**Sample**	**Country**	**Framework/Theory**	**Analysis software**
Dzimiera, 2017	Quantitative- PLS-SEM	289 German citizens, 18-year-old or more	Germany	UTAUT with self-efficacy, physical risk, surveillance anxiety and privacy and security risk	Smart-PLS
Hoque and Sorwar, 2017	Quantitative- PLS-SEM	274 participants of age 60 years and above	Bangladesh	UTAUT with technology anxiety and resistance to change	Smart-PLS
Idrish et al., 2017	Quantitative- PLS-SEM	908 urban mobile phone users	Bangladesh	UTAUT2 with perceived financial cost, perceived self-efficacy and personal innovativeness	Smart-PLS
Macedo 2017	Quantitative- PLS-SEM	278 computer and internet users	Portugal	UTAUT2	Smart-PLS
Quaosar et al., 2017	Quantitative- PLS-SEM	245 respondents	Bangladesh	UTAUT with perceived credibility	Smart-PLS

Ravangard et al., 2017	Quantitative- PLS-SEM	170 patients	Iran	UTAUT2 with usability and the ability to use technology	SPSS and Smart-PLS
Alaiad et al., 2019	Quantitative- PLS-SEM	280 younger citizens who were students of JUST	Jordan	UTAUT, dual-factor model and health belief model	Microsoft Excel and Smart-PLS
Duarte and Pinho, 2019	Qualitative and quantitative- (PLS-SEM) and fuzzy-set qualitative comparative analysis (fsQCA)	120 users of mHealth devices and applications	Portugal	UTAUT2	Smart-PLS and fsQCA
Nisha et al., 2019	Quantitative- PLS-SEM	927 urban residents	Bangladesh	UTAUT with system quality, interaction quality, personal innovativeness, anxiety and perceived credibility	Smart-PLS
Alam et al., 2020(b)	Qualitative and quantitative- (PLS-SEM) and Artificial Neural Network Approach	400 respondents	Bangladesh	UTAUT2 with privacy, lifestyles, self-efficacy and trust	Not mentioned specifically
Alam et al., 2020(a)	Quantitative- PLS-SEM	296 Generation Y participants	Bangladesh	UTAUT model with perceived reliability and price value	Smart-PLS
Yamin and Alyoubi, 2020	Quantitative- PLS-SEM	348 citizens	Saudi Arabia	UTAUT with task technology fit model, awareness and self-efficacy	Smart-PLS
Arfi et al., 2021	Quantitative- PLS-SEM	267 users	France	UTAUT2 with perceived risk and trust	xlstat-PLSPM software
Chang et al., 2021	Quantitative- PLS-SEM	629 patients at a hospital	Taiwan	UTAUT2 with e-health literacy and personal innovativeness	SPSS and Smart-PLS
Gu et al., 2021	Quantitative- PLS-SEM	353 patients in major hospitals	Pakistan	UTAUT2, trust, privacy, task-technology fit, and personal innovativeness of users' intentions	Smart-PLS

Napitupulu et al., 2021	Quantitative- PLS-SEM	118 users of Telehealth	Indonesia	UTAUT with doctor's opinion and computer anxiety	Smart-PLS
Octavius and Antonio, 2021	Quantitative- PLS-SEM	787 users of mHealth apps	Indonesia	UTAUT2, Diffusion of innovation, and the Internet customer trust model	Smart-PLS
Semiz and Semiz, 2021	Quantitative- PLS-SEM	354 individuals who had used at least one mHealth application before.	Turkey	UTAUT2 with perceived trust	SPSS and Smart-PLS
Palas et al., 2022	Qualitative and quantitative- (PLS-SEM) and fuzzy-set qualitative comparative analysis (fsQCA)	493 elderlies aged 60 or more, users of mHealth	Bangladesh	UTAUT2 with service quality and quality of life	Smart-PLS and fsQCA

It is evident from Table 1 that the researchers have exclusively used Partial Least Square-Structural Equation Modeling (PLS-SEM) based on the quantitative approach by using Smart-PLS software, with respondents of the survey being young as well as the elderly across different studies. A thing to note here is that not all these studies have surveyed only the users of mHealth apps/services.

Table 2 provides a comparative analysis of the significant and non-significant variables of the studies included in Table 1. The variation between the results of the studies reviewed in Table 1 exists mainly due to the difference in the specific characteristics of the study as well as due to the additional variables incorporated by them (Duarte and Pinho, 2019). Moreover, it can be deduced from Table 2 that none of the variables consistently have a significant or non-significant impact on the adoption of mHealth apps, which further indicates that among the variables of UTAUT, none are neither necessary nor sufficient in and of themselves to have an impact on the adoption of mobile health, as is also confirmed by Duarte and Pinho (2019) in their study.

Table 2. Results of Studies of the Factors of UTAUT viz-a-viz Behavioral Intention

Variable	**Significant effect**	**Non-significant effect**
Performance expectancy	Duarte and Pinho, 2019; Napitupulu et al., 2021; Yamin and Alyoubi, 2020; Octavius and Antonio, 2021; Semiz and Semiz, 2021; Chang et al., 2021; Alam et al., 2020(a); Alaiad et al., 2019; Alam et al., 2020(b); Dash and Sahoo, 2022; Hoque and Sorwar,	Gu et al., 2021; Arfi et al., 2021; Palas et al., 2022; Arfi et al., 2021.

	2017; Nisha et al., 2019; Idrish et al., 2017; Macedo 2017; Quaosar et al., 2017; Nisha et al., 2019; Dzimiera, 2017.	
Effort expectancy	Napitupulu et al., 2021; Yamin and Alyoubi, 2020; Gu et al., 2021; Semiz and Semiz, 2021; Alaiad et al., 2019; Arfi et al., 2021; Dash and Sahoo, 2022; Hoque and Sorwar, 2017; Nisha et al., 2019; Idrish et al., 2017; Macedo 2017; Quaosar et al., 2017; Nisha et al., 2019; Arfi et al., 2021.	Duarte and Pinho, 2019; Octavius and Antonio, 2021; Chang et al., 2021; Alam et al., 2020(a); Alam et al., 2020(b); Palas et al., 2022; Dzimiera, 2017.
Social influence	Yamin and Alyoubi, 2020; Gu et al., 2021; Semiz and Semiz, 2021; Alam et al., 2020(a); Alaiad et al., 2019; Arfi et al., 2021; Alam et al., 2020(b); Palas et al., 2022; Dash and Sahoo, 2022; Hoque and Sorwar, 2017; Macedo 2017; Quaosar et al., 2017; Dzimiera, 2017; Arfi et al., 2021.	Duarte and Pinho, 2019; Napitupulu et al., 2021; Chang et al., 2021; Nisha et al., 2019; Idrish et al., 2017; Nisha et al., 2019.
Facilitating conditions	Napitupulu et al., 2021; Yamin and Alyoubi, 2020; Gu et al., 2021; Semiz and Semiz, 2021; Chang et al., 2021; Alam et al., 2020(a); Arfi et al., 2021; Alam et al., 2020(bTIS); Nisha et al., 2019; Idrish et al., 2017; Macedo 2017; Nisha et al., 2019; Dzimiera, 2017; Arfi et al., 2021.	Duarte and Pinho, 2019; Alaiad et al., 2019; Palas et al., 2022; Dash and Sahoo, 2022; Hoque and Sorwar, 2017; Quaosar et al., 2017.
Price value	Palas et al., 2022; Ravangard et al., 2017.	Duarte and Pinho, 2019; Alam et al., 2020(a); Alam et al., 2020(b); Macedo 2017.

RESEARCH MODEL

This study follows the research framework based on the five constructs of UTAUT2, which are performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC) and price value (PV) alongwith the three moderators, i.e., age, gender and experience as shown in Fig. 1.

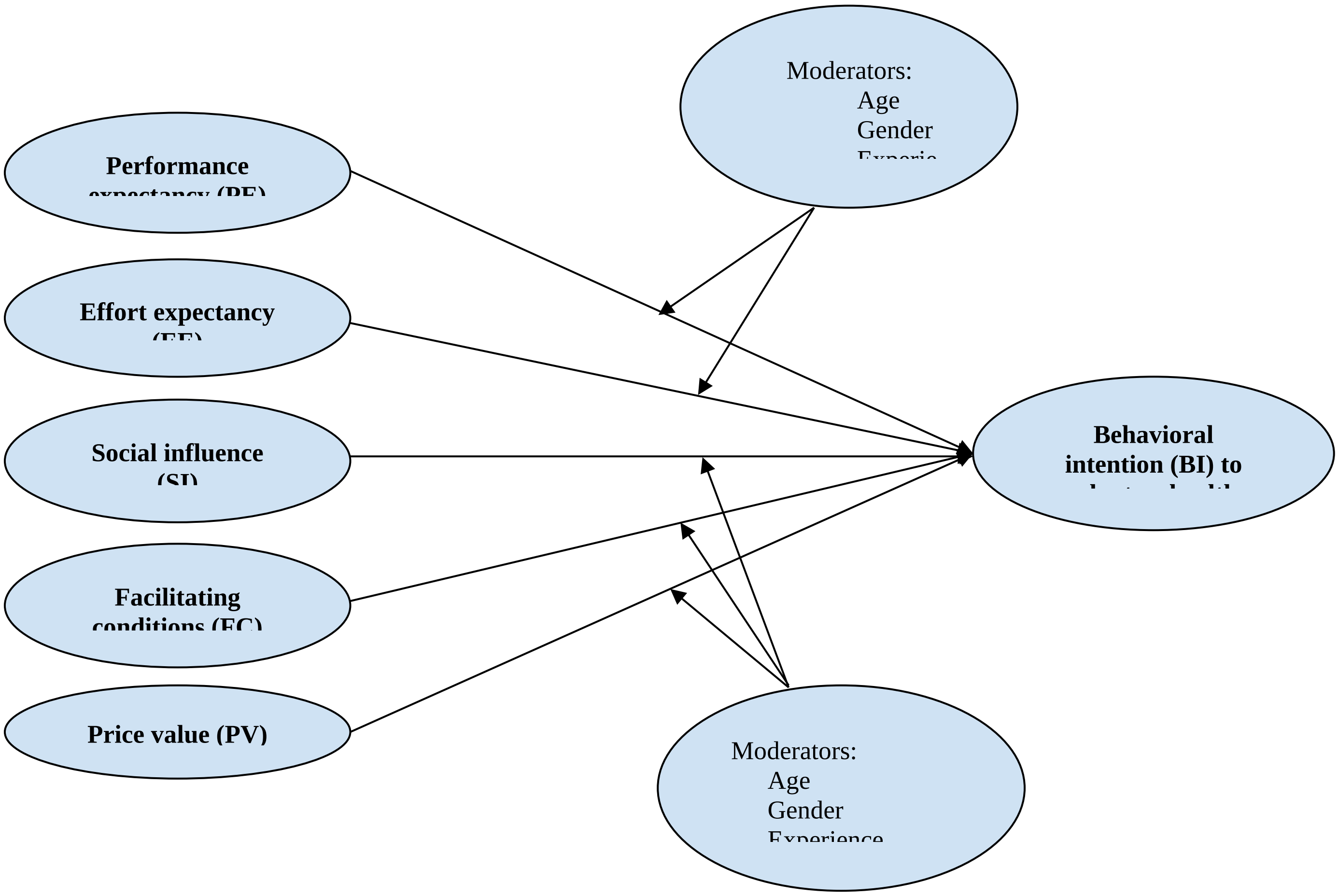
HYPOTHESES

Based on the research model depicted in Fig. 1, the following hypotheses were formulated:

H1: PE significantly influences behavioral intention (BI) of users to adopt mHealth apps.
H2: EE significantly influences behavioral intention of users to adopt mHealth apps.
H3: SI significantly influences behavioral intention of users to adopt mHealth apps.
H4: FC significantly influences behavioral intention of users to adopt mHealth apps.

H5: PV significantly influences behavioral intention of users to adopt mHealth apps.
H6: Age will moderate the effects of PE, EE, SI, FC, SI and PV on BI to adopt mHealth apps.
H7: Gender will moderate the effects of PE, EE, SI, FC, SI and PV on BI to adopt mHealth apps.
H8: Experience will moderate the effects of PE, EE, SI, FC, SI and PV on BI to adopt mHealth apps.

Fig 1. Research framework



METHODOLOGY:

Measurement scale

To assess the behavioral intention to use mHealth apps, the questionnaire was set using a prior-validated scale developed by Venkatesh et al (2012), also referred to as UTAUT2. However, for the purpose of this study, among the eight total variables of UTAUT2, habit and hedonic motivation were not included in the proposed framework. Since the mHealth apps under study are used to consult with an HCP, it can be safely concluded that no user uses such apps for the purpose of enjoyment. Moreover, one cannot evaluate the development of a habit towards a specific app in a cross-sectional study (Ashraf et al., 2015). Price value has been included since these apps come with a subscription fee for both the user groups and an individual HCP consultation fee as well for the users, the effect of which on behavioral intention can be studied.

The multi-item questionnaire statements (19 items), grouped into 6 factors were slightly modified to fit the mobile health context with the respondents rating their responses on a 7-point Likert scale (1 = strongly disagree; 7 = strongly agree). A demographic profiling section was also added with 4 questions.

Data collection

Since it was not possible to obtain the list of all the users registered on mHealth apps, the survey was uploaded on Google Forms and the link of the same was then shared and distributed through convenience sampling, followed by snowball sampling to the residents of north-Indian states. Except for two questionnaire items, one each from Facilitating conditions and Price value, all factor loadings exceeded the 0.70 thresholds in the pilot study of 40 respondents. These two items were removed from the questionnaire and the questionnaire link was shared again with the appropriate sample population across India. A total of 278 responses were collected, out of which 63 did not have any prior experience using a mHealth app which rendered their responses hypothetical, 12 had no experience using smartphones and 3 respondents had left at least 1 questionnaire item unanswered. The final sample included a total of 200 respondents, out of which 63% were females and 60% users were post-graduate or higher degree holders. The demographic profile also shows 54.5% of the users are between the ages of 20-29 years which suggests that the younger generation is more inclined to the use of technology with 81.5% having the experience of using smartphones for more than 5 years.

DATA ANALYSIS AND RESULTS

The descriptive analysis was conducted through Google Sheets, followed by PLS-SEM analysis using Smart-PLS 4.0, which aligns with the reviewed studies (Table 1). The analysis included assessing the measurement model and the structural model.

Assessment of the measurement model includes determining the validity and reliability of the measures included in the questionnaire. Table 3 depicts the factor loadings (all.0.7), the reliability indicators, i.e., the Cronbach's alpha and the composite reliability (all >0.7) and the convergent validity indicator, i.e., the average variance extracted values (all >0.5) (Hair et al., 2011). The findings of the measurement model indicate that the construct reliability and convergent validity is confirmed since all the values are above the threshold mentioned by Hair et al. (2011).

The HTMT (Heterotrait-Monotrait) Ratio of Correlations and the Fornell and Larcker criterion were applied to further assess the discriminant validity (Hair et al., 2011). For the HTMT ratio to show that the constructs measure distinct concepts and are discriminant, the values obtained must be less than 0.90 (Henseler et al., 2015). Furthermore, in the Fornell and Larcker criterion, the square root of the AVE of each construct should be higher than its correlation with any other construct. Pertaining to this analysis, both the criteria to ascertain discriminant validity were met, as is depicted in Table 4**,** thus, ensuring all the constructs are valid and reliable. Additionally, the cross-loadings also confirmed the discriminant validity of constructs since the results showed that factor loadings of each construct were higher than other construct loadings (Table 5) (Hair et al., 2011).

Table 3. Measurement Model

Scales	Loadings	α	CR	AVE
PE1: I find that using mHealth app for routine consultation with a doctor will be useful in my daily life.	0.913	0.892	0.933	0.823
PE2: Using mHealth app may help me to accomplish things more	0.926			

quickly.				
PE3: Using mHealth app may increase my productivity.	0.882			
EE1: Learning to use mHealth app will be easy for me.	0.919	0.937	0.955	0.842
EE2: It is easy for me to become skillful at using mHealth app.	0.925			
EE3: Interacting and navigating through mHealth app will be clear and understandable for me.	0.898			
EE4: I would find mHealth app easy to use.	0.929			
SI1: People whose opinions that I value prefer that I use mHealth app.	0.949	0.936	0.959	0.886
SI2: People who are important to me think that I should use mHealth app.	0.934			
SI3: People who influence my behavior think that I should use mHealth app.	0.942			
FC1: I have the resources (mobile device, internet connection, etc.) necessary to use mHealth app.	0.898	0.825	0.896	0.742
FC2: I have the knowledge (technical know-how with respect to using a mobile device as well as a mobile application) necessary to use mHealth app.	0.897			
FC3: Confidentiality of information is something I would consider before adopting mHealth app.	0.783			
PV1: mHealth applications are a good value for the money.	0.873	0.751	0.888	0.799
PV2: I find economical using mHealth applications.	0.915			
BI1: I intend to use mHealth app for consulting with a healthcare professional.	0.919	0.91	0.944	0.848
BI2: I predict I would use mHealth app for consulting a healthcare professional.	0.937			
BI3: I am curious to use mHealth app in my routine follow-ups/check-ups.	0.906			

Table 4. Discriminant Validity Results

	HTMT ratio							**Fornell and Larcker Criterion**					
Constructs	BI	EE	FC	PE	PV	SI		BI	EE	FC	PE	PV	SI
BI								**0.921**					
EE	0.683							0.632	**0.918**				
FC	0.58	0.794						0.507	0.706	**0.861**			
PE	0.752	0.73	0.595					0.68	0.669	0.517	**0.907**		

PV	0.776	0.687	0.631	0.641				0.647	0.576	0.501	0.533	**0.894**	
SI	0.726	0.622	0.439	0.672	0.572			0.67	0.582	0.393	0.614	0.482	**0.941**

Note: The bold and italic values show the square root of AVE for the Fornell and Larcker criterion.

Once the measurement model was assessed for reliability and validity measures, the structural model was analyzed. This was done through bootstrapping using a re-sample of 5000 (Hair et al., 2011). Path coefficients, t statistics and significance levels are depicted in Table 6**.**

Table 5. Cross Loadings

	BI	**EE**	**FC**	**PE**	**PV**	**SI**
BI1	**0.919**	0.542	0.451	0.622	0.614	0.629
BI2	**0.937**	0.622	0.485	0.651	0.592	0.598
BI3	**0.906**	0.58	0.463	0.605	0.58	0.625
EE1	0.599	**0.919**	0.708	0.648	0.506	0.503
EE2	0.562	**0.925**	0.627	0.584	0.528	0.523
EE3	0.567	**0.898**	0.579	0.601	0.549	0.59
EE4	0.589	**0.929**	0.674	0.621	0.533	0.523
FC1	0.492	0.662	**0.898**	0.498	0.49	0.355
FC2	0.438	0.67	**0.897**	0.445	0.384	0.422
FC3	0.368	0.474	**0.783**	0.383	0.418	0.221
PE1	0.655	0.63	0.543	**0.913**	0.495	0.544
PE2	0.631	0.613	0.448	**0.926**	0.52	0.583
PE3	0.558	0.576	0.408	**0.882**	0.431	0.543
PV1	0.519	0.51	0.404	0.406	**0.873**	0.399
PV2	0.629	0.521	0.486	0.536	**0.915**	0.459
SI1	0.6	0.533	0.336	0.575	0.462	**0.949**
SI2	0.65	0.51	0.386	0.531	0.415	**0.934**
SI3	0.64	0.6	0.384	0.626	0.485	**0.942**

Note: Factor loadings of construct are in bold and italic.

Table 6. Hypotheses Testing

Hypothesis	**Relationship**	**Path coefficient**	**t statistics**	**Significance**	**Results**
H1	PE -> BI	0.259	3.856	0.000*	**Supported**
H2	EE -> BI	0.074	0.976	0.329	Not supported
H3	SI -> BI	0.307	4.477	0.000*	**Supported**
H4	FC -> BI	0.055	0.814	0.416	Not supported
H5	PV -> BI	0.291	4.913	0.000*	**Supported**
H6	AGE->BI	0.048	0.829	0.407	Not supported
H7	GENDER->BI	0.021	0.252	0.801	Not supported
H8	EXPERIENCE->BI	-0.066	1.384	0.166	Not supported

Note: *point of significance p < 0.05.

This study follows the UTAUT2 model to determine the behavioral intention of users to adopt mHealth apps for consulting with a healthcare professional. Results of Table 6 indicate that performance expectancy, social influence and price value have a significant impact on the user intention to adopt mHealth apps with path coefficients greater than 0.10 and $p < 0.05$, approving H1, H3 and H5. However, for effort expectancy and facilitating conditions neither of the two criteria are met, with both having path coefficients less than 0.10 and p values > 0.05. Thus, H2 and H4 are not supported. In addition to these variables, the hypotheses pertaining to the three moderators of UTAUT2, i.e., H6, H7 and H8 based on age, gender and experience respectively, are found to have insignificant moderating effects on behavioral intention.

CONCLUSION AND IMPLICATIONS

This study aimed at determining the factors that affect the behavioral intention of a user towards using mHealth applications. Going by the R2 value of **0.644,** it can be concluded that the model moderately explains the variance in measuring behavioral intention of users to adopt mHealth apps (Hair et al., 2011). As per Table 6, social influence (H3) followed by price value (H5) and performance expectancy (H1) are the significant determinants of behavioral intention based on their path coefficient values.

These results imply that while choosing to adopt these applications, users are often influenced by the opinions of the people in their social circles, getting their money's worth through online consultation as well as the perceived advantages of using such systems over the traditional ones in their day-to-day lives. In order to promote the adoption of these apps more and more, developers can focus on issues like data security, record maintenance, appointments and/or medicine reminders, user-friendly interface and inclusion of interactive features within the apps. Additionally, users will be attracted towards such platforms if they are able to access them on their current devices and do not face issues in figuring out how to navigate through an app, thus minimizing effort and facilitating the usage of the same.

Taking into consideration the results of moderation analysis, based on age, gender and experience, all of which were insignificant, it can be further concluded that with regards to the Indian population, these moderators have no effect on the behavioral intention to adopt mHealth apps. This can be explained due to the growing familiarity and access to smartphones among people in India, irrespective of age and gender which was estimated to reach over 1 billion in 2023 (Statista, 2023) and also, to the usage of mobile apps in general.

LIMITATIONS AND FUTURE RESEARCH

This study has a number of limitations. The study only analyzed the effect of the constructs of UTAUT2 on behavioral intention. However, the effect of behavioral intention on actual usage was not studied. Researchers can also follow the same model for a longitudinal study to examine and compare results across different time periods. Future research can also focus on and build upon the existing factors/constructs of UTAUT2 by including more constructs that can affect behavioral intention to adopt these apps. This study has also focused on mHealth apps that provide the facility of consulting online with an HCP through audio/video chat and text messaging. Other categories of mHealth apps like mHealth apps based on privately owned firms and mHealth apps of established hospitals like Apollo available on the app stores can also be studied and compared in terms of adoption among people. Additionally, researchers can also gather similar data from different countries for a comparative and thus, more constructive analysis.

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