Received: 2 October 2024 | Revised: 31 December 2024 | Accepted: 27 January 2025

Healthcare Technology Letters

DOI: 10.1049/htl2.70005

The Institution of Engineering and Technology WILEY

LETTER

Identifying factors shaping the behavioural intention of Nepalese youths to adopt digital health tools

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Abstract

The digitalization of healthcare has gained global importance, especially post-COVID-19, yet remains a challenge in developing countries due to the slow adoption of digital health tools. This study aims to identify major predictors impacting the behavioural intention of Nepalese youths to adopt digital health tools by utilizing the framework based on the extended unified theory of acceptance and use of technology (UTAUT-2). The cross-sectional data from 280 respondents was collected from youths (i.e., aged 16-40) in the Kathmandu Valley and were analyzed through PLS-SEM. Most of the respondents were using smartwatches followed by blood pressure monitors and pulse oximeters. The findings revealed hedonic motivation as the strongest predictor of behavioural intention to use digital health tools followed by facilitating conditions, social influence, habit, and performance expectancy. The behavioural intention significantly influenced actual usage behaviour. Additionally, behavioural intention mediated the relationship between the above-mentioned five constructs and usage behaviour, except for effort expectancy and price value. The study emphasizes the role of major predictors such as facilitating conditions in shaping the intention of youths to adopt digital health tools providing insights for government, hospitals, and developers to understand consumer perceptions and motivations.

1 | INTRODUCTION

Digital technologies in healthcare have been transforming medical and health practices shifting the focus of healthcare towards people rather than the healthcare professionals [1]. Adoption of digital health tools is eminent in digital health as they gather health data, which along with the use of information and communications technology (ICT) transmit data to healthcare providers enabling them to provide digital health solutions [2, 3]. Through digital health tools such as portable health monitoring devices, health wearables, and health and fitness apps, people have become more empowered to monitor their vital parameters that help prevent or manage many chronic diseases allowing user to take action related to healthcare more quickly [4, 5]. Portable health monitoring devices include healthcare products such as digital thermometer, sphygmomanometer, glucometer, pulse oximeter, and ECG monitor that can be operated easily by consumers or their caregivers to track health metrics [6]. Similarly, digital health wearables such as smart watches and fitness trackers monitor an individual at home, at work, or during activities without interference [7, 8]. The use of health apps allow users to take online health consultations, inquire, and order medicines online [9]. Fitness apps monitor activities such as walking, running, cycling, and sleeping, help set activity and weight goals, suggest nutrition and diet, and provide guidance on exercise techniques [10]. Some apps synchronize with health wearables such as smart watches and fitness bands [11]. These digital health tools connect the users and health care centres providing individuals the benefit of digital health solutions [12].

The use of digital health technology has already saved a lot of healthcare costs in the developed countries [13, 14]. In case of low-income countries, the full potential of digital health technologies is yet to be explored [15]. Despite the rapid innovations in digital technologies, their adoption in different social segments and countries differ due to the various levels of socio-technical development [16]. Many Nepalese are hesitant about self-monitoring either due to limited digital literacy or because they doubt the reliability of digital health tools [17]. This along with the poor healthcare access and infrastructure has resulted in slow adoption of digital health tools in Nepal [18, 19]. Since Nepal is a country with a low economy, health care services can be made accessible and cost-effective through the use of digital health tools in co-ordinance with the ICT [20].

Few studies have been done for assessing the digital health readiness of Nepal [18], exploring the challenges and opportunities for implementing digital health interventions [21], and assessing the attitude and self-care practice among hypertension patients [22] but rarely any studies assessed the factors affecting the adoption of the digital health tools in Nepal. There is a need to study the impact of different factors in the adoption of health technologies among Nepalese individuals as the degree of significance may vary across countries due to various socio-economic factors. For instance, price value had a significant impact on people's intention to adopt wearable health technologies in many countries [1, 23] while in a study in Saudi Arabia, price value did not influence the intention to adopt health wearables [24]. Assessing the impact of various factors on the adoption of digital health tools in Nepal will help strengthen the digital health initiatives. As the studies examining the practice of digital health tools in Nepal are scarce, to fill this empirical gap, this study aims to assess the different factors influencing the adoption of digital health tools among Nepalese youths utilizing the extended (UTAUT-2), a model widely used for assessing the acceptance of technology [25, 26].

2 | LITERATURE REVIEW

This section reviews previous studies that have assessed the acceptance of various digital health technologies by utilizing the UTAUT. Furthermore, it presents the conceptual framework used in the study along with the formulation of hypotheses.

2.1 | UTAUT and its extension

Various theoretical models have been implemented to examine the acceptance of technology such as the technology acceptance model, the UTAUT, the theory of reasoned action, and the social cognitive theory [27]. Among the various theoretical models, UTAUT and its extended models are highly used and relevant in the field of healthcare because of its enhanced explanatory capability of behavioural intention [25, 28]. Venkatesh et al. [29] developed UTAUT by integrating eight theories into four factors to assess technological acceptance: performance expectancy, effort expectancy, social influence, and facilitating conditions. Later in 2013, UTAUT was extended by adding three more factors: hedonic motivation, price value, and habit which significantly improved the variance in intention and use of technology proposing the UTAUT-2 [26]. Table 1 enlists different studies that have examined the adoption of various digital health tools in different countries.

TABLE 1 Previous studies on acceptance of digital health technologies.

Country	Technology	Theory	Reference
Bangladesh	mHealth services	UTAUT	[30]
Taiwan	Wearable health devices	UTAUT	[31]
Saudi Arabia	Wearable health technology	UTAUT-2	[24]
China	Fitness mobile apps	UTAUT, HBM	[32]
Iraq	Mobile health monitoring systems	UTAUT-2	[33]
Africa	Wearable health devices	UTAUT-2	[34]
Thailand	Telemedicine	UTAUT, TPB	[35]
United States	Health and fitness apps	UTAUT-2	[36]

Note: HBM, health belief model; TPB, theory of planned behaviour; UTAUT, unified theory of acceptance and use of technology; UTAUT-2: extended unified theory of acceptance and use of technology.

Several previous studies [32, 35] have combined the UTAUT model with other theories such as HBM and TPB. Some studies have expanded the UTAUT models with outside factors such as government health policy, risk perception, health consciousness and trust [24, 31, 32]. In this study, the researcher has developed the conceptual framework from the extended UTAUT-2 without any addition of external variables as presented in Figure 1.

2.2 | Hypothesis formulation

Based on insights from the literature and conceptual framework used in the study, following hypotheses were formulated to study the relationships between core constructs and the dependent variables.

2.3 | Performance expectancy (PE) and behavioural intention (BI)

People are more likely to adopt health technologies if the devices can increase their effectiveness in health monitoring and care activities [26, 37]. Several studies have found that performance expectancy impacts the user's behavioural intention to adopt digital health technologies [38, 39]. Performance expectancy was found to influence the adoption of mobile health services [40] and fitness wearables [41].

H1: Performance Expectancy positively influences the user's intention to use digital health tools.

2.4 | Effort expectancy (EE) and behavioural intention (BI)

Venkatesh et al. [29] have defined effort expectancy as the level of ease associated with operating the system. Higher levels of ease while using the digital health tools were found to positively impact the behavioural intention to use healthcare wearable technologies [41, 42]. In the context of fitness app too, effort

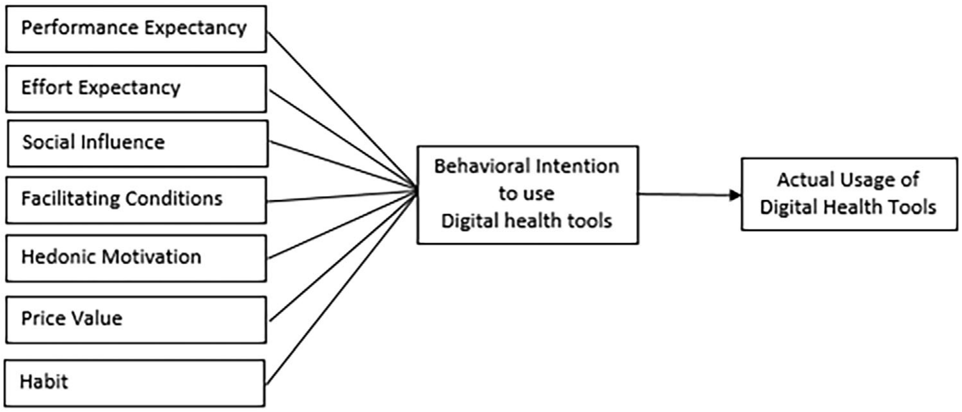

FIGURE 1 Research model. *Note*: Adapted from Venkatesh et al. (2012).

expectancy was found to positively influence the behavioral intention to continue using the app [43].

H2: Effort Expectancy positively influences the user's intention to use digital health tools.

2.5 | Social influence (SI) and behavioural intention (BI)

Nowadays, health wearables incorporate fashion elements [44] which persuades the consumer to perceive that wearing such devices will improve their image among others [45]. Several empirical studies showed that social influence has a positive impact on the behavioural intention to adopt fitness and healthcare related wearable devices [46–48].

H3: Social Influence positively influences the user's intention to use digital health tools.

2.6 | Facilitating conditions (FC) and behavioural intention (BI)

Facilitating conditions concerns the availability of resources and knowledge while using technological tools [26]. Several studies have concluded that facilitating conditions positively influenced the user intentions of using digital health tools such as mHealth applications [30, 40] and wearable health technologies [24].

H4: Facilitating Conditions positively influences the user's intention to use digital health tools.

2.7 | Hedonic motivation (HM) and behavioural intention (BI)

Consumers not only seek for utility but also consider the hedonic aspects of technology [26]. Hedonic factors were found to significantly impact the use of health wearables [49]. Fitness trackers allow users to track the steps taken to keep them engaged with the product [50]. Hedonic motivation was also observed to positively influence the behavioural intention to use smartwatch [42] and apps [36] for monitoring health.

H5: Hedonic Motivation positively influences the user's intention to use digital health tools.

2.8 | Price value (PV) and behavioural intention (BI)

When the perceived benefits of using a technology are greater than the price paid, the price value becomes positive [26]. Price value was found to have a positive impact on intent to adopt wearable devices in studies conducted among elderly people [51] and cancer patients [52]. Similarly, the positive relationship between price value and intent to use was also seen in a study on mHealth acceptance [53].

H6: Price Value positively influences the user's intention to use digital health tools.

2.9 | Habit (H) and behavioural intention (BI)

The prior use of technology was found to be a strong predictor for the future use of technology [54]. The use of health apps and fitness trackers has started to become a habit of many smartphone users [36, 55]. Habit was found to be one of the most significant influences on the intention to use health wearables [24] and mHealth including special apps [36, 56].

H7: Habit positively influences the user's intention to use digital health tools.

2.10 | Behavioural intention (BI) and actual use of digital health tools (AU)

Behavioural intention is the readiness of a consumer to participate in a certain activity and is observed to have a major impact in actual use of a technology [29, 57]. In several studies, behavioural intention has been found to have a positive effect on the actual use of health technologies including mHealth applications [30] and wearable health devices [58].

H8: Behavioural Intention of using digital health tools has a positive effect on the actual usage of digital health tools.

2.11 | Mediating role of behavioural intention (BI)

Behavioural intention significantly mediates the influence of various factors on the actual use behaviour of information systems [59]. The mediating effect of behavioural intention was observed to be significant in previous studies regarding the adoption of eLearning [60] and adoption of IoT applications in healthcare [61].

H9: Behavioural intention mediates the relationship between factors affecting the adoption of digital health tools (PE, EE, SI, FC, HM, PV, and H) and actual use behaviour.

3 | RESEARCH METHODOLOGY

Following the positivist approach, quantitative research design was employed to study the empirical relationships between the variables. This section discusses on the sample size, participants, data collection, and analysis techniques used in the study.

3.1 | Participants and procedure

The respondents of the study were youths (aged 16–40, as defined by the Nepal government [62]) residing in Kathmandu Valley and having experience in using at least one of the digital health tools. Youths, being the most tech enthusiast among all age groups, are early adopters of digital technologies and play a central role in disseminating technological innovations [63]. There are multiple reasons for choosing the Kathmandu Valley: it is the technological hub of the country and rapid advancements in technology can be observed here [64]. Furthermore, most of the youths from different parts of Nepal migrate to Kathmandu Valley in search of a quality life, jobs, and for education purpose [65, 66]. Since youths from various geographical regions of the country reside in Kathmandu Valley, it makes the sample taken within the valley more representative of the country.

Since there is no official data on the exact number of youths within Kathmandu Valley, the population of this study is unknown. Using Cochran's formula [67], the sample size for the study was initially estimated to be 385 (confidence interval = 95%, margin of error = 5%). The online questionnaire was developed via Kobo toolbox and sent to 25 respondents for a pilot study. Since no problem of multicollinearity was observed, 642 questionnaires were distributed to respondents assuming the average response rate of 60%, as suggested by Fowler [68] and Baruch & Hultom [69]. The participants were approached mainly in gyms, restaurants, corporate offices and colleges, and asked for their email addresses. The link for the survey and details of the study were then sent to them via email. Furthermore, potential respondents within network were approached via social media and were requested to share the questionnaire further. Only 332 responses were received among which 42 responses were discarded from initial screening for not fulfilling the age criteria of the study, resulting in 290 eligible responses. In the second phase of screening, 10 more responses were excluded as they did not have prior experience of using digital health tools leaving a final sample of 280 respondents. We further validated our sample size through a detailed literature review. As per the guidelines by Kline [70], the sample size of more than 200 was considered large and adequate for data analysis through (SEM). Similarly, the sample size used in this study was also validated by the sample to variable ratio guidelines [71, 72].

3.2 | Measurement instrument

To test the hypotheses, a structured questionnaire was prepared that consisted of three sections. The first section inquired about sociodemographic information while the second section was about the general understanding and application of digital health tools. While observing the second section, if the respondent had no prior experience of using any of the digital health tools, the collected questionnaire was discarded. The third section consisted of 35 items for measuring nine latent constructs that were adapted from previous studies with slight adjustments to match the study [24, 26, 42, 73]. For measuring the items, five-point Likert scale (1: strongly disagree, 5: strongly agree) was adopted.

3.3 | Data analysis

In this study, PLS-SEM technique was applied to test the relationships between the study variables via the SmartPLS software. PLS-SEM has been broadly used for validating theory and testing hypotheses [74]. Furthermore, it is appropriate for this study as it requires a smaller sample size and does not mandate a normally distributed data [75]. Prior to the analysis, data were imported to excel from the Kobo toolbox for data cleaning and encoding. Data analysis was then carried out in various steps. Initially, descriptive analysis was employed to summarize the data and examine its distribution and variation. In the next step, validity and reliability of the constructs were examined through the assessment of measurement model. Finally, structural model analysis was carried out to analyse the path diagram and test the hypotheses.

TABLE 2 Demographic profile of the participants.

	Frequency	Percentage (%)		Frequency	Percentage(%)
Gender			**Underlying disease**		
Female	155	55.36	None	247	88.21
Male	125	44.64	Others	19	6.79
Age			Hypertension	15	5.36
24-32	202	72.14	Diabetes	9	3.21
16-24	57	20.36	Asthma	7	2.5
32-40	21	7.5			
Marital status					
Unmarried	208	74.29			
Married	72	25.71			
Education					
Bachelors	141	50.36			
Masters and above	119	42.5			
Intermediate	17	6.07			
Up-to SLC/SEE	3	1.07			
Employment sector					
Private sector	129	46.07			
Students	56	20			
Business/entrepreneur	27	9.64			
Government sector	24	8.57			
NGO/INGO	22	7.86			
Others	22	7.86			

4 | RESULTS

The findings of the study based on analysis of the collected data are outlined in this section. The first part of the section includes the demographic profile of the participants, their familiarity with digital health tools and descriptive statistics of the collected data. It is followed by the detailed analysis of measurement and structural model for drawing inferences.

4.1 | Demographic profile of the participants

Demographic profile displays the gender, age, marital status, education, employment sector, and their status of health as presented in Table 2. The majority of the participants were female and from the age group of 24–32 years. Likewise, the highest percentage of the respondents (50.36%) had a bachelor's degree, while 42.50% had a minimum of Master's degree. The data showed that most of the respondents were unmarried (74.29%). Among the data collected, it was observed that majority of the responding individuals were employees of private sector followed by students. While 88.21% of the respondents did not have any underlying disease, 5.36% were suffering from hypertension, 3.21% from diabetes, and 2.5% from asthma whereas the remaining 6.79% were suffering from other diseases such as thyroid and high blood cholesterol. This suggests that most of the participants of the study were using digital health tools for general wellbeing, lifestyle enhancement, and fitness monitoring rather than disease management while others were using the digital health tools for managing their health conditions.

4.2 | Prior experience of using digital health tools

As presented in Table 3, the majority of the participants (65%) were using smart watches followed by blood pressure monitors (37.12%) and pulse oximeters (36.43%). This was further subsequent to fitness trackers, gym-related apps, blood glucose monitors, and other digital health tools respectively.

4.3 | Descriptive statistics

The normality of the collected data was analysed with the SmartPLS software and is presented in Table 4. According to the data of 35 items collected from 280 respondents, the mean was observed within the range of 3 to 4.2. The standard deviation of data was in the range of 0.75 to 1.2, implying that most of the responses are not much spread from the mean. Similarly, the skewness of data fell between −2 and +2, implying that the data was normally distributed. Furthermore, the excess kurtosis of data was observed in the range of −4 to +4 implying that the data was leptokurtic [76].

TABLE 3 Prior experience of digital health tools.

Digital health tools	Frequency	Percentage (%)
Smart watch	182	65
Blood pressure monitor	104	37.14
Pulse oximeter	102	36.43
Fitness trackers	67	23.93
Gym related apps	61	21.79
Blood glucose monitor	51	18.21
Cardio related apps	50	17.86
Diet-tracking apps	38	13.57
Pharmacy apps	32	11.43
Online health consultation apps	24	8.57
ECG monitor	13	4.64
Smart ring	7	2.5
Others	5	1.79

4.4 | Assessment of measurement model

The measurement model was employed to assess the construct's validity and reliability [77]. Table 5 presents the factor loadings of each item of the variables, the Cronbach's alpha, composite reliability, and the average variance extracted (AVE) of each variable as analysed through the PLS-SEM. The factor loadings of each item exceeded 0.6 as recommended by Hair Jr et al. [78] which represents adequate item reliability. Similarly, composite reliability (CR) and the Cronbach's alpha exceeded the acceptable value of 0.70 [77]. In this study, the values of AVE were above 0.50 which confirms the satisfactory convergent validity [79].

4.5 | Fornell and Larcker

The criterion of Fornell and Larcker for discriminant validity was found to be met in the study as all the square root of average variance extracted (AVE) was greater than the correlation of that variable with other variables as stated by Ab Hamid et al. [80] and can be observed in Table 6.

4.6 | Hetero-monotrait ratio

Hetero-monotrait ratio provides a measure to determine the correlation of a particular construct with other constructs and the value less than 0.9 is considered acceptable [81]. All the values of the ratio were less than 0.85 which confirms the discriminant validity of the constructs as presented in Table 7.

4.7 | Assessment of structural model

After using the measurement model to examine the reliability and validity, structural model was used to analyse the variance inflation factor (VIF), perform path analysis, and test the hypothesis and mediation.

TABLE 4 Descriptive statistics.

Item	Mean	Standard deviation	Excess kurtosis	Skewness
PE_1	4.121	0.815	3.293	−1.382
PE_2	4.121	0.862	0.822	−0.911
PE_3	4.154	0.776	2.666	−1.152
PE_4	4.157	0.826	2.661	−1.294
EE_1	4.043	0.759	2.491	−1.007
EE_2	4.111	0.774	2.79	−1.171
EE_3	4.025	0.79	1.963	−0.962
EE_4	4.061	0.788	2.179	−1.032
SI_1	3.775	0.868	0.553	−0.569
SI_2	3.729	0.947	0.033	−0.497
SI_3	3.754	0.874	0.484	−0.562
SI_4	3.893	0.9	0.938	−0.851
FC_1	3.861	0.764	1.263	−0.675
FC_2	3.979	0.765	1.667	−0.83
FC_3	3.818	0.836	0.647	−0.568
FC_4	3.975	0.776	2.24	−1.015
HM_1	3.829	0.801	1.558	−0.811
HM_2	3.807	0.801	1.251	−0.77
HM_3	3.832	0.856	0.816	−0.667
HM_4	3.961	0.838	1.088	−0.805
PV_1	3.168	0.962	−0.351	−0.076
PV_2	3.404	0.809	0.276	−0.05
PV_3	3.536	0.792	0.518	−0.357
H_1	3.471	1.038	−0.111	−0.636
H_2	3.071	1.187	−0.789	−0.1
H_3	3.496	1.039	0.024	−0.779
H_4	3.611	1.122	−0.057	−0.774
BI_1	3.714	0.912	0.76	−0.764
BI_2	3.796	0.955	0.349	−0.695
BI_3	3.85	0.882	1.078	−0.865
BI_4	3.918	0.843	1.226	−0.813
AU_1	3.839	0.765	2.024	−0.97
AU_2	3.782	1.014	−0.089	−0.71
AU_3	3.811	0.892	0.796	−0.861
AU_4	3.382	1.125	−0.749	−0.34

4.8 | Variance inflation factor (VIF)

If the value of VIF is greater than five, the problem of multicollinearity may exist [82]. The data presented in Table 8 presents that all the VIF values were less than three demonstrating no correlations among variables.

TABLE 5 Measurement model assessment.

Constructs	Indicator	Loadings	Cronbach's alpha	Composite reliability (CR)	Average variance extracted (AVE)
Actual usage (AU)	AU_1	0.791	0.825	0.884	0.657
	AU_2	0.855			
	AU_3	0.855			
	AU_4	0.734			
Behavioural intention (BI)	BI_1	0.86	0.876	0.915	0.73
	BI_2	0.885			
	BI_3	0.856			
	BI_4	0.814			
Effort expectancy (EE)	EE_1	0.844	0.879	0.917	0.734
	EE_2	0.851			
	EE_3	0.855			
	EE_4	0.875			
Facilitating conditions (FC)	FC_1	0.791	0.802	0.871	0.627
	FC_2	0.804			
	FC_3	0.747			
	FC_4	0.824			
Hedonic motivation (HM)	HM_1	0.802	0.857	0.903	0.7
	HM_2	0.822			
	HM_3	0.865			
	HM_4	0.856			
Habit (H)	H_1	0.911	0.911	0.937	0.789
	H_2	0.864			
	H_3	0.9			
	H_4	0.878			
Performance expectancy (PE)	PE_1	0.856	0.869	0.91	0.718
	PE_2	0.825			
	PE_3	0.845			
	PE_4	0.862			
Price value (PV)	PV_1	0.658	0.753	0.852	0.662
	PV_2	0.89			
	PV_3	0.872			
Social influence (SI)	SI_1	0.846	0.863	0.907	0.709
	SI_2	0.847			
	SI_3	0.874			
	SI_4	0.8			

4.9 | Path analysis

Path analysis is a statistical tool built upon multiple regression that helps us understand how a dependent variable is influenced by two or more independent variables while considering the mediating and moderating effects of other variables [83]. While analysing the path diagram generated from the data of the study as illustrated in Figure 2, 71.8% of the variance in behavioural intention to use digital health tools was explained by the seven independent variables. Additionally, results indicates that approximately 51.7% of the variance in dependent variable can be attributed to the mediating variable's and seven independent varible influence, demonstrating a relatively strong relationship between the two variables (i.e., BI and AU).

4.10 | Hypothesis testing

The structural path is found to be statistically significant only if the lower limit of confidence interval and the upper limit of confidence interval does not contain any zero in between [84]. The significance should further be validated by the acceptable

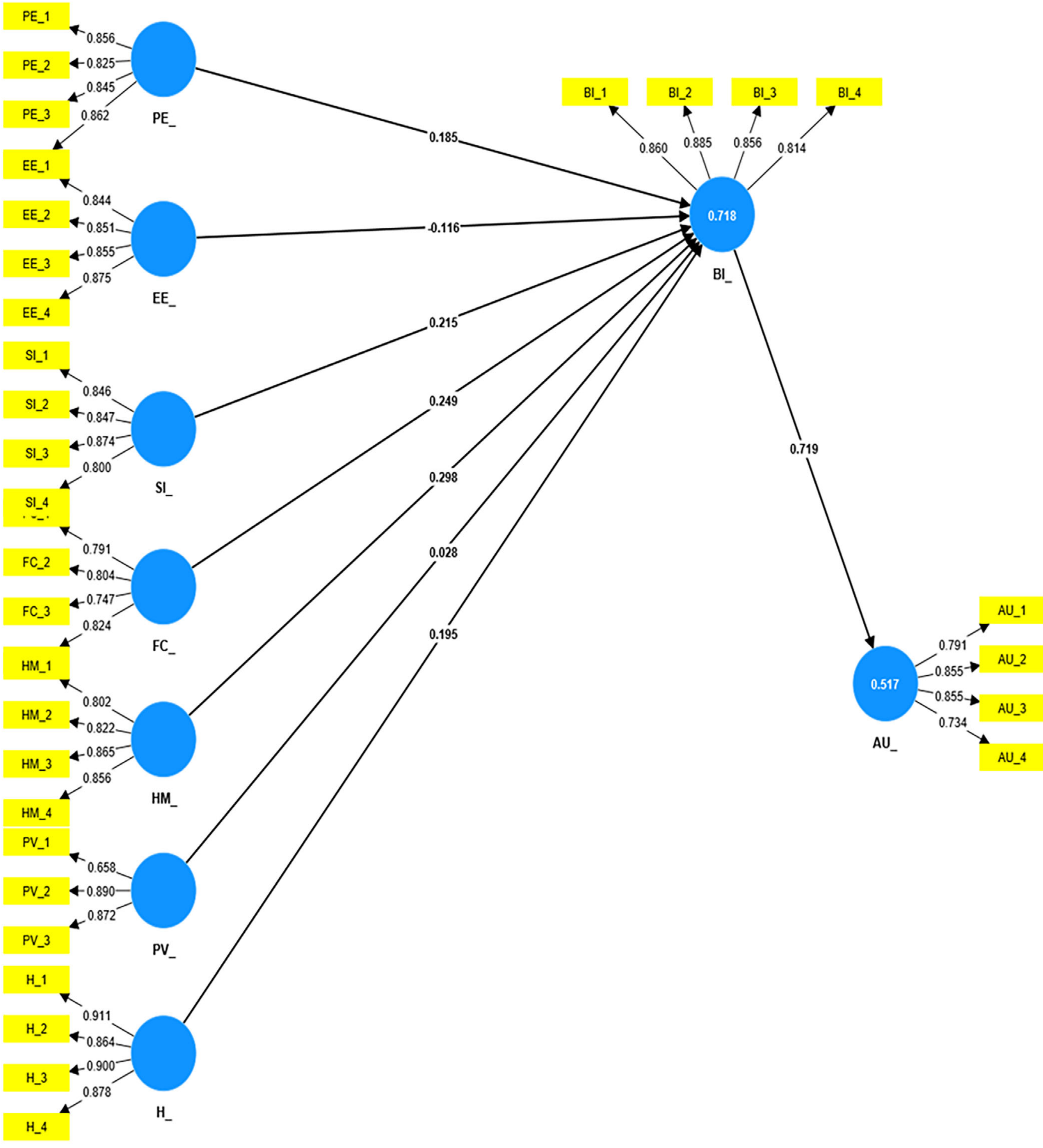

FIGURE 2 Path diagram.

p-value of less than 0.05 and *t*-value of greater than 1.96 [85]. In this study, as displayed in Table 9, performance expectancy ($\beta = 0.185$, $p < 0.05$), social influence ($\beta = 0.215$, $p < 0.05$), facilitating conditions ($\beta = 0.249$, $p < 0.05$), hedonic motivation ($\beta = 0.298$, $p < 0.001$) and habit ($\beta = 0.195$, $p < 0.001$) showed a significant relationship with behavioral intention supported by their non-zero confidence interval and acceptable *t*-value. Similarly, the behavioural intention ($\beta = 0.719$, $p < 0.001$) was found to strongly influence the actual usage behaviour. While these six hypotheses were supported, effort expectancy and price value did not show a positive relationship with behavioural intention because of the unacceptable *p*-value ($p > 0.05$), *t*-value of less

TABLE 6 Fornell and Larker criterion.

	AU	BI	EE	FC	HM	H	PE	PV	SI
AU	**0.81**								
BI	0.719	**0.854**							
EE	0.543	0.547	**0.856**						
FC	0.609	0.707	0.639	**0.792**					
HM	0.634	0.698	0.633	0.609	**0.837**				
H	0.617	0.594	0.289	0.439	0.42	**0.888**			
PE	0.606	0.657	0.705	0.609	0.613	0.416	**0.847**		
PV	0.411	0.404	0.352	0.364	0.429	0.309	0.368	**0.813**	
SI	0.621	0.696	0.556	0.665	0.533	0.523	0.6	0.325	**0.842**

TABLE 7 Heterotrait–monotrait ratio (HTMT).

	AU	BI	EE	FC	HM	H	PE	PV	SI
AU									
BI	0.838								
EE	0.624	0.623							
FC	0.741	0.842	0.761						
HM	0.746	0.803	0.732	0.737					
H	0.717	0.662	0.321	0.513	0.474				
PE	0.709	0.752	0.806	0.725	0.711	0.466			
PV	0.496	0.464	0.42	0.466	0.52	0.352	0.408		
SI	0.735	0.8	0.638	0.798	0.62	0.589	0.693	0.368	

TABLE 8 VIF (variance inflation factor) value.

Constructs	VIF
Effort expectancy (EE)	2.559
Facilitating conditions (FC)	2.403
Hedonic motivation (HM)	2.147
Habit (H)	1.511
Performance expectancy (PE)	2.466
Price value (PV)	1.283
Social influence (SI)	2.237

than 1.96 and the inclusion of zero in their confidence interval. Hence, these two hypotheses were not supported. Further, beta-coefficient determines the strength of the relationship between the variables [77]. In this study, hedonic motivation ($\beta = 0.298$) had the strongest influence on the behavioural intention to use digital health tools.

4.11 | Mediation analysis

The mediation model illustrates how a mediating variable influences the relationship between two other variables [84]. As presented in Table 10, behavioural intention only mediated the relationship of hedonic motivation ($\beta = 0.214, p < 0.001$), performance expectancy ($\beta = 0.133, p < 0.05$), facilitating condition ($\beta = 0.179$, $p < 0.05$), habit ($\beta = 0.140$, $p < 0.05$), and social influence ($\beta = 0.154$, $p < 0.05$) with the actual usage of digital health tools. The study concludes that behavioural intention partially mediates the relationship between the different factors of UTAUT-2 and actual usage of digital health tools.

5 | DISCUSSION

This study examined the behavioural intention and adoption of digital health tools among Nepalese youths utilizing the extended [UTAUT-2]. This section discusses the findings of the study which demonstrated the significant impact of performance expectancy, facilitating conditions, hedonic motivation and habit on the behavioral intention and actual use of digital health tools.

The findings indicated that performance expectancy had a positive relationship with behavioural intention to use digital health tools indicating that digital health tools enhance the quality of healthcare, improve the ability to manage health and enable users to take action related to health more quickly. This relationship is also confirmed by studies on wearable electronics by [73] and smartwatches by [42] but unlike these studies where performance expectancy was among the strongest predictor of behavioral intention, the results of this study indicated that performance expectancy had the least influence among other variables of the study that were shown to have a positive influence which aligns with the findings of study on wearable health monitoring technology [24].

The results did not indicate any influence of effort efficiency on the behavioural intention to adopt digital health tools unlike the positive influence seen in many studies [39, 85]. One possible reason for this might be that many digital health tools such as health wearables and apps may require no more effort than wearing them at a wrist or loading the app. However, the result of this study aligns with the findings of previous studies on wearable health technology [24] and mHealth [56]. The third hypothesis suggested that social influence positively influences the behavioural intention to use digital health tools which is supported by the findings of this study. This indicates that the behavioral intention of people to use digital health tools is influenced by people who are important to them or influence them. This relationship between social influence and behavioural intention is parallel with the findings of previous studies on wearable technologies [39, 73].

Similarly, facilitating condition was seen as the second highest predictor of behavioral intention to use digital health tools. The finding is consistent with the findings of [85] and [42] where they assessed the key factors affecting the adoption of health apps and smart watches respectively. This implies that the availability of the resources, knowledge, support, and compatibility of digital health tools play a huge role in motivating people to use digital health tools.

Most importantly, hedonic motivation was the strongest predictor of behavioural intention to use digital health tools in this study. This implies that the fun and enjoyment of using digital

TABLE 9 Hypothesis testing.

Structural path	Beta-coefficient	*t*-value	*p*-value	LLCI (2.5%)	ULCI (97.5%)	Conclusion
H1: PE → BI	0.185	3.214	0.001	0.072	0.3	Supported
H2: EE → BI	−0.116	1.566	0.117	−0.252	0.036	Not-supported
H3: SI → BI	0.215	2.932	0.003	0.062	0.349	Supported
H4: FC → BI	0.249	2.857	0.004	0.066	0.403	Supported
H5: HM → BI	0.298	3.851	0.000	0.153	0.455	Supported
H6: PV → BI	0.028	0.721	0.471	−0.046	0.109	Not-supported
H7: H → BI	0.195	3.628	0.000	0.097	0.309	Supported
H8: BI → AU	0.719	20.234	0.000	0.646	0.786	Supported

Note: LLCI, lower limit confidence interval; ULCI, upper limit confidence interval.

TABLE 10 Mediation analysis.

Structural path	Beta-coefficient	*t*-value	*p*-value	LLCI (2.5%)	ULCI (97.5%)	Conclusion
HM → BI → AU	0.214	3.644	0.000	0.107	0.336	Supported
PE → BI → AU	0.133	3.314	0.001	0.053	0.211	Supported
PV → BI → AU	0.020	0.721	0.471	−0.034	0.079	Not-supported
EE → BI → AU	−0.083	1.593	0.111	−0.178	0.026	Not-supported
FC → BI → AU	0.179	2.92	0.004	0.048	0.285	Supported
H → BI → AU	0.140	3.413	0.001	0.067	0.228	Supported
SI → BI → AU	0.154	2.938	0.003	0.045	0.25	Supported

Note: LLCI: lower limit confidence interval; ULCI: upper limit confidence interval.

health tools makes the health monitoring and fitness activities more enjoyable which in turn influences the behavioral intention to use digital health tools. This relationship aligns with the findings among health wearable users in Saudi Arabia [32] and among health and fitness app users in Bangladesh [86] while contrasts with the studies among Czech women using fitness electronics [73] and among Turkish health app users [85]. The difference in the impact may be attributed to the cultural differences in different countries.

In this study, the price value did not have an influence on the behavioural intention of people to adopt digital health tools. This might be because the quality and benefits of the product might be more important than the price for consumers to be motivated to buy them. In the case of apps, even if the app is free, consumers expect benefits or else they discontinue using it as it takes up disk space [43]. The findings in previous studies on smart watch [42] and fitness wearable [39] also did not find a positive relationship between price value and behavioural intention.

The results showed that habit positively influenced the adoption of digital health tools. This implies that when the use of digital health tools becomes a habit for consumers they feel the need to use digital health tools which in turn motivates them to use the devices. This result is consistent with the findings of previous studies on health wearables [22] and mobile health applications [85].

It was hypothesized that behavioral intention positively influences the actual use behaviour of people which was found to be supported by the findings of this study. The behavioral intention was found to strongly influence the actual usage behaviour of people. This implies that the people who have high intentions to use digital health tools are most likely to actually use them. This finding is consistent with the findings of several studies on health technology acceptance [24, 85]. The study also investigated the mediating role of behavioral intention between factors affecting the adoption of digital health tools and their actual usage behaviour. The findings from this study show that behavioral intention mediates the relationship between all other factors (performance expectancy, social influence, facilitating conditions, hedonic motivation, and habit) and the actual usage of digital health tools except for the two factors: effort expectancy and price value.

5.1 | Theoretical implications

This study fills the existing empirical gap in the literature by examining the key factors influencing the behavioral intention of Nepalese individuals to adopt digital health tools, an area that has received little scholarly attention. Further, it empirically validates the extended UTAUT-2 in the healthcare domain of Nepal so that this study can be used as a reference for further studies regarding acceptance of health technologies in least developed countries such as Nepal.

5.2 | Practical implications

This study provides practical insights to policymakers in the government seeking to develop effective digital health initiatives. Furthermore, hospitals seeking to integrate digital health services gain insights into the prevalence and perception of digital health tools among consumers. Since this study provides an understanding on the strengths of various factors impacting the behavioral intention to use digital health tools; this also benefits the digital health tool developers to build user-friendly and impactful digital health tools.

5.3 | Limitations and future areas of study

This study has various limitations. First, this study was conducted in the urban setting (i.e., Kathmandu Valley) which limits the insights from other geographical (i.e., rural) areas of Nepal which may have provided different insights. Second, this study was conducted among the youths. This excludes the individuasl from other generational cohorts elderly people which could have added a significant insight into how factors affecting the adoption of digital health tools vary with age. Third, the data used in the study are cross-sectional which increases the chance of selection bias.

Since there are rarely any studies assessing the factors affecting the behavioral intention to use digital health tools in Nepal, there are plenty of areas where further research could be done. This includes conducting research among elderly people and people with chronic diseases to understand factors impacting their adoption of digital health tools. Similarly, future studies can focus on a specific digital health tool or expand the study to rural areas of Nepal. In addition to this, external constructs can be added to UTAUT-2 such as perceived trust and technological accuracy in order to make studies more entailed.

AUTHOR CONTRIBUTIONS

Sujal Mani Timsina: Conceptualization; formal analysis; investigation; methodology; resources; writing—original draft. **Ujjwal Bhattarai**: Software; supervision; validation; writing—review and editing.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The datasets supporting the findings of this paper will be available from the corresponding author upon request.

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How to cite this article: Timsina, S.M., Bhattarai, U.: Identifying factors shaping the behavioural intention of Nepalese youths to adopt digital health tools. Healthc. Technol. Lett. 12, e70005 (2025). https://doi.org/10.1049/htl2.70005