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Analyzing health service employees' intention to use e-health systems in southwest Ethiopia: using UTAUT-2 model

Wasihun Admassu[1*] and Kasahun Gorems[2]

Abstract

Background E-health systems have the potential to improve healthcare delivery and access to medical services in resource-constrained settings. Despite its impact, the system exhibits a low level of consumer acceptance and intention to use it. This research paper aims to analyze the intention of health service employees to use e-health systems in southwest Ethiopia using the UTAUT-2 model.

Method Institutional-based cross-sectional studies were conducted at four referral hospitals (two private and two public) to examine the acceptance of e-health among consumers. Employees who had previous experience with diagnostic information systems and the health logistic information system were given structured questionnaires based on the UTAUT-2 model. The data were analyzed using the PLS-SEM method to identify the key factors that influence the intention to use e-health systems. The data were analyzed using SPSS version 20 and SmartPLS 3 software.

Result Out of the 400 surveyed employees, 225 (56.25%) valid questionnaires were collected. The findings indicate that three factors—effort expectancy ($\beta = 0.276$, $t = 3.015$, $p = 0.001$), habit ($\beta = 0.309$, $t = 3.754$, $p = 0$), and performance expectancy ($\beta = 0.179$, $t = 1.905$, $p = 0.028$)—had a significant positive impact on employees' intention to use e-health systems. On the other hand, factors such as social influence, facilitating conditions, hedonic motivation, and price values did not appear as significant predictors of intention to use e-health. The study model was able to predict 63% of employees' intentions to use e-health systems.

Conclusion Effort expectancy, habit, and performance expectancy were significant predictors of employees' intention to use e-health systems among health service employees in southwest Ethiopia. The study supports the ideas that ease of use, experience with information systems, and the role of the systems in improving job performance contribute to employees' intention to use e-health. Policymakers and healthcare organizations in the region can use these findings to develop strategies for successful implementation and adoption of e-health systems, ultimately improving healthcare services and outcomes for the population.

Keywords UTAUT-2, Hospital information system, e-health, Behavioral intention, Structural equation model, Ethiopia

*Correspondence:
Wasihun Admassu
gashiyetu4us@gmail.com
[1]Immunology and Molecular Biology Unit, Jimma University Medical Center, Jimma, Ethiopia
[2]Department of Microbiology, Immunology and Parasitology, St Paul's Hospital Millennium Medical College, Addis Ababa, Ethiopia

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Introduction

Electronic health service (E-health) refers to the delivery of health services via Internet portals [1]. E-health as an integral part of the health service systems' in resource limited setting improves health services by: enhancing continuity and coordination of care, improving efficiency in completing a task, improving quality of care, improving consumer satisfaction, managing inventory and medications, improving workflow, reducing error, enhancing data quality, reducing service costs, enhancing efficient use of scarce resources, and enabling access to health services from remote areas [2–6].

The implemented e-health systems in Ethiopia have allowed healthcare providers to convert patient health records into digital formats, enhance the management and quality of data, improved the work flow of supply chain management, make better clinical decisions by exchanging real-time patient data, improve interoperability, efficiently store and share electronic health information, boost customer satisfaction, and enhance the quality of care [7–9].

Employees in health service delivery are generally considered key consumers and are strongly correlated to the implementation and usage of E-health [4], and their perception of E-health is important and strongly correlated to their behavioral intention to use E-health [10, 11]. This poorly applied medical application in developing countries [2, 3, 12]; despite its potential impact on service delivery, healthcare professionals in the country have shown low readiness and willingness to embrace e-health, with poor utilization and difficulties in implementation being observed [8, 13–15]. Additionally, there was uncertainty about healthcare employees' intention to use e-health and resistance to adoption has been noted among healthcare professionals [11, 12].

In Ethiopia, there exists a glaring gap between the potential of e-health systems and employees' intent to use E-health [11, 16]; low readiness and utilization of E-health systems [13–15, 17]; difficulties in implementation of e-health [8]; change in resistance behaviors due to staff negative perceptions about E-health [12]; low behavioral intentions to use E-health and a low actual usage rate of E-health [3, 18] observed among consumers.

Besides variation in employees' intention to utilize e-health service systems, far too little attention has been paid to the assessment of consumers' behavioral intention to use E-health in Ethiopia [5, 11], and despite this interest, to the best of our knowledge, no one has analyzed E-health consumers' behavioral intentions to use the systems in study settings South-west Ethiopia, further highlight the need for further research in this area [19].

Previous studies showed limited studies on e-health service employees' intent to use the systems and have primarily focused on physicians' and patients' acceptance of adoptions of e-health service systems [5, 20], there is a gap in the literature regarding assessing acceptance and of adoptions of e-health service systems on healthcare providers as well as considering us a multidisciplinary team (employees who have experience on laboratory information system (LIS) and, radiology information system (RIS), and the pharmacy information system (PIS)) [20, 21]. Thus, we try to assess employees' intention to use e-health services systems considering the specific characteristics of the target population using the UTAUT-2 model.

To analyze the determinants of e-health consumers' behavioral intention to use the systems in our study settings, we polled hospital information system (HIS) consumers from two private and two public referral hospitals across a range of information systems (LIS, RIS, and PIS).

The terms e-health and HIS are utilized interchangeably in this paper to refer to study-setting facilities that have diagnostic information systems LIS and RIS, and the health logistics information system (PIS). At the time of the study, the e-health systems implemented supported the health facilities' help service delivery through physicians' diagnostic service ordering (laboratory and radiology diagnostic service), medical record-keeping, supply chain management, and the decision-making process.

Thus, this study aimed to analyze the predictors of intent (performance expectation, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit) on employees of a study setting facilities who have prior experience with LIS, PIS, and RIS portals usage using UTAUT-2 model. Applying this model helps us understand the factors that influencing employees' intention to adopt e-health technologies. By considering the predictors acceptance of e-health services identified by the model, interventions can be designed to be more effective and sustainable [11, 22].

Literature review

Theoretical model and research hypothesis

The unified theory of acceptance and use of technology (UTAUT) is quickly becoming a fundamental model for assessing end-user intention and actual usage of IS [23–26]. The model composes four independent variables influencing end-users behavioral intent to use and actual use of information systems: performance expectancy, effort expectancy, social influences, and facilitating conditions [27]. Later, the model incorporates independent factors like hedonic motivation, price value, and habit into the UTAUT model to adapt it to the UTAUT-2 model. While the preceding model analyzes employees' technology adoption and usage in the context of the organization, the later model, UTAUT-2, looks at individual consumer use of an array of information technologies [28].

In choosing the UTAUT-2 model for our study, several key reasons stand out. Firstly, the model has been proven to effectively predict the probability of customers intending to use e-health systems services [11, 16, 29, 30], which is directly relevant to our research focus. Secondly, the UTAUT and UTAUT-2 models have been widely used in the e-health domain to explore the factors affecting the acceptance of e-health services [11, 21]; in our study, we assessed employees' intent to use e-health service systems using the UTAUT-2 model construct since it has greater predictive power from an individual or consumer perspective [28]. This preference is based on the concerns that have been raised about the UTAUT model in perspectives of individuals' consumers such as older adults and patients [31]. Additionally, the literature reveals that the UTAUT-2 model, when compared to the UTAUT model, may better reflect customer perspective or organizational context information system behavioral intention and/or actual use [28, 32]. As a result, we built our study on the UTAUT-2 model, which is the most comprehensive theory for assessing HIS intentions and actual use.

Accordingly, we assessed seven variables regarding the behavioral intention to use e-health: performance expectancy, effort expectancy, social influences, facilitating conditions, hedonic motivation, price value, and habit (Fig. 1).

Impact of performance expectations on behavioral intention to use HIS

Performance expectancy is the label given to a consumer who believes that using information systems will help him or her attain his or her goal in job performance [27, 28]. As a result, the variable performance expectancy in our study setting is that health facility employees' perceptions of using e-health systems improve their job performance. Numerous studies in the healthcare industry indicate a significant positive association between behavioral intention to use and a variety of e-health practices adopted by increasing job efficiency, performance, and service

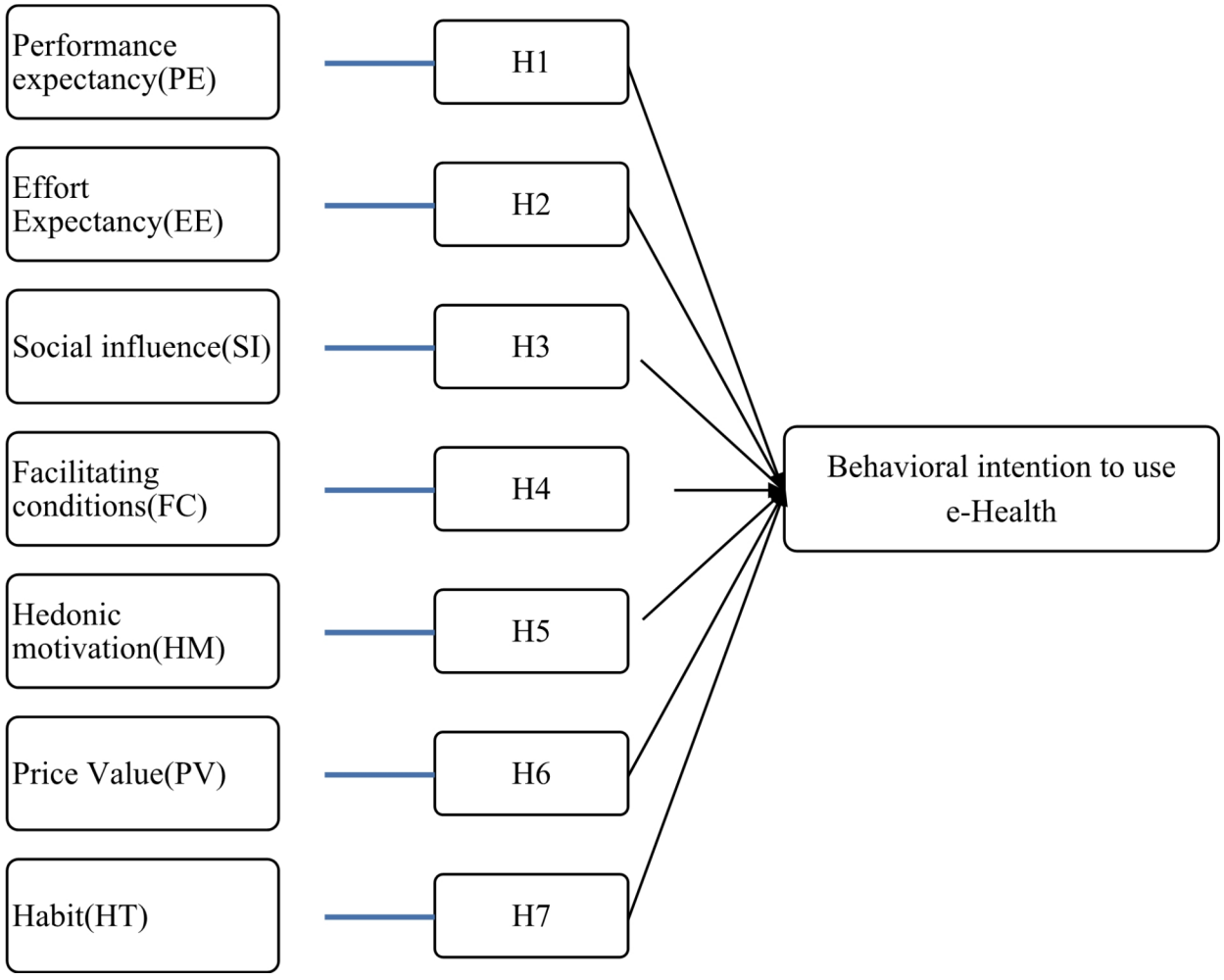


Fig. 1 Proposed theoretical model

quality [11, 19, 22, 29, 33, 34]. Further studies suggest that performance expectancy was a significant predictor of employees' intention to use e-health and employees who perceived e-health as beneficial were more likely to adopt and utilize these systems effectively [11, 24, 30, 35]. Therefore, performance expectancy plays crucial role in enhancing employees' intent to use e-health systems. Hence, it could conceivably be hypothesized that:

H1: Performance Expectancy (PE) has a positive effect on consumers' behavioral intention to use hospital information systems (HIS).

Impact of effort expectancy on behavioral intention to use HIS

The term effort expectancy has come to be used to refer to the degree to which the technology is supposed to be easy to use [27, 28]. Several studies highlight the impact of effort expectancy on the adoption and success of e-health systems implying that perceived ease of use significantly influenced employees' towards e-health acceptance; effort expectancy was a key determinant of user acceptance of e-health; and effort expectancy influenced consumers' willingness to use e-health systems services [11, 22, 29, 36, 37]. Overall, the studies suggest that effort expectancy plays critical role impacting consumers' intention to use the platform [11, 19]. As a result, the determining factor of effort expectancy in our study setting was defined as E-health ease of use associated with employee intention to use E-health. It can therefore be assumed that:

H2: Effort expectancy (EE) has a positive effect on consumers' behavioral intention to use hospital information systems (HIS).

Impact of social influence on behavioral intention to use HIS

Social influence refers to the extent to which the use of information technology is valued within the social networks of consumers [27, 28]. An analysis of how social influence affects consumers' intention to use information systems showed that social influence has a positive impact on employees' intention to use information system. This indicates that the support of colleagues, the opinions of administrative staff, and peer groups significantly impact the acceptance of e-health [10, 11, 14, 24]. As a result, social influence in our study is defined as key others in our study context, defined as friends, colleagues, and administrative staff, feels that employees should use e-health. Hence, it could conceivably be hypothesized that:

Social Influence (SI) has a positive effect on consumers' behavioral intention to use Hospital information systems (HIS).

Impact of facilitating conditions on behavioral intention to use HIS

According to a definition provided elsewhere [27], facilitating conditions are "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system". Recent pieces of evidences suggest a significant positive impact of facilitating conditions on consumers' behavioral intentions on the breadth of health services industries e-health systems; inferring reliable internet availability, technical support, training and user support on utilization of e-health, and ongoing support to enhance employees intention to use e-health positively impacts employees intent to use [10, 11, 19, 24, 36, 38]. Therefore, facilitating conditions in our study are defined as a hospital information system consumer believing in the presence of organizational and technical infrastructure required for the intention to use the system. Therefore, we proposed the following hypothesis:

H4: Facilitating conditions (FC) has a positive effect on consumers' behavioral intention to use hospital information systems (HIS).

Impact of hedonic motivation on behavioral intention to use HIS

Perceived enjoyment is an ultimate intrinsic motivation that describes the amount to which fun can be acquired from using IS defined as hedonic motivation [25]. This viewpoint is backed further by a well-known study on consumer intention to use IS [28], which claims that hedonic motivation is fun or pleasure obtained from using IS and that motivation is one of the main predictors of consumer intention to use IS. On assessment of the effects of hedonic motivation on the breadth of IS in healthcare industries, studies showed that perceived enjoyment had a significant and positive impact on the intention to use e-health systems [30, 38]. Together, these studies outline that enjoyment, entertainment in e-health systems can motivate individuals to interact and long term utilization of the e-health service systems. As a result, in our study, Hedonic motivation was defined as the pleasure, enjoyment, and entertainment ability of e-health associated with employees' intention to use e-health systems. Hence, this study postulates the following hypothesis:

H5: Hedonic motivation (HM) has a positive effect on consumers' behavioral intention to use hospital information systems (HIS).

Impact of price value on behavioral intention to use HIS

Price value is defined as consumers' cognitive tradeoff between the perceived benefits of the IS and the monetary cost of using them. When the benefits of utilizing technology are regarded as greater than the monetary

cost, the price value has a significant positive impact on the intention to use IS and positive price value influences the consumer's behavioral intentions to use IS [28]. Studies found a positive and significant relationship between price value and consumers' intention to use IS [30]. As a result, in our study setting, the variable price value, defined as higher perceived benefits for monetary cost utilized of using E-health systems was associated with the behavioral intention to use E-health systems. Hence, price value has a positive impact on the intention to use HIS. Based on the results of previous studies, the hypothesis of this study in line with price value is that:

H6: Price value (PV) has a positive effect on consumers' behavioral intention to use hospital information systems (HIS).

Impact of habit on behavioral intention to use HIS

Habit is defined as "the degree to which individuals perform behaviors automatically" [39]. This viewpoint is shared by [28], who states that habit is developed by prior experience and influences IS use. Elsewhere, scholars have argued that habit is the habitual behavior of technology users over a long period time [40]. There has been a substantial amount of research published on the impact of habit on behavioral intention in the healthcare industry [29, 35], they indicate that habit is a powerful predictor of behavioral intention when it comes to IS use. As a result, the variable habit defined in our study setting as prior experience with HIS use was associated with the behavioral intention to use e-health systems. Hence, this study postulates the following hypothesis:

H7: Habit (HT) has a positive effect on consumers' behavioral intention to use hospital information systems (HIS).

Methodology

Study design

We conducted an institutional-based cross-sectional study at selected referral hospitals in Southwest Ethiopia from March 1 to April 30, 2023, to assess consumers' behavioral intentions to use HIS. We enrolled 400 participants in this study. Participants were recruited from four purposefully selected referral hospitals (two private and two public) by making a sampling frame as a list of the target population from which the sample is selected in southwest Ethiopia. The criteria for choosing the subjects were as follows: volunteers' willingness to participate, employees with prior experience in e-health (LIS, RIS, and PIS), and completed items of the study questionnaires. For this study's sampling frame, we calculated the ratio of health professionals working in the selected four hospitals to ensure a representative sample size.

Study participants and sampling procedure

Survey questionnaires were administered to eligible consumers who matched the selection criteria identified by convenience sampling. Eligible consumers who matched the selection criteria were identified by a convenience sampling survey questionnaire that was administered. Of the four hospitals that received 400 survey questionnaires, usable responses were obtained from 225 respondents, resulting in an overall response rate of 56.25%. This response rate was higher than 50%, which minimized the concern of nonresponse bias in the survey [41].

Data collection

The questionnaire framework is divided into two parts: (1) constructed self-administered closed-ended questions based on the UTAUT-2 model; and (2) demographic characteristics of respondents. All questionnaire section one indicators were scored on a five-point Likert scale with anchors ranging from "strongly disagree" to "strongly agree." The section includes seven exogenous variables: There were four indicators for performance expectation, four indicators for effort expectancy, three indicators for social impact, four indicators for facilitating conditions, three indicators for hedonic motivation, four indicators for price value, and four indicators for habit. There were three indicators for the dependent variable, behavioral intentions. The original English language UTAUT-2 incorporated questionnaires translated into local Amharic and Oromiffa languages, which were then back-translated into the original English survey items by independent expert translators for consistency assessment. According to study conducted elsewhere [42, 43], a 20 (5%) of sample size was utilized for pilot study questionnaires pre-assessment to evaluate the clarity, length, and appropriateness of questionnaire items as well as the feasibility of data collection procedures; before conducting a full scale study.

Data quality was ensured by creating appropriate data collection material, and questionnaire reliability was calculated using Cronbach's alpha coefficient (α) [44]. Finally, when informed consent was established, respondents were informed about HIS and their prior HIS experience, and they were given two local language-translated questionnaires to assess their behavioral intention to use HIS.

Data analysis

Questionnaires were input into Epidata version 3.1 and imported into SPSS version 20 (IBM Corporation, Armonk, NY, USA) for descriptive statistics analysis. Before describing the links between latent variables and their observed indicators, we assessed the measurement model for construct reliability, convergent validity,

and discriminate validity before structural equation modeling.

The validity and reliability of the research instruments were assessed in our study utilizing the partial least square structural equation modeling (PLS-SEM) technique using the software application SmartPLS3, which determines the quality of the indicators (items) and constructs (factors) in their measurement [45, 46]. Thus before describing the links between latent variables and their observed indicators, we evaluated the reliability and validity of our measurement model for construct reliability, convergent validity, and discriminant validity.

Construct reliability evaluates how well results can be repeated when the same instrument is used in various circumstances. Validity evaluates the level of accuracy in a measurement on its specified measure. Internal consistency reliability and composite reliability are the two primary methodologies used to evaluate construct reliability in the PLS-SEM technique. Internal consistency reliability measures the degree to which items within a construct are associated with one another. Internal consistency reliability measured by Cronbach's alpha and higher Cronbach's alpha (generally above 0.7) imply higher internal consistency reliability. Another way to gauge reliability in PLS-SEM is by composite reliability, which assesses both the internal consistency of items within a construct and the construct's overall reliability; a composite reliability coefficient higher than 0.7 ensures reliability [47].

The two main techniques used for evaluating the validity of research instruments in PLS-SEM are convergent validity and discriminant validity. The assessment of items' correlation within the construct is termed convergent validity. Three pre-requests were suggested by studies when assessing convergent validity. First, to show the proper strength of correlations between indicators and their factors, indicators' factor loadings were evaluated and generally greater than 0.7. Second, we used AVE to assess how much of the variation caused by measurement error is captured by latent variable; this ratio must be greater than 0.5 to fulfill convergent validity. Third, the value of items' composite reliability inside the latent construct should be measured and should be greater than 0.7 [48].

Discriminant validity refers to the difference between constructs in their measurement. Assessment of discriminant validity evaluated using three methods: (1) using Fornell Larcker criterion method to assess discriminant validity by comparing the square root of the AVE for each construct with the correlations between that construct and another construct in the study and the square root of AVE's for a particular construct needs to be greater than the correlations between the construct and other constructs for discriminant validity; (2) using Heterotrait Monotrait ratio in this method, the ratio assesses discriminant validity by calculating the ratio of the correlations between indicators of different constructs to the correlations between indicators of the same construct and a value less than 0.85 generally considered fulfillment of discriminant validity but here in our study we used the HTMT ratio inference method to assess the distinctiveness of constructs and ensure that they are measuring unique concepts in our study; and (3) using cross-loading which assesses the loadings of items on their respective construct; items need to show low loading on a different construct to maintain discriminant validity [48, 49].

In summary, our research evaluated the reliability and validity parameters, meeting the recommended standards. This suggests that the theory aligns with the sample data, confirming the validity and reliability of the construct being assessed.

Our study constructs utilized to assess the conceptual model once our measurement model is judged satisfactory. Bootstrapping is a non-parametric inferential technique used to obtain path coefficients and R2 values for testing the conceptual model. The strength of links between exogenous and endogenous factors is inferred by a route coefficient. The R2 value describes variants that can be explained by independent variables. To analyze and validate our suggested model and interactions among the predicted constructs, we employed the PLS method to test metrics such as construct reliability, composite reliability, indicator loadings, AVE, convergent, and discriminant validity. Finally, the standardized root mean square residual (SRMR) is used to assess the overall model fit. SRMR is the square root of the sum of the squared discrepancies between the model-implied and empirical correlation matrices; an SRMR value close to zero indicates best fitness, and less than 0.08 shows good labeling [50–52].

For the purpose of assessing the impact of the PE, EE, SI, FC, HM, PV, and HT on behavioral intentions for using HIS, the PLS regression was used. Bootstrapping resampling was used to assess the relevance of the path coefficients in the SEM using bootstrapping samples, 4999 [45]. The study analyzed path coefficients (β), t-statistics, and *P* values to assess the relationships between independent and dependent variables. Finally, the overall fitness model was determined by applying SRMR.

Results

Sociodemographic characteristics of the study population

Over half of the respondents were males (123, 54.7%). Most of the participants were in the age range of 22 to 31 ($n=163$, 72.4%) and 32 to 41 ($n=38$, 16.9%), followed by 42 to 51 ($n=13$, 5.8%). The most of the participants were from public hospital ($n=168$, 74.7%) and professional personnel ($n=159$, 70.7%). Study participants had demonstrated a varied distribution of educational

backgrounds. A considerable majority 140(62.2%) held first-degree qualifications, while 55(24.4%) possessed diplomas, and 30(13.3%) had attained master's degrees. The majority of respondents had received e-health training, and the untrained to trained ratio was 1:1.9. The results show that the majority of participants, comprising 41.8% of the total, possess good computer skills. Additionally, 20.4% of participants have average skills, while 15.1% were rated as having excellent computer skills. A small proportion, 6.2% were noted as below average, and 3.6% were rated as having poor computer skills. The survey results indicate that 82 participants 36.4% have more than 3 years of experience with HIS. A significant portion of participants, 49(21.8%), have no more than 6 months of experience, while 39(17.3%) have 1–2 years of experience. Additionally, 31(13.8%) of participants have more than 6 months but less than 1 years of experience, and 24 (10.7%) have 2–3 years of experience with HIS (Table 1).

Criteria for E-Health project success

In terms of measuring HIS project success, study participants believe that customer satisfaction (44%) is the most important factor for E-health project success, followed by quality of service (38.7%), project cost (20%), and time (19%) as the next most important factors (Table 1).

Measurement model

The UTAUT-2 model was employed to analyze the factors influencing consumers' behavioral intentions to use HIS in our study. This model was chosen because it is one of the most practical and comprehensive models for assessing people's behavioral intentions to use information technologies [28, 32].

The UTAUT-2 model included endogenous and exogenous variables. Validity tests were carried out using structural equation modeling (SEM). Of the SEM modeling types, the PLS-SEM were selected because it is one of the most practical approaches for assessing IS consumers' intention [29, 32, 53, 54].

The two most important parts of structural equation modeling are measurement and structural model assessment. The relationship between observed variables and their latent constructs is established through measurement model assessment. Construct reliability, composite reliability, cross-loading review, convergent validity, and discriminatory validity assessments were carried out to check the validity of the measurement model before proceeding with structural models.

A Cronbach's alpha (α) is used to assess construct reliability; the coefficient ranges from 0 to 1 and quantifies the degree to which the items in an array of data are connected. Composite reliability (CR) refers to instances in which latent construct indicators or groups of construct indicators consistently measure the same latent variable. The reliability coefficient (α) and composite reliability (CR) for the construct defined as reliability and internal consistency were more than 0.7 [48]. For our study, the calculated ranges of Cronbach's alpha (α) were 0.773 to 0.863, and for composite reliability, 0.858 to 0.916, thus showing evidence of reliability and internal consistency of the construct (Table 2).

Table 1 Consumers' characteristics

Items	Category	*N* (%)	Items	Category	*N* (%)
Gender	Female	102(45.3)	Training on HIS	Trained	147(65.3)
	male	123(54.7)		Untrained	78(34.7)
Age	18–21	8(3.6)	Experience on HIS	Not more than 6 months	49(21.8)
	22–31	163(72.4)		6 month-1 year.	31(13.8)
	32–41	38(16.9)		1–2 yrs.	39(17.3)
	42–51	13(5.8)		2–3 yrs.	24(10.7)
	52–60	3(1.3)		> 3 yrs.	82(36.4)
Educational qualification	Diploma	55(24.4)	work experience	1–10 years	177(79)
	First degree	140(62.2)		11–20 years	36(16)
	Masters' degree	30(13.3)		21–28 years	8(3.6)
Computer skill	Poor	8(3.6)		> 28years	4(1.8)
	Below average	14(6.2)	Employees	Professionals	159(70.7)
	Average	46(20.4)		Administrative	66 (29.3)
	Good	94(41.8)	Criteria for HIS project success	cost	20(8.9)
	Above average	29(12.9)		time	19(8.4)
	Excellent	34(15.1)		Quality of service	87(38.7)
				Customers' satisfaction	99(44)
Institution	public	168(74.7)			
	private	74(25.3)			

Notice: Hospital information systems(HIS)

Table 2 Cronbach's alpha, composite reliability and average variance extracted

Construct	Cronbach's alpha(α)	Composite reliability(CR)	Average variance extracted(AVE)
Behavioral intention (BI)	0.863	0.916	0.785
Effort expectancy (EE)	0.858	0.904	0.702
Facilitating conditions (FC)	0.783	0.858	0.662
Habit (HT)	0.813	0.875	0.637
Hedonic motivation (HM)	0.828	0.897	0.744
Performance expectancy (PE)	0.773	0.869	0.688
Price Value (PV)	0.826	0.895	0.74
Social influence (SI)	0.828	0.897	0.745

Convergent validity is defined as sets of the same construct indicators with correlations in their measurement within the constructs [48]. According to studies, the following are the primary characteristics of convergent validity: Internal consistency reliability Cronbach's alpha should be greater than 0.7; composite reliability coefficients for each unobserved variable should be greater than 0.7; the average variance extracted (AVE) for the latent variable should explain more than 50% of its indicator (AVE should be greater than 0.5); standardized factor loadings should be greater than 0.5 [24, 54]. As a result, the study's results had Cronbach's alpha (α) greater than 0.7, composite reliability coefficients greater than 0.7, average variance extracted greater than 0.5, and standardized factor loadings greater than 0.5 (data not present here). The results indicate that our constructs have convergent validity (Tables 2 and 3).

The degree to which each construct measures different variables in the study is termed discriminant validity. The study used Fornell-Larcker test criteria for assessing discriminant validity, which suggests that square roots of AVE are higher than absolute values in their respective rows and columns correlations [48], and the heterotrait-monotrait(HTMT) ratio needs to be below 0.9 [49]. In our study, one of the values showed a higher than 0.9 between performance expectancy and effort expectancy. In this case, according to studies conducted elsewhere [45, 53], we performed bootstrapping with 4999 subsamples, and our result ensured discriminant validity. The findings indicate the discriminant validity of our constructs (Tables 4 and 5).

Table 3 Factor loadings

Constructs	Coding	Items	Loadings
Behavioral intentions	BI1	I intend to continue using hospital information systems in the future.	0.861
	BI2	I will always try to use the hospital information system in my daily Job	0.898
	BI3	I plan to continue to use the hospital information system frequently.	0.898
Effort expectancy	EE1	Learning how to use hospital information systems is easy for me.	0.871
	EE2	My interaction with the hospital information system is clear and understandable.	0.803
	EE3	It is easy for me to become skillful at using hospital information system	0.834
	EE4	I find hospital information systems easy to use.	0.842
Facilitating conditions	FC1	I have the resources necessary to use the hospital information system.	0.763
	FC2	I know necessary to use the hospital information system.	0.828
	EC3	The hospital information system is compatible with other technologies I use	0.803
	FC4	I can get help from others when I have difficulties using the hospital information system	0.708
Hedonic motivation	HM1	Using a hospital information system is fun.	0.84
	HM2	Using a hospital information system is enjoyable.	0.91
	HM3	Using a hospital information system is very entertaining.	0.836
Habit	HT1	The use of hospital information systems has become a habit for me.	0.778
	HT2	I am addicted to using hospital information systems.	0.81
	HT3	I must use the hospital information system.	0.841
	HT4	Using a hospital information system has become natural to me.	0.759
Performance expectancy	PE1	I find the hospital information system I used useful in my job.	0.808
	PE2	Using the hospital information system enables me to accomplish things that are important to me	0.842
	PE3	Using the hospital information system increases my productivity.	0.838
Price Value	PV1	The hospital information system is reasonably priced.	0.781
	PV2	The hospital information system is a good value for the money.	0.907
	PV3	At the current price, the hospital information system provides a good value.	0.887
Social influence	SI1	People who influence my behavior think that I should use the hospital information system	0.874
	SI2	People who are important to me think that I should use the hospital information system	0.895
	SI3	People whose opinions I value prefer that I use a hospital information system	0.818

Table 4 Discriminant validity: correlations and the square root of AVEs and Fornell-Larcker criterion

Constructs	AVE	BI	EE	FC	HT	HM	PE	PV	SI
Behavioral intention	0.785	**0.886**							
Effort expectancy	0.702	0.685	**0.838**						
Facilitating conditions	0.603	0.633	0.608	**0.777**					
Habit	0.637	0.715	0.646	0.699	**0.798**				
Hedonic motivation	0.744	0.593	0.527	0.708	0.658	**0.863**			
Performance expectancy	0.688	0.679	0.767	0.633	0.671	0.561	**0.83**		
Price Value	0.74	0.566	0.522	0.571	0.645	0.649	0.529	**0.86**	
Social influence	0.745	0.519	0.675	0.602	0.592	0.508	0.636	0.508	**0.863**

Note: Average variance extracted(AVE), Behavioral intention (BI), Effort expectancy (EE), Facilitating conditions (FC), Habit (HT), Hedonic motivation (HM), Performance expectancy (PE), Price Value (PV), Social influence (SI)

The bold diagonal values are the square root of the shared variance between the constructs and their measures.

Off-diagonal elements are correlations.

Table 5 Discriminant validity: Heterotrait-Monotrait ratio (HTMT)

	BI	EE	FC	HT	HM	PE	PV	SI
Behavioral intention								
Effort expectancy	0.792							
Facilitating conditions	0.747	0.731						
Habit	0.828	0.767	0.862					
Hedonic motivation	0.699	0.623	0.88	0.783				
Performance expectancy	0.827	0.942	0.805	0.832	0.698			
Price Value	0.654	0.608	0.718	0.772	0.79	0.642		
Social influence	0.615	0.802	0.753	0.727	0.614	0.796	0.611	

Note: Average variance extracted(AVE), Behavioral intention (BI), Effort expectancy (EE), Facilitating conditions (FC), Habit (HT), Hedonic motivation (HM), Performance expectancy (PE), Price Value (PV), Social influence (SI)

Table 6 Structural model results and hypothesis testing

	β-value	t-value	*p*.value		
R^2	**0.63**	**16.093**	**0**		
Adjusted R^2	**0.619**	**15.295**	**0**		
Path	**Path coefficient**	**t-value**	***p*.value**	**Hypothesis**	**Result**
EE-> BI to use HIS	0.276	3.015	0.001	*H2*	supported
FC -> BI to use HIS	0.1	1.209	0.113	*H4*	Not supported
HT-> BI to use HIS	0.309	3.754	0	*H7*	supported
HM -> BI to use HIS	0.079	0.823	0.205	*H5*	Not supported
PE -> BI to use HIS	0.179	1.905	0.028	*H1*	supported
PV -> BI to use HIS	0.072	0.913	0.181	*H6*	Not supported
SI -> BI to use HIS	-0.102	1.397	0.081	*H3*	Not supported

Notice: Behavioral intention (BI), Effort expectancy (EE), Facilitating conditions (FC), Habit (HT), Hedonic motivation (HM), Performance expectancy (PE), Price Value (PV), Social influence (SI)

Structure model and hypothesis testing

The structural model is evaluated by measuring the strength of links between the endogenous and exogenous variables and by evaluating the predictive power of models generated by path loading and R^2 values [50]. The bootstrapping technique from the SmartPLS3 used to assess path coefficients and R^2 values for hypothesized relationships between dependent and independent variables [52].

According to the findings (Table 6; Fig. 2), effort expectancy (β=0.276, t=3.015, p=0.001), habit (β=0.309, t=3.754, p=0), and performance expectancy (β=0.179, t=1.905, p=0.028) were found to be predictors of behavioral intention to use HIS. As a result, H1, H2, and H7 were supported. In our study setting, social influence (β =-0.102, t=1.397, p=0.081), facilitating conditions (β=0.1, t=1.209, p=0.113), hedonic motivation (β=0.079, t=0.823, p=0.205), and price values (β=0.072, t=0.913, p=0.181) did not appear to be significant predictors of behavioral intention to use HIS. As a result, hypotheses H3, H4, H5, and H6 are not supported.

Figure 2 illustrates the outcome of the PLS-SEM. Overall, our model explains around 63% of the variance in behavioral intention to use HIS after passing the SRMR appropriateness of the model fit index value of 0.061, which is less than the cut-off value of 0.08 [45].

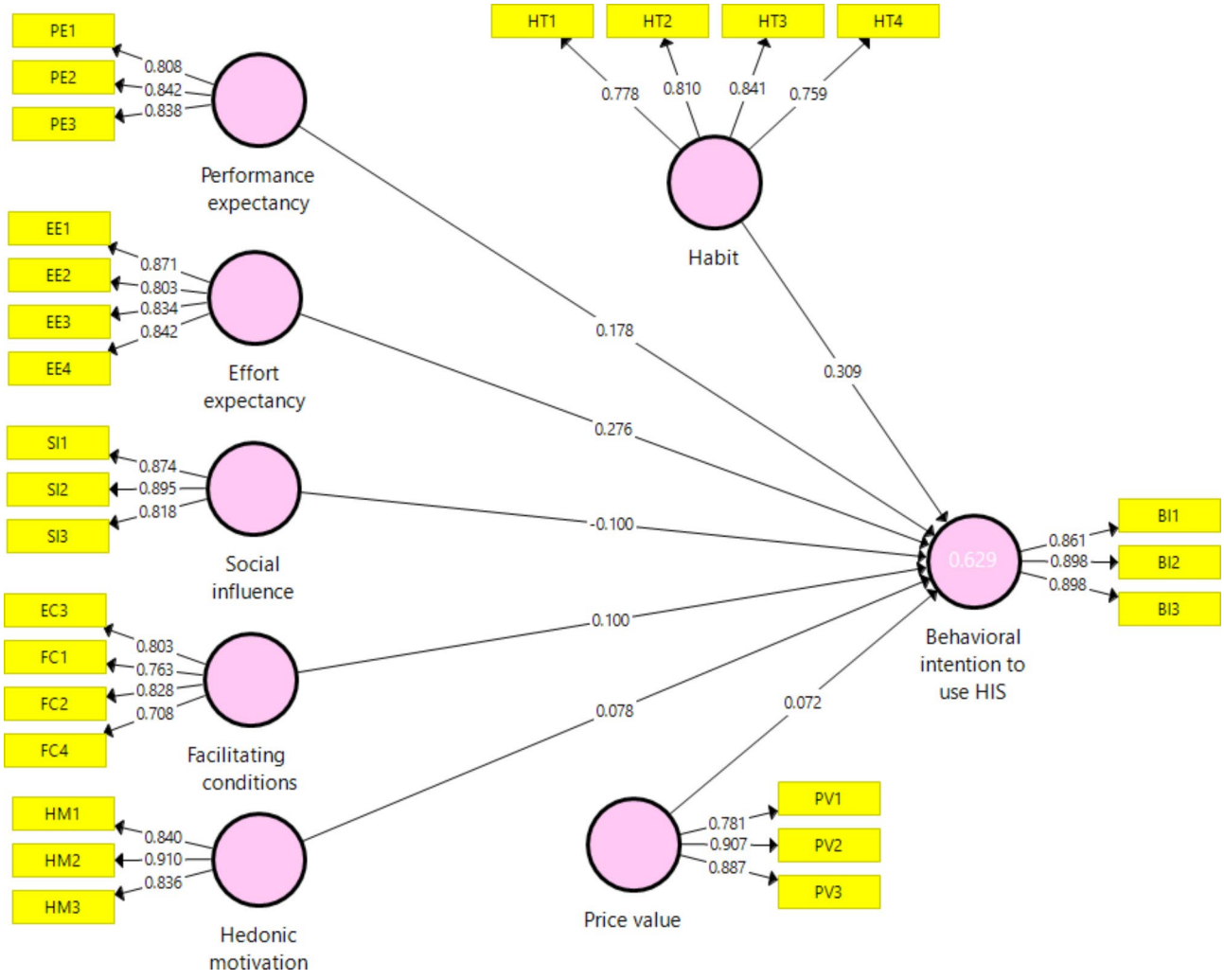


Fig. 2 Path coefficients for the research model

Discussion

In this study, it was found that the proposed model explained about 63% of the variance in behavioral intention to use E-health. Out of the seven factors examined (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit); only effort expectancy, habit, and performance expectancy were found to be valid predictors of consumers' behavioral intention to use e-health.

The findings from this study showed a statistically significant positive relationship between effort expectancy and consumers' behavioral intentions to use e-health (β=0.276, t=3.015, p=0.001). This finding is in line with studies conducted in Northwest (β=0.24, p<0.001) [11], and Northern Ethiopia (β=0.124, p<0.05) [22], Pakistan (β=0.24, p<0.001) [36],Iran (β=0.247, t=6.631) [38], Finland (β=0.191, P<0.001) [37], Portugal (β=0.17, p<0.01 [29], and a comparative study conducted in Portugal and U.S [33]. These results further supported a systematic review conducted in Ethiopia on the idea that effort expectancy is a major facilitator of e-health sustainable acceptance and use in Ethiopia [19]. These studies remained consistent with our findings that the ease of systems has a significant and direct impact on employees' intention to use e-health systems. The findings emphasize the crucial role of effort expectancy in influencing consumers' intention to use e-health systems, highlighting the significance of addressing the ease of use for successful adoption in healthcare industries, particularly in resource-limited settings. These implications highlight the need for practitioners and policymakers to prioritize the design of user-friendly e-health systems to promote acceptance and use.

Another important finding was that habit has a significant positive impact on behavioral intention to use e-health (β=0.309, t=3.754, p=0). This finding complements earlier meta-analysis correlations studies into this brain area that relate the idea that IS systems' prior experience influences their intention to use HIS [40]. This result is consistent with a study conducted in Portugal

(β=0.28, $p<0.001$) [29], Taiwan(β=0.308, $p<0.05$) [54], and Ethiopia (β=0.093, $P<0.05$) [55]. The present findings seem to be consistent with other studies conducted in Ethiopia, which found that habit is one of the facilitators of the sustainable acceptance of e-health systems solutions in Ethiopia [19]. However, the findings of the current study do not support the previous study conducted in Northwest Ethiopia (β=0.01, $p>0.05$) [11]. A possible explanation for this might be related to the e-health system assessed from the prior study being in the implementation stage and not in use, since habit develops from prior experience the possible interface of habit on experience label cannot be ruled out. The findings reveal that habit significantly impacts e-health system use, emphasizing the crucial role of understanding and addressing user habits in theoretical and practical aspects of e-health adoption. This contributes to the knowledge based on e-health systems employees' intention and highlights the importance of interventions and strategies focused on shaping positive e-health usage habits to enhance user acceptance and utilization of such systems.

The study found that performance expectancy has a positive effect on consumers' intentions to use e-health (β=0.179, t=1.905, $p=0.028$). This result is consistent with several studies conducted in different countries in China (β=0.259, $p<0.001$) [24], Portugal (β=0.17, $p<0.001$) [29], Northwest (β=0.39, $p<0.001$) [11] and Northern Ethiopia (β=0.296, $P<0.001$) [22]. The possible explanation for this finding is that the perceived benefits of e-health systems, such as increased productivity, better task prioritization, and improved work performance, positively influence individual's intention to use e-health. For instance, the factor loadings (see Table 3) in the study further supported this idea, indicating the consumers' behavioral intention to use e-health is associated with prioritizing important tasks and thereby increasing overall productivity. These findings highlight the importance of performance expectancy as a facilitator of sustainable acceptance of e-health system solutions in resource-limited settings [19]. Overall, the study suggests that performance expectancy plays a crucial role in promoting the intention to use e-health in southwest Ethiopia. Therefore, healthcare providers and policymakers should focus on enhancing the perceived benefits of e-health systems to improve their adoption and utilization by consumers.

The result of this study did not show that price value has a significant impact on hospital employees' behavioral intentions to use e-Health (β=0.072, t=0.913, $p=0.181$). However, the findings suggest that perceived benefits and the monetary cost of using e-Health systems are not associated with the behavioral intentions to use them. This finding is consistent with the studies conducted in other countries such as China (β=0.039, $p>0.05$) [35] and Portugal (β=0.00, $p>0.05$) [29]. Some authors have speculated that the lack of a significant impact of price value on consumers' intentions to use e-health systems may be because that it related to free internet services for e-health services and no direct involvement of consumers in the procurement of the system [11, 29]. The study highlights the need to focus on factors beyond price value to improve the intention of employees to use e-health systems and promote their effective use in healthcare delivery. Overall, the study provides insight into factors that influence employees' intention to use e-health systems in southwest Ethiopia and emphasizes to the need for more research into this area to improve the healthcare delivery system in the country.

Contrary to expectations, we did not find a significant impact of facilitating conditions on the intention to use e-health (β=0.1, t=1.209, $p=0.113$). Our study considers that the organizational and technical infrastructure present within the facilities does not impact behavioral intention to use E-health. The findings of the current study do not support the previous studies conducted in resource-limited settings throughout the world such as Pakistan (β=0.160, $p=0.00$) [36], Iran (β=0.1580, t=5.708) [38], and Ethiopia (β=0.23, $p<0.001$) [11]. It is difficult to explain this result, but it might be related to a significant proportion of the study participants who received training in E-health, with a higher number of trained-to-untrained ratios (add the proportion). Furthermore, a considerable number of healthcare professionals who participated in the study received education and preparation related to e-health systems. This finding may suggest that employees' considerable training and organizational preparation as key components of facilitating conditions in implemented e-health systems' intent to use [17]. Overall, the result of the study suggests that organizational and technical infrastructure present within the facilities don't impact behavioral intention to use e-health. However, given the limitations of the study, including a small sample size, unanalyzed moderators role, and limited geographical area, further research is needed to confirm this finding and explore the factors that influence the intention to use e-health in study settings.

One unanticipated finding was that social influence did not show any significant impact on hospitals' employees' behavioral intentions to use e-health (β =-0.102, t=1.397, $p=0.081$. Our result indicates that friends, colleagues, and administrative staff may not impact employees' behavioral intentions to use e-health. Whereas past researchers have found peer pressures from social networks enhance employees' inspiration and utilization of E-health in different setting such as china (β =-0.296, $p<0.001$) [24], Portugal (β =-0.10, $p<0.05$) [29], and Ethiopia (β =-0.18, $p<0.001$) [11], the present study

has shown friends, colleagues, and administrative staff may not impact employees' behavioral intentions to use E-health. Although the results need to be interpreted with caution; the possible interference of study settings with relatively higher computer literacy and E-health systems training cannot be ruled out; hence, computer literacy and E-health systems training enhance their readiness to use E-health systems beyond the employees' peer influences [14]. Therefore hospital administrators should focus on providing adequate training on e-health to support their readiness to use e-health systems.

Our study found that the behavioral intention of consumers to use e-health was not affected by hedonic motivation (β=0.079, $p>0.05$). This suggests that the fun, enjoyment, and entertain ability of e-health systems don't significantly impact consumers' behavioral intentions to use e-health. However, our result differs from earlier studies that have found perceived enjoyment to be a predictor of employees' intention to use e-health systems in different settings such as the United States (β =-0.24, $p<0.001$) [30] and Iran (β =-0.231, t=7.694) [38]. The findings observed in this study mirror those of previous studies that have examined the effect of hedonic motivation on healthcare providers in Northwest Ethiopia [11], Portugal (β =-0.07, $p>0.05$) [29]. However, more research on this topic needs to be undertaken before the association between hedonic motivation and e-health systems is established. Overall, our study contributes to the growing body of research on e-health employees' intention by shedding light on the role of Hedonic motivation.

In addition, our study profiled the major success determinants of HIS projects. The study participants expressed their belief that customer satisfaction was the most crucial factor in E-health success, accounting for 44% of responses. Following customer satisfaction, the quality of service was deemed to be the next significant factor at 38.7%. Project cost and time were also considered important, but to a lesser extent, with respective percentages of 8.9% and 8.4%. These findings highlight the importance placed on consumer satisfaction and the quality of service as key determinants of success in e-health initiatives, thus emphasizing the need for healthcare organizations to prioritize these aspects in the implementation and management of e-health systems. Besides our interpretation of the data, an additional explanation warrants a comment. For example, researchers have suggested health professionals who are willing to accept the implementation of E-health are more likely to be ready to use the E-health system, and HIS due system quality directly affects E-health use [9, 14].

Several limitations of our study should be mentioned. Firstly, the fact that it focused exclusively on healthcare employees' intention to use E-health in southwest Ethiopia may decrease confidence in the generalizability of the findings. It would be beneficial for future research to examine differences in behavioral intentions for using e-health systems among healthcare workers in various healthcare institutions across Ethiopia. Secondly, this study only looked at behavioral intentions towards e-health system use and didn't examine actual utilization by healthcare professionals or considered the potential mediators and moderators effect. Thirdly, due to limitations in data collection, we are unable to randomly split the data into public and private health facilities, run the model twice, and compare the results. A future study investigating the factors influencing healthcare professionals' intentions to use e-health in both the public and private healthcare industries with an equal number of participants would provide valuable insights. Fourth, another limitation of our study is that it utilized a cross-sectional study design, which limited our ability to establish cause-and-effect relationships. To address this limitation, we recommend employing a longitudinal study technique in the future research. Additionally, this study doesn't address the importance of incorporating additional constructs to the UTAUT-2 model, as suggested by recent studies on e-health consumers' intention assessment. This is an important issue for the future studies.

Conclusions

The main goal of the current study was to determine factors influencing the intentions of healthcare employees' to utilize e-health services at selected public and private referral hospitals in southwest Ethiopia. Effort expectancy, habit, and performance expectancy emerged as reliable predictors of employees' intention to use the e-health service systems (LIS, RIS, and PIS). Nonetheless; our findings also raise non-significant relationships regarding the impact of price value, facilitating conditions, social influence, and hedonic motivation on consumers' intentions to use the e-health system. In general, therefore, it seems that the user-friendliness of systems has a significant and direct impact on employees' willingness to adopt e-health systems. Additionally, employees' previous experiences influence their inclination to use hospital information systems, and the notable positive effect of e-health on enhancing job performance significantly influences employees' intention to utilize the e-health system. The findings from this study make several contributions to the current literature. First, this study has demonstrated, for the first time, that factors impacting employees' intention to use e-health systems in southwest Ethiopia. Second, a researcher has typically focused on the adoption of e-health services on physicians and patients, overlooking the acceptance of these services by healthcare providers as a team. These highlight the gap in the existing literature and emphasizing

the need to consider their unique characteristics using the UTAUT-2 model. The practical implications of the study are significant. The findings emphasize the importance of evaluating the case of e-health systems, recognizing e-health's role in enhancing job performance, and considering consumers' prior experience to promote their adoption. These implications provide valuable guidance for policymakers and hospital administrators, highlighting the need to prioritize user experience and optimize the e-health system implementation to maximize their effectiveness in healthcare settings.

Abbreviations

AVE	average variance extracted
CR	Composite reliability
EE	Effort Expectancy
E-health	Electronic health service
EMR	Electronic medical or health records
FC	Facilitating Condition
HIS	Hospital information system
HM	Hedonic motivation
HT	Habit
HTMT	Heterotrait-monotrait ratio
IS	Information system
LIS	Laboratory information systems
PE	Performance Expectancy
PLS	partial least square
PIS	Pharmacy information systems
PV	Price value
RIS	Radiology information system
SI	Social Influence
SRMR	Standardized root mean square residual
UTAUT	unified theory of acceptance and use of technology, UTAUT-2:Unified theory of acceptance and use of technology 2 model

Supplementary Information

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Supplementary Material 1

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Author contributions
WA: principal investigator, study conception and design, data collection, data analysis and wrote manuscript. KG: Data collection and reviewed the manuscript. And all authors read and approved the final manuscript.

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Data availability
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
This study adhered to the guidelines specified in the Declaration of Helsinki. Ethical clearance was sought from institutional review boards of Jimma University, Ethiopia (Ref: JUIH/IRB/469/23). Permission to collect data from respective health facilities was sought from the respective directors of the hospitals. All participants provided informed consent before fill in the questionnaire.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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