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Research Article

Intentions to Use Electronic Community Health Information System and Associated Factors Among Health Extension Workers of West Gojam Zone, Amhara, Ethiopia

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ABSTRACT

Introduction: Digital health technology including electronic community health information system (eCHIS) are promising for improving healthcare services. However, developing countries including Ethiopia encounter different challenges to employ digital health technologies. As a result, burdens on health care services such as low provider effectiveness, inability to track clients and provide quality service, disparities in health service coverage, and poor quality of data for decision making have been major issues. Therefore, this study aimed to assess health extension workers intention to use electronic community health information system and associated factors in Ethiopia.

Methods: A facility based cross sectional study was conducted on 649 health extension workers from March 10 to April 12, 2023 at West Gojam Zone, Amhara, Ethiopia. A Simple random sampling technique was used to select participants. Self-administered questionnaire was used to collect data. Descriptive statistics were produced using SPSS version 25 software and presented using tables and pie charts. Structural equation modeling analysis with SPSS AMOS version 26 software was employed to identify predictors associated with intention to use electronic community health information system in Ethiopia.

Results: A total of 612 health extension workers, with a 94.3% response rate, participated in the study. The percentage of HEWs with intention to use electronic community health information system was 70.8% (95%: CI: 67.0–74.3). Attitude (β =0.60, P < 0.001, 95%: CI: [0.47, 0.74)], social influence (β = 0.16, P < 0.05, 95%: CI: [0.01, 0.34]), and facilitating condition (β = 0.17, P < 0.001, 95% CI: [0.08, 0.30]) had a positive direct relationship with intention to use electronic community health information system. Facilitating condition and performance expectancy were positively moderated by age.

Conclusion: Generally, it was encouraging to see that health extension workers intended to use electronic community health information systems. The intention to use electronic community health information system was positively related to Attitude, facilitating conditions, and social influence. Thus, increasing health extension workers utilization of it could be achieved through capacity building, access to technology, and technical support.

Keywords: Intention to use, Electronic community health information system, Health extension workers, Ethiopia

1. Introduction

Mobile health (mHealth) is defined by the world health organization (WHO) as the health-related use of mobile telecommunications and multimedia technologies within health service delivery and public health systems[1]. mHealth applications are defined as tools that assist in medicine and public health via mobile devices. Mobile devices, such as cellphones, tablets, personal digital assistants (PDAs), and wearable devices, such as smart watches, are widely used for health care information, and data collection[2]. Electronic Community Health Information System (eCHIS) is a digitized version of paper-based community health information system (CHIS) in which its content is digitized into a mobile platform application that works in online and offline environments for use by health extension workers (HEWs)[3]. Worldwide there are burdens on primary health care services especially in hard-to-reach low-resource settings including low provider effectiveness, unimproved tracking and service provision, inequity of coverage of their target populations, and low quality of the health-related information provided[4,5].

Successful eCHIS interventions resulted in improvements in reproductive, maternal, newborn and child health (RMNCH) and nutrition in India[5,6], breastfeeding in China[7], maternal and child health care attendance in Rwanda[8], antenatal care services in Nigeria[9], and Maternal and Neonatal Health (MNH) monitoring in Kenya[10], maternal health care in Ethiopia[11]. Ethiopia began to implement eCHIS in September 2018 and took an important and guiding program management, policy development to extract and use data for decision making, and national electronic health management information system to promote one of the five transformation agendas in the country's second health sector transformation plan (HSTP II) which is "Information Revolution"[12]. eCHIS is a high-priority initiative and is taken as one of the major programs of the National Digital Health Strategy of the Ethiopian Ministry of Health (MOH) to improve the quality of health services provided through HEP at the community level[13].

In the context of developing countries like Ethiopia, with limited resources, deployment of mobile technology, needs users' intention to use mobile technologies including eCHIS. Health extension workers better understanding and intention in using eCHIS can influence the adoption of the technology[14]. A study conducted in Ghana shows healthcare providers intention to use EHRs was high (85%)[15]. In contrast a study conducted in Ethiopia shows healthcare providers intention to use EMRs was low (40%)[16]. Evidences revealed that health professionals' low intention to use new technology is the major barrier to implement it successfully[17,18].

In spite of the fact that mHealth applications are a well-established technology supported by a community of software developers and healthcare professionals, many nations are still having difficulty in implementing them due to a variety of obstacles, including cultural, technological, personal, organizational, and social issues[19]. The majority of health professionals in developing countries who want to employ mHealth technology encounter challenges such as inadequate ICT infrastructure, lack of technical assistance and training, skill and experience gaps in mobile technology[20]. According to the findings of various studies performance expectancy, effort expectancy, social influence, facilitating conditions and attitude are determinant factors in healthcare providers' intention to use mHealth application including Echis[21-25].

In Ethiopia favorable attitude, internet access, computer training, the technical skill of healthcare provider, and availability of IT support staff were the most notable factors of mHealth application use[26]; User resistance, shortage of infrastructure, technical difficulty, gaps in routine monitoring, inadequate training, and poor supportive supervision were also reported to be the primary hindering factors against the successful implementation of eCHIS[3,27].

According to the program manager and office reports; eCHIS deployment and distribution are still in their early stages. To implement proven eCHIS interventions there should have confirmed the intention of health extension workers. However, it has not been scientifically well studied in Ethiopia in general and in West Gojam Zone in particular. Therefore, this study aimed to assess intentions to use electronic community health information system and associated factors among health extension workers of West Gojam Zone, Amhara, Ethiopia.

The findings of this study are anticipated to benefit West Gojam Zone primary health care units (PHCU) and their administrative health office by offering support for the creation of interventions and policies that are based on health extension workers' (HEWs) intentions to use electronic community health information system (eCHIS). Additionally, it offers important information for Amhara Regional Health Bureau regarding the current situation, the justifications for intention to use eCHIS, and the difficulties in doing so.

The findings of this study will help the PHCUs in West Gojam Zone to understand the factors that influence the intention to use eCHIS. This will provide opportunities to solve the issues and perhaps implement the approach throughout all health posts. Moreover, the study benefits health institutions, by helping them to identify their weakness to improve intention to use eCHIS and provide scientifically sound information and recommendation on determinant factors of intention to use the eCHIS. Furthermore, this study will have greater input to program managers for designing, implementing and evaluating eCHIS programs; and also serve as base line for further study.

1.1. Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) has been introduced in 2003 as a model. It contains four constructs (performance expectancy, effort expectancy, social influence and facilitating conditions)[28]. In this study, the original UTAUT model was adapted and modified by adding one construct (attitude). In the modified UTAUT model, performance expectancy was assessed with four indicators (PE1: effectiveness in healthcare delivery, PE2: quality in work, PE3:

timelines to accomplish tasks, PE4: usefulness in job), effort expectancy was assessed with four indicators (EE1: easiness for use, EE2: clarity and understandability for use, EE3: easiness to become skillful, EE: flexibility to interact with), social influence was assessed with three indicators (SI1: recommendation from important people, SI2: belief by colleagues, SI3: motivation by senior management), facilitating condition was assessed with four indicators (FC1: knowledge and experience in using smart phone/tablet, FC2: availability of IT support staff, FC3: attendance of training on eCHIS, FC4: availability of technical and organizational infrastructure), attitude was assessed with four indicators (ATT1: having good idea at work, ATT2: having interest in the work, ATT3: having enjoyment during work, ATT4: thinking with the current system is better than the old one). The modified model measures the intention of HEWs to use eCHIS (IU) using three indicators (IU1: start thinking to use eCHIS, IU2: plan to use eCHIS, IU3: aspire to use eCHIS).

1.2. Performance expectancy (PE)

The degree to which a person expects that using the system would enable him or her to improve performance at work is known as performance expectancy[29]. According to the study conducted in China, India and Korea Performance expectancy (PE) has a significant effect on health workers intention to use mHealth technology and or EHR[20,21,23,25,30,31]. In contrast the study conducted in Tanzania reveals that PE has an insignificant effect on health workers intention to use the mHealth app in the case of eIDSR[32]. Additionally, the study conducted in Cameroon, Kenya and Burundi shows that PE has significant effect on health professional's intention to use DHIS2 and or mobile health technology[24,33-35]. In contrast another study conducted in Tanzania (mobile app in case of DHIS2) and Kenya reveals PE has an insignificant effect on health workers intention to use DHIS2[32,36]. The study conducted in Ethiopia shows that PE has a significant effect on health professionals' intention to use EMR[37,38]. The direct effect of PE was moderated by age[33,37,39-42].

1.3. Effort expectancy (EE)

Effort expectancy is defined as "the degree of ease associated with the use of the system"[28]. According to the study conducted in India, Korea and Tanzania EE has a significant effect on health workers intention to use mHealth technology and or EHR[20,23,25,30-32,39]. In contrast the study conducted in China reveals that EE has an insignificant effect on health workers intention to use mobile nursing applications[21]. Additionally, the study conducted in Cameroon, Kenya and Burundi shows that EE has a significant effect on health professional's intention to use DHIS2 and or mobile health technology[33-36]. In contrast the study conducted in Tanzania reveals that EE has an insignificant effect on health workers intention to use DHIS2[32]. The study conducted in Ethiopia shows that EE has a significant effect on health professionals' intention to use EMR[37,38]. The direct effect of EE was moderated by age[33,34,39-42].

1.4. Social influence (SI)

Social influence is the degree of importance a person place on the beliefs of other people (peers, colleagues, and family members, etc.) and how this influences their decision to use technology[43,44]. According to the study conducted in India, China, Bangladesh and Korea SI has a significant effect on the intention to use mHealth technology and or EHR[20,21,23,25,30,31,39,45]. In contrast; the study conducted in Tanzania reveals SI has an insignificant effect on health workers intention to use a mobile app in the case of eIDSR[32]. Additionally; the study conducted in Cameroon and Kenya shows that SI has a significant effect on health professionals' intention to use DHIS2[24,33,34,36]. According to a study conducted in Ethiopia SI has significant effect on the intention to use EMR(37, 38). The direct effect of SI was moderated by age[33,34,39,40,42,44].

1.5. Facilitating conditions (FC)

Facilitating conditions include perceptions of existing infrastructure, internal and external resource constraints, or skills, resources, and opportunities necessary to use the existing technology[46]. According to the study conducted in china, India, Korea, and Bangladesh FC has a significant effect on the intention to use mHealth technology and or EHR[19,20,21,23,30,37,39,45]. According to a study conducted in Tanzania FC has a significant effect on the intention to use mobile applications in the case of eIDSR; in the same study FC has an insignificant effect on the intention to use DHIS2[32]. Additionally, the study conducted in Ethiopia shows FC has significant effect on health professionals' intention to use EMR[37]. The direct effect of FC was moderated by age[29,40].

1.6. Attitude towards use (ATT)

Attitude is an individual's positive or negative feelings about performing the system[28,47]. According to the study conducted in Taiwan, Korea, Ghana, and Ethiopia ATT has a significant effect on the intention to use eHealth/mHealth technology[30,38,48-50].

1.7. Intention to use (IU)

Intension to use is a measurement of user's conscious intent to engage in a particular future behavior for using technology[37]. It is the extent to which a person has made conscious decisions to engage in or refrain from engaging in a particular future conduct[51].

According to a study conducted in china nurses' intention to use mobile nurse applications was 70.2%[21]. Additionally, the study conducted in India shows that Physicians' Intention to use mobile-based information technology was 56%[20], medical doctors Intention to use ICT was 47.5%[39], clinical staffs Intention to use EHR and TM was 48%[52], medical doctors Intention to use EHR was[25]. Furthermore, the study conducted in Taiwan reveals medical staffs' intention to use an online reporting system was 38%[53]. The study conducted in Belgium shows healthcare professionals intention to use web-based systems for personal data records and sharing was 30.8%[54]. The study conducted in Pakistan shows physicians intention to use E-prescription was 56.10%[23]. The study conducted in America shows doctors intention to use EMR was 44%[40].

According to the study conducted in Cameroon health professionals intention to use DHIS2 was 81.9%(24). Another study conducted in Cameroon showed that health professionals intention to use web-based HIS was 46%.(34) Additionally the study conducted in Kenya reveals health professionals intention to use DHIS2 was 63.4%(36). Another study conducted in Kenya shows health workers intention to use DHIS2 was 30.9% and up to 37% when moderated by age and gender. (33). Furthermore the study conducted in Tanzania reveals health professionals intention to use mobile health applications in the case of eIDSR was 72.2%(32). The study conducted in Ethiopia shows that health workers intention to use EMR was 40.2%(38).

2. Methods

2.1. Study design, area and period

A Facility-based cross-sectional study design was conducted in West Gojjam Zone; one of the 20 administration zones in the Amhara regional state. The estimated population of the zone in 2016 was 2,611,925[55]. It has 16 woredas (14 rural districts and 02 city administrations) within this there are about 404 health posts and 1329 HEWs. The study was carried out in West Gojam Zone, North West Amhara, Ethiopia from March 10, 2023 to Jun 12, 2023.

2.2. Source and study population

The source population was all health extension workers who are working in West Gojjam Zone. The study population was all health extension workers worked in West Gojjam Zone during the study period.

2.3. Inclusion and exclusion Criteria

All health extension workers who are currently working in West Gojjam Zone were included. Health extension workers who are newly recruited with less than 6-month of work experience were excluded.

3. Sample Size Determination

3.1. Model specification

Model specification is a visual representation of theoretical variables of interest and expected relationships among them, as well as an expression of hypotheses with graphical conceptual models[56]. The exogenous observed variables on the left (PE, EE, SI, FC, ATT) are predictors that was examined.

3.2. Model identification

Based on the above paths the following are the rules for determining model parameters that could be estimated (57).

Rule 1: All the variances of the exogenous and endogenous variables are free parameters (22 error terms, 1 disturbance, and 5 exogenous latent variables totally=28)

Rule 2: All covariance between exogenous variables are free parameters (10 covariance between exogenous variables)

Rule 3: All factor loadings between latent and its indicators are free parameters (16 load factors between latent and its indicator without considering fixed load factor)

Rule 4: All regression coefficients between latent variables are free parameters (5 regression coefficients between exogenous and endogenous)

Rule 5: The variances of endogenous variables, the covariance between endogenous variables, and the covariance between endogenous and exogenous variables, are never parameters (as would be explained by other parameters)

Rule 6: For each latent variable must be set its metric: Set its variance to a constant (typically 1) and fix a load factor between the latent and its indicator for independent latent. There is only one way to set the metric for the latent dependent: fix a coefficient between it and one of the observed variables to a constant (usually 1).

Our model computes the degree of freedom (DF) using AMOS software. There are 88 parameters (29 fixed values with 1(known parameter) and 28 variances of the independent variables, 10 covariance between exogenous variables, 16 load factors between latent and its indicator, 5 regression coefficients between exogenous and endogenous, totally of 59 free/unknown parameters).

Variances and covariance are always included in the number of distinct parameters. As a result, the total number of distinct parameters to estimate (excluding the 29 preset values) is k (k+1)/2 =22 x 23/ 2 = 253 Where k is the number of observed variables in our study. DF= distinct parameters − free parameters = 253 − 59 = 194. Since the degree of freedom is> 0, the model is over-identified. Working with an over-identified model is generally preferred[56].

The minimum sample size is determined based on the number of free parameters in the hypothetical model; a 1:10 ratio of respondents to free parameters to be estimated has been recommended(58). Accordingly, considering the 59 parameters to be estimated based on the hypothesized model and taking participants to a free parameter ratio of 10, the minimum sample required is 590. The sample size calculated accounts for the non-response rate of 10% and is therefore considered to demonstrate the final sample size. Thus, the final sample size becomes 649.

$$Fn = (FP \times R) + nr$$

$$Fn = (59 \times 10) + 10\%$$

$$Fn = 649$$

Where: Fn: final sample size, FP: free parameter to be estimated, R: the number of individuals to be selected for each free-estimable parameter and nr: non-response rate using 10%.

3.3. Sampling procedure

Simple random sampling technique was used to select health extension workers from each woredas list of HEWs until the required sample size was achieved. The lists of the study population were obtained from West Gojam Zonal Health Department.

3.4. Study variables

In this study dependent variables are termed as endogenous variables and independent variables are termed as exogenous variables.

3.4.1. Endogenous variable: Intention to use electronic community health information system (IU).

3.4.2. Exogenous variables:

- Performance expectancy (PE)
- Effort expectancy (EE)
- Social influence (SI)
- Facilitating condition (FC)
- Attitude towards use (ATT)

3.4.3. Health extension workers Socio-demographic characteristics: Age, Marital status, Religion, Experience, Educational Status.

3.5. Operational definition

Intention to use electronic community health information system (IU): Three indicators/items with a five-point Likert scale question on health extension workers intention to use

eCHIS was computed and the median was calculated from the computed variable, median and above the median intended to use eCHIS else not intended to use eCHIS.

4. Data Collection Tools and Procedures

A questionnaire was adapted and contextualized from various literatures[41,42,44,51]. The questionnaire have two parts: the first section contains HEWs sociodemographic characteristics, and the second part contains key constructs of the UTAUT model. The questionnaire was constructed to test the formulated hypothesis. A total of 22 items of questions were used for the second section of model constructs (4 items for performance expectancy, 4 items for effort expectancy, 4 items for facilitating condition, 3 items for social influence, 4 items for attitude and 3 items for intention to use. Data Collection was done through a self-administered questionnaire and had closed-ended questions; and 5-point Likert-scale questions (1=Strongly Disagree, 2= Disagree, 3= Neutral, 4=Agree, 5=Strongly Agree) were used to measure each item. Four skilled personnel were recruited for data collection and one Public Health Officer was recruited to supervise the overall data collection processes. Data were collected after making communications and getting informed consent from each study participant.

5. Data Quality Assurance

The quality of data was assured by questionnaires that were initially prepared in English, translated into Amharic, and then back-translated into English to check the consistency of the question. A pre-test was done outside of the study area with 5% of the total estimated sample units to check the readability, and consistency of the tool. Orientation was given to data collectors and supervisors, the orientation included the study objectives, data collection procedures, and coding of the questionnaire. The computed questionnaires were reviewed and checked for completeness and relevance by the supervisors and principal investigator.

5.1. Data management and analysis

Before data analysis, the missing value of the data in the dataset was managed, and the data were coded and cleaned in Statistical Package for Social Science (SPSS) version 25. To prevent data loss, data backup procedures were carried out, such as storing data in different locations and making hard and soft copies of the data. The descriptive statistics of demographic and other variables were calculated using SPSS version 25 software, and the model was fitted using structural equation modeling (SEM) using an SPSS add-in software called analysis of moment structure (AMOS) version 23.

To test the measurement model Confirmatory factor analysis (CFA) with standardized estimates were used. Data multivariate normality was evaluated using multivariate kurtosis <5 and the critical ratio between − 1.96 and + 1.96. Multicollinearity was tested using variance inflation factor (VIF <10) and tolerances >0.1. As well as the correlation between constructs less than 0.8 and factor loadings more than 0.6 for each item was checked[59,60]. The chi-square ratio (≤3), the tucker-Lewis index (TLI>0.9), the comparative fit index (CFI>0.9), the goodness of fit index (GFI >0.9), the adjusted goodness of fit index (AGFI >0.8), the root means square error approximation (RMSEA<0.08), and the root mean square of the standardized residual (SRMR<0.08) were used to assess the model's goodness of fit[60-62]. Construct reliability and validity were evaluated to determine the extent to which a variable or combination of variables is consistent in what it wants to measure and to evaluate how effectively the selected construct item measures the construct. composite reliability (CR) and Cronbach's alpha with a value above 0.7 thresholds were used to assess the internal consistency of items[63]. Convergent validity was determined using standard loadings, of every indicator that met the recommended value of above 0.6 and the Average Variance Extracted (AVE) method, with values above the 0.5 thresholds. Fornell Larcker criterion, which is the correlations with other latent constructs should have a lower value than the square root of each construct's AVE, was used to assess divergent/discriminant validity[59,61,64].

To test a structural model, squared multiple correlations (R^2), the critical ratio, and the path coefficients(β) were estimated to measure the relationship between exogenous and endogenous variables, as well as 95% confidence intervals, and a P-value <0.05 was employed to determine statistical significance. The moderating effects of predictor among the hypothesized paths within the core research model were tested using multiple group analysis. Estimating the chi-square difference and p-value between unconstrained and constrained models were applied to determine the effect of the moderator[65].

6. Results

6.1. Socio-demographic characteristics of HEWs

A total of 612 (94.3% response rate) respondents participated in this study. The respondent's median age was 28 years, with (IQR =25–31) years. About 307(50.2%) of the study participants had less than 5 years working experience, 391 (63.9%) of HEWs were married, and 254 (41.5%) of HEWs were Level III followed by 358(58.5%) with Level VI educational status **(Table 1)**.

Table 1: Socio demographic characteristics of health extension workers in west Gojjam, Amhara, Ethiopia, 2023.

Variable	Category	frequency	Percent
Age	20-29 30-39 40-49	388 200 24	63.4 32.7 3.9
Work experience	1-5 6-10 >10	307 221 84	50.2 36.1 13.7
Educational level	Level III Level IV	254 358	41.5 58.5
Marital status	Single Married Widowed Divorced	178 391 16 27	29.1 63.9 2.6 4.4

6.2. Intention to use electronic community health information system

In this study, 70.8% (95%: CI: 67.0–74.3) of the study participants, intended to use electronic community health information system. Intention to use electronic community health information system was measured using three questions with five-point Likert Scales and the median score of Intention to use electronic community health information system was 12 (IQR = 10–13), and the minimum and maximum scores were 3 and 15, respectively.

6.3. Measurement model

Assessment of the measurement model includes checking

the model fit, reliability, convergent and discriminant validity of indicators/items using confirmatory factor analysis (CFA). We used covariate error terms with high modification indices to improve model fit. Accordingly, depending on their respective highest modification indices, we allowed to covariate e5 with e7, e9 with e11, and e12 with e14. In this study, the multivariate normality assumption was not met as the multivariate kurtosis value is > 5 (kurtosis = 250.7) and multivariate critical ratio did not range between − 1.69 and + 1.69 (CR = 95.4). In this case, bootstrapped sampling is recommended to normalize non-normal data[66]. Thus, 5000 bootstrap samples with a 95% bias-corrected confidence interval in AMOS were applied. To be sure there were no strong relationships between exogenous constructs, Multicollinearity was also assessed using variance inflation factor (VIF) and tolerance. Accordingly, VIF and tolerance were below 10 and above 0.1, respectively. Proving that multicollinearity was absent in this study (Table 5).

6.4. Reliability and validity of the construct

Based on outcomes indicated in the table below, the composite reliability ranges from 0.82 to 0.90 and also the Cronbach alpha range from 0.82 to 0.89 which indicates that the construct reliability of the proposed model was achieved. The Average Variance Extracted (AVE) values range from 0.54 to 0.73. As a result, findings showed that the proposed model's convergent validity was achieved **(Table 2).**

Table 2: Convergent validity and Reliability between constructs for intention to use electronic community health information system among health extension workers in west gojjam, Amhara, Ethiopia 2023.

Construct	Indicators /Items	Standard factor loading	Composite Reliability (CR)	Cronbach alpha	Average Variance Extracted (AVE)
IU	IU1 IU2 IU3	0.80 0.90 0.86	0.889	0.89	0.729
ATT	ATT1 ATT2 ATT3 ATT4	0.85 0.82 0.86 0.83	0.905	0.87	0.705
PE	PE1 PE2 PE3 PE4	0.78 0.78 0.85 0.80	0.877	0.85	0.641
EE	EE1 EE2 EE3 EE4	0.72 0.84 0.78 0.81	0.869	0.86	0.624
SI	SI1 SI2 SI3	0.80 0.84 0.70	0.826	0.82	0.614
FC	FC1 FC2 FC3 FC4	0.76 0.78 0.74 0.65	0.822	0.82	0.537

The Farnell-Larcker criterion was used to determine discriminant validity. According to this criterion, the squared correlation with any other construct should be smaller than the square root of each construct's AVE. The average variance extracted (AVE) in the model for all the constructs were higher than 0.50. The square root of the average variance extracted, which is ranging from 0.73 to 0.85, (diagonal/bolded values) for each of the constructs, was also higher than its highest correlation with any other constructs. As a result, the model's constructs' discriminant/divergent validity was achieved[67] **(Table3)**.

Table 3: Discriminant validity between constructs using Fornell Larcker criterion for intention to use electronic community health information system among health extension workers in west gojjam, Amhara, Ethiopia 2023.

Constructs	IU	ATT	PE	EE	SI	FC
IU	0.854					
ATT	0.823	0.840				
PE	0.704	0.748	0.801			
EE	0.604	0.646	0.788	0.790		
SI	0.661	0.637	0.746	0.751	0.784	
FC	0.609	0.553	0.556	0.527	0.567	0.733

6.5. The goodness of model fit

The results in confirmatory factor analysis showed that model fit indices with respective values were chi squire ratio (x2/df = 2.1), Goodness-of-fit-index (GFI = 0.95), Adjusted goodness-of-fit-index (AGFI = 0.93), Comparative fit index (CFI = 0.98), Tucker-Lewis's index (TLI = 0.97), Root mean square error of approximation (RMSEA =0.043) and standardized root mean squared residual (SRMR = 0.05). Accordingly, the goodness of fit model's values met the requirements **(Tables 4,5)**.

Table 4: Model fit indices between constructs of intention to use electronic community health information system among health extension workers in west gojjam, Amhara, Ethiopia 2023.

Fit indices	Threshold Value	Results obtained	Conclusion
Chi-square/degree of freedom	≤3	2.1	Supported
Goodness-of-fit-index (GFI)	>0.9	0.95	Supported
Adjusted goodness-of-fit-index (AGFI)	>0.8	0.93	Supported
Comparative fit index (CFI)	>0.9	0.98	Supported
tucker-lewis index (TLI)	>0.9	0.97	Supported
Root means square error of approximation (RMSEA)	<0.08	0.043	Supported
standardized root mean squared residual (SRMR)	<0.08	0.05	Supported

Table 5: Multicollinearity test between constructs for intention to use electronic community health information system among health extension workers in west gojjam, Amhara, Ethiopia 2023.

Exogenous Construct	Tolerance	Variance Inflation Factor
Attitude towards use (ATT)	0.34	2.96
Facilitating condition (FC)	0.52	1.91
Performance expectancy (PE)	0.18	5.49
Effort expectancy (EE)	0.23	4.28
Social influence (SI)	0.25	4.07

6.6. Structural equation model

SEM analysis was used to evaluate the hypotheses after evaluating the measurement model. According to SEM analysis, respondents' attitude had a direct significant effect on the intention of HEWs to use eCHIS ($\beta = 0.60$; $P < 0.001$). The facilitating condition had a direct significant effect on the intention of HEWs to use eCHIS ($\beta = 0.170$; $P < 0.001$), and social influence had a direct significant effect on the intention of HEWs to use eCHIS ($\beta = 0.163$; $P < 0.05$). Health extension workers intentions to use

eCHIS were more influenced by attitude than other predictors, saying that attitude play a significant role in the use of eCHIS in developing nations **(Table 6)**. The exogenous constructs such as attitude, social influence, and facilitating explained 73% of the endogenous construct (intention to use the eCHIS), which has an R^2 of 0.73, this showed that the proposed model has the strong predictive power.

Table 6: SEM analysis of intention to use electronic community health information system among health extension workers in west gojjam, Amhara, Ethiopia 2023.

Path	Estimate	S. E	C.R	P-value	95% confidence interval		Result
					Lower	**Upper**	
ATT IU	0.60	0.052	11.483	***	0.47	0.74	Supported
PE IU	0.10	0.067	1.432	0.263	-0.08	0.27	Not supported
EE IU	-0.07	0.057	-1.25	0.305	-0.22	0.07	Not supported
SI IU	0.16	0.066	2.823	0.033*	0.01	0.34	Supported
FC IU	0.17	0.044	4.143	***	0.08	0.30	Supported

*p value < 0.05, *** p value < 0.001 C, R: critical ratio S.E: standard error.

6.7. Moderation effect of age

Unconstrained and constrained (structural weight) model comparisons were estimated to test moderators. The unconstrained model assumption showed that there is a moderator or static difference in the given variable to influence the exogenous and endogenous variables, whereas the constrained model assumption suggests the variable has a similar effect on influencing the relationship between the exogenous and endogenous variables. If the significant difference between the two models was found to be significant (p-value less than 0.05 or chi-square difference >5), then the proposed moderator variable was confirmed as a moderator. According to the results, the effects of effort expectancy and social influence on the intention to use electronic community health information system were not significantly different between individuals by age. However, the relationship between facilitating conditions and intention to use electronic community health information system was positively moderated by age and significantly stronger for respondents above the age of 30 (β = 0.356, p-value <0.001) compared to respondents under the age of 30 (β = 0.204, p-value < 0.001), and also the relationship between performance expectancy and intention to use electronic community health information system was positively moderated by age and significantly stronger for respondents under the age of 30 (β = 0.711, p-value <0.001) compared to respondents above the age of 30 (β = 0.437, p-value <0.001) **(Table 7)**.

Table 7: Moderation effect of age on intention to use electronic community health information system among health extension workers in west gojjam, Amhara, Ethiopia 2023.

Path	Moderator (Age)	Path coefficient	P-value	Model test (unconstrained & constrained model)		Result
				ΔX^2	P-value	
PE	< 30	0.711	***	5.098	0.024*	Supported
IU	≥30	0.437	***			
EE	< 30	-0.144	0.011*	0.793	0.373	Not supported
IU	≥30	-0.520	0.554			
SI	< 30	0.304	***	1.599	0.206	Not Supported
IU	≥30	0.153	0.120			
FC	<30	0.204	***	4.178	0.041*	Supported
IU	≥30	0.356	***			

*p value < 0.05, *** p value < 0.001.

7. Discussion

This study investigates the intention to use electronic community health information system and its predictors among health extension workers. The study showed that health extension workers intention to use electronic community health information system was 70.8% (95.0%: CI: 67.0-74.3). This revealed that more than half of respondents intended to use electronic community health information system for managing, analyzing and promoting data with respect to health of their client. This finding is higher than another study done in North West Ethiopia (40%)[16]. this discrepancy may be due to technology advancement, attentions given by the Ethiopian Government, and HEWs' exposure to eCHIs related systems. In contrast our investigation was lower than the study conducted in Ghana (85%)[15]. This discrepancy may be due to the high internet penetration rate in Ghana (68.2%), but the low internet penetration rate in Ethiopia (20%). The other possible reasons for the differences might be variations in awareness about the use of mobile health technology in a resource-limited setting. Moreover, there is a low level of mobile technology development in Ethiopia.

In our study, the intention to use electronic community health information system was significantly associated with attitude, social influence and facilitating condition indicating that 3 out of 5 path relationships in the proposed model were directly associated with the intention to use electronic community health information system. According to our study, social influence (SI) had a positive significant influence on the

intention to use electronic community health information system (β = 0.16, 95% CI: [0.01, 0.34], P = 0.033). The result indicated that the availability of peers, colleagues, and senior managers or supervisors who support the use of electronic community health information system is necessary to motivate health extension workers intention to use electronic community health information system. This is consistent with studies conducted in previous studies in Ethiopia (β = 0.18 P < 0.001)[16], Cameroon (β=0.269, P=0.001)[68], India (β = 0.205, P = 0.034)[69], China (β = 0.296, P < 0.01)[70].

The possible explanation to the above finding is health extension workers might perceive that external pressure towards using a new system could be possibly from the Supervisors, colleagues, and patients or health professionals[68]. So, health extension workers need to perceive pressure from the external body, which is important for them to increase their motivation of intention to use electronic community health information system in their organization. Mechanisms that encourage role modeling and peer support, such as champions and super users, might increase health extension workers intention to use electronic community health information system. Accordingly, social influences are important to motivate users[67].

According to our study, facilitating conditions (FC) had a positive significant influence on the intention to use electronic community health information system (β = 0.17, 95% CI: [0.08, 0.30], P < 0.001). The result implies that the availability of organizational and technical infrastructure, support, and knowledge is necessary to motivate health extension workers intention to use electronic community health information system. This is similar with studies conducted in previous studies in Ethiopia (β = 0.23, P < 0.01)[16], Tanzania (β = 0.550, P < 0.001)[67], India (β = 0.284, P < 0.001)[69], China (β = 0.063, P = 0.037)[70]. The possible reason could be due to health extension workers believing that their organization will be able to help them by giving them supportive trainings and providing organizational and technical infrastructures so they can easily perform their task[49]. Another possible reason might be that respondents believe that electronic community health information system may also be supported by the technical support staff to overcome any difficulties they face. Therefore, facilitating conditions play an important role in resource-limited settings to motivate users[67].

According to our study, attitude (ATT) had a positive significant influence on the intention to use electronic community health information system (β = 0.60, 95% CI: [0.47, 0.74], P < 0.001). This indicates that participants are motivated and have positive feeling to employ electronic community health information system when those technologies make their work interesting and enjoyable. This is supported by studies conducted in previous studies in Ethiopia (β = 0.280, P < 0.001)[16], Ghana (β = 0.980, P < 0.001)[15], Taiwan (β = ٠,٢٢٧, P < ٠,٠١)[49]. The possible reason for this could be health extension workers with a positive stable way of thinking or feeling about electronic community health information system will be highly motivated by the systems(69). Thus, a positive attitude should be considered as a strong determinant, while intention to use electronic community health information system is concerned.

The finding of this study revealed that the relationship between facilitating conditions and health extension workers intention to use electronic community health information system was positively moderated by age (β = 0.356, P < 0.001). This shows that a significant difference existed in facilitating conditions between young and adult age groups for those who intend to use electronic community health information system. This finding revealed that the relationship between facilitating conditions and intention to use electronic community health information system was more influenced by respondents' adult age. This result is similar with other finding conducted in India (β = 0.357, P < 0.001)[69]. The possible explanation might be that adult health extension workers prefer personal support, having someone there to help them, as the most helpful type of technology use, whereas younger health extension workers are the least likely to ask for help and preferred help as an option[37].

Our study showed that the relationship between performance expectancy and health extension workers intention to use electronic community health information system was positively moderated by age (β = 0.711, P < 0.001). This shows that a significant difference existed in performance expectancy between young and adult age groups for those who intend to use electronic community health information system. This finding revealed that the relationship between performance expectancy and intention to use electronic community health information system was more influenced by respondents with young age. This is supported by studies conducted in previous studies in Ethiopia (β = -0.50, P < 0.01)[37], Kenya[33], USA (β = 0.250, P < 0.001)[40]. A probable reason for this could be that older health extension workers have less exposure to emerging technology. Conversely, younger health extension workers are more likely to feel more the value of electronic community health information system, since they might be exposed to information technology[40].

8. Conclusion

Generally, it was encouraging to see that health extension workers intended to use electronic community health information systems. Attitude, facilitating conditions, and social influence were statistically significant predictors of intention to use electronic community health information system among health extension workers. Among the three influencing predictors, Attitude had a more significant prediction power of health extension workers intention to use electronic community health information system. Performance expectancy and facilitating conditions were positively moderated by age.

9. Limitation of the study

Since this study is cross-sectional, it has the limitation of causality. Since data were collected by self-administered technique, it can have social desirability bias Therefore Future studies may use a mixed methods approach that combines qualitative and quantitative research approaches.

9.1. Acronyms and abbreviations

AMOS: Analysis of Moment Structure, ATT: Attitude, IU: Intention to Use, CHIS: Community Health Information System, DF: Degree of Freedom, DHIS2: District Health Information Software Version2, eCHIS: electronic Community Health Information System, EE: Effort Expectancy, EHR: Electronic Health Record, eIDSR: Electronic Integrated Diseases Surveillance and Response, EMR: Electronic Medical Record, FC: Facilitating Condition, HEWs: Health Extension Workers, ICT: Information Communication Technology, IT: Information Technology

mHealth app: Mobile Health Application, PE: Performance Expectancy, SEM: Structural Equation Modeling, SI: Social Influence, TM: Tele Medicine, UTAUT: Unified Theory of Acceptance and Use of Technology.

10. Declarations

10.1. Ethics approval and consent to participate

Furthermore, the study was done according to the Declaration of Helsinki. Ethical clearance was obtained from Bahir Dar University College of medicine and health sciences Ethical Review Committee with protocol number IRB/679/2023. A letter of support was obtained from the Amhara Public Health Research Institute and the West Gojam zonal health department. For the health extension workers, information about the study was given before the study began. The information included the objectives of the study, voluntary participation, the right to decline to study participate, anonymity and confidentiality. The data collector got verbal consent from all study participants and permission from respective offices. Participation was voluntary including the right to withdraw from the study at any time without any preconditions. To keep data confidentiality no personal identifiers such as names, positions and/or other identifiers were collected. After entering into the computer, the data were not disclosed to any person other than the principal investigator.

10.2. Consent for publication

Not applicable.

10.3. Availability of data and materials

The datasets generated and/or analyzed during the current study will be available upon reasonable request from the corresponding author.

10.4. Competing interests

The authors declare that we have no competing interests.

10.5. Funding

No funding was given for this study.

10.6. Authors' contributions

GWM was responsible for a significant contribution to the conceptualization, study selection, data curation, formal analysis, funding acquisition, investigation, methodology, and original draft preparation. Project administration, resources, software, supervision, validation, visualization, and reviewing are all handled by MAA, HAG, TNB, YAM, and TAA wrote the final draft of the manuscript, and the final draft of the work was read, edited, and approved by all writers.

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