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# Users Expectations as Determinants of Continuance Intention towards mHealth amongst health workers: Case of Cstock in Malawi

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# Users Expectations as Determinants of Continuance Intention towards mHealth amongst Health Workers: Case of Cstock in Malawi

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## ABSTRACT

The main objective of this study is to identify and test user expectations as potential antecedents and determinants of continuance intention towards use of Cstock mHealth in Malawi. Cstock mHealth is a rapid short message service (SMS) used by Health Surveillance Assistants (HSAs) to supply, re-supply, and report stock data of medical supplies through mobile phones. The study developed an integrated model based on Expectation Confirmation model (ECM) complimented by other theories from extant literature. A paper-based survey questionnaire was developed and administered randomly to 176 HSAs in health facilities in three districts (Chitipa, Rumphi, and Nkhata-bay) of Malawi. The data analysis followed the partial least squares method to structural equation modelling (PLS-SEM). The findings showed that out of 15 path relationships hypothesised, nine were accepted. The study also confirmed that satisfaction (SATIS) and post-usage usefulness (PUU) have direct influence on continuance intention towards Cstock mHealth. Further to this, the study showed that trust had positive influence on both SATIS and PUU. The unexpected results were that IS success model's quality triads (system quality, information quality, and service quality) had no influence on SATIS. This was contrary to established existing literature that reports quality triads as dominant predictors of user satisfaction. The research model proposed in this study also revealed a coefficient of determination ($R^2$) of 0.271, which was considered substantial. This study has shown the role that user expectations play in the continuance usage behaviour of mHealth in Malawi. The study implication is that mHealth policy-makers, designers and practitioners ought to focus on raising the user expectations to enhance successful adoption of future mHealth initiatives in developing countries.

### Keywords

mHealth, User Expectations, Information system Continuance, Expectation confirmation model, PLS-SEM, Malawi, Africa, Developing country


## INTRODUCTION

The literature is replete with the consequence of information systems (IS) failures, as organisations and governments across the globe continue to invest in information and communication technologies (ICTs) (Szajna & Scamell, 1993).The ability to predict and explain IS failure before and after implementation could help to facilitate the changes in IS and lead to successful adoption (Linda, 2012). User expectations are one possible cause of success or failure of an information systems (Gursel, 2016; Gursel, 2015; Petter, 2008). In the health context, the use of mobile health (mHealth) in developing countries has become increasingly common (Nyemba-Mundenda & Chigona, 2018). The use of mHealth is touted as potential to address some of the barriers affecting the healthcare sector (Chipeta & Malanga, 2022; Nyemba-Mudenda & Chigona, 2018). mHealth is simply defined as the use of mobile phones and other mobile devices to deliver health services (Ndazigayime & Maharaji, 2017). However, the implementation of mHealth technologies has at times not met user expectations, resulting in discontinued use by intended users (Malanga & Chigona, 2018; Nyemba-Mudenda & Chigona, 2013).

Initial acceptance of IS is a determinant of its success (Akter et al., 2013). However, long-term sustainability of such a system depends on its user continuance usage behaviour (Bhattacherjee, 2001). Users may evaluate their earlier acceptance decision or experience some psychological motivational changes after their initial acceptance (Gilani et al., 2016). Contextually, IS continuance is defined as an individual’s intention to continue using the system following initial acceptance decisions (Min, 2007). Literature suggests number of factors that influence user’s continuance behaviour. However, user continuance of IS tends to be successful when user expectations are taken into context (Gursel, 2015).

In this study, user expectations are defined as a set of beliefs held by target users of technology, or associated with the technology and their performance of using the systems (Bhattacherjee, 2008; Bhattacherjee, 2001; Szajna & Scamell, 1993). User expectations are important in emerging technologies like mHealth. They can reveal how users conceptualise the technology, and how the technology is expected to benefit them (Olsson, 2014). Recent studies have reported a total of 33 critical factors that are identified as determinants of IS success on various IS projects, with user expectation ranked second (Gursel, 2015; Petter, 2008). Thus, understanding regarding the role of user expectations play in IS continuance research like mHealth is important. This may help in determining whether or not an IS innovation meets the needs of the users. Helping users to set their expectations of the new systems at an appropriate level could help them improve their satisfaction and continued use of the new system (Linda, 2012). Besides this, an IS that does not meet the user expectations is considered a failure, whether from a voluntary or mandatory environment (Battacherjee, 2001).

There is a plethora of literature on information systems continuance in general, however, few have focused on understanding user expectations as determinants of continuance intention of mHealth among health workers, particularly in developing countries like Malawi. User expectations that influence continuance behaviour of mHealth in the developed world may differ from developing countries, due to differences in local, political and socio-economic contexts (Nyemba-Mudenda & Chigona, 2018; Osah & Kyobe, 2017; Nyemba-Mudenda & Chigona, 2013). This implies that the study findings reported from developed world cannot be extrapolated to developing country contexts. For this reason, the dearth of literature on this phenomenon warrants empirical investigation. Thus, the main research objective was to investigate the influence of user expectations on continuance intention towards use of mHealth in Malawi.

This study uses Cstock mHealth as a case study. Cstock mHealth is a short message service (SMS) used by community health workers (CHWs) for reporting stock data of medical supplies in Malawi via mobile phones. This mHealth application was developed by the Ministry of Health and other cooperating partners. It aimed to solve the problems that CHWs were facing when requesting medical supplies from health centers and district health facilities. For this reason, this study is beneficial to informing health policymakers, mHealth designers and implementers to understand users' expectation beliefs that CHWs hold for their continued use of Cstock mHealth. The specific objectives were as follow:

1. to identify user expectations that have influence on benefits realised towards use of Cstock mHealth;
2. to establish the expectations that have effect on users' satisfaction with Cstock mHealth; and
3. to examine antecedents of expectations likely to influence users' continuance intention towards use of Cstock mHealth.

To achieve these objectives, a conceptual model was developed based on Expectation Confirmation Model (ECM) complemented with other theories from extant literature. About eight predictor variables were conceptualised as user expectation factors (effort expectancy, system quality, information quality, service quality, post usage usefulness, satisfaction, confirmation, and trust) likely to influence continuance intention of mHealth (criterion variable). Altogether, 15 hypotheses were formulated in order to test and validate the conceptualised research model.

## LITERATURE REVIEW

Mobile health (mHealth), defined as the use of mobile devices and technologies to provide healthcare services (Ndayizigamiye & Maharaji, 2017), has emerged as a cost-effective way of addressing health disparities in developing countries, especially in rural communities (Remaire, 2011). mHealth has the potential to overcome the traditional physical geographical barriers, such as lack of physical access to a public health facility. mHealth applications can also support the performance of healthcare personnel, disseminate clinical updates, and reminders. They can likewise decrease the abuse of medical resources such as drugs, and deliver learning materials to patients or clients situated in remote communities (Colander et al., 2013; Watkins, Robinson & Delius, 2013). Despite the positive effects of mHealth, its uptake remains low from users such as health personnel, who are supposed to benefit from such technologies (Gilani, Iranmanesh, Nikbin & Zailani, 2016; Nyemba-Mudenda & Chigona, 2013).

Increasingly, the majority of mHealth projects in most developing countries tend to target Community Health workers (CHWs) as primary users. CHWs are frontline healthcare providers that work at community level. They provide preventative care of diseases especially in rural community hospitals, village clinics, health post, and dispensaries. Despite the potential benefits of mHealth, there seems to be a gap between what CHWs expect from mHealth and what they get from it. This is probably because CHWs health workers are not involved in the design and implementation of such projects. As a result, it is estimated that nearly 60-80% of mHealth projects in developing countries have generally failed or not moved beyond pilot phase. This is attributable to the failure to meet users' expectation, and other contextual factors (Gursel, 2015; Cucciniello et. al., 2015).

## CONTEXT OF THE STUDY

Malawi's population is estimated at 17.2 million of which 87 percent live in rural areas (National Statistic Office, 2017). Malawi is one of the world's least developed countries, with a gross domestic product (GDP) estimated at 11.6 billion US dollars. Agriculture remains the economic backbone of the country (World Bank, 2017). About 43 percent of the population lives below poverty line. The country faces a number of challenges such access to timely and quality healthcare; poor infrastructure; shortage of skilled healthcare workers; chronic child malnutrition; maternal mortality rates; and HIV/AIDS prevalence remain high (Larsen-Cooper, Bancroft, Rajagopal, O'Toole, & Levin, 2016). The average life expectancy is estimated at 46.3 years, adult literacy (64%), GDP per Capita (USD 667), and the proportion of under-weight children and under-five-year-old remains (UNDP, 2017).

### *Healthcare Delivery System In Malawi*

Malawi's healthcare delivery system is categorised into: (i) community; (ii) primary; (iii) secondary; and (iv) tertiary (African Health Organisation [AHO] 2018; Ministry of Health [MOH], 2010). The community and primary healthcare delivery systems are organised to meet the needs of the primary health care services. This includes health posts, maternity units, village clinics, dispensaries, health centre, rural hospitals, and community health centres (MHSSP, 2016).

The secondary healthcare provides specialised services to patients referred from the primary and community healthcare levels. The tertiary healthcare consists of highly specialised services for specific diseases with the specific group of patients (AHO, 2018). The community, primary, and secondary (district) healthcare service delivery levels belong to the district health systems under the mandate of the councils, while the provision of tertiary healthcare service delivery is the responsibility of the MOH (MOH, 2010). The four-tier level healthcare delivery systems are linked to each other through a robust referral system that has been established within the Ministry of Health (AHO, 2018; UNDP, 2020).

The CHWs, known as health surveillance assistants (HSAs), form the largest healthcare workforce in Malawi. They are employed under the Environmental Health Department of the Malawi Ministry of Health (Nyasulu & Chawinga, 2018).Their duties and responsibilities include health education, disease surveillance, immunisation, sanitation assessments, collection of vital statistics, and maintenance of village registers (Kadzamira & Chilowa, 2001). It is estimated that there are over 10,000 HSAs who work (health posts, village clinics, dispensaries, etc.) in rural areas of Malawi (Nyasulu & Chawinga, 2018). For these reasons, HSAs are frontline healthcare providers that provide a link between the health facility and the communities that they serve. They also directly interface with local community on behalf of the Ministry of Health.

## *ICT Landscape In Malawi*

With regards to ICT landscape, mobile phone penetration rate is estimated at 45.5 percent. The proportion of fixed phone ownership and Internet access are estimated at 1precent and 4.5 percent, respectively. In addition, the proportion of individuals who own computer devices is as follows: 13.9 percent are people from rural areas, while 36.1percent are from urban areas (Malawi Communication and Regulatory Authority, 2015). The low penetration of ICT is attributed to Malawi’s weak economy and high taxes imposed on importation of ICT gadgets. Despite the outstanding challenges facing the ICT sector, the Malawian government recognises the role of ICT in human development agenda (Malanga & Banda). In 2010, the Government developed an Electronic Health (e-Health) Strategy for 2011-2016 as a roadmap for implementation of ICT projects in the health sector. Some of the ICT projects that have been deployed in the public health sector include various mHealth initiatives currently at different stages of development (Nyemba-Mudenda, 2018; Malanga & Chigona, 2018; Malanga, 2017). These mHealth initiatives focus on promotion of education and awareness; drug supply chain management; remote data monitoring; training and communication of health workers; treatment and diagnostic support; disease outbreak tracking; and public health surveillance (Chipeta & Malanga, 2022; Malanga & Chigona, 2018).

Case Study Description: Cstock Mhealth

Improved availability of mobile phones in Malawi offers the opportunity to improve the delivery of integrated Community Case Management (iCCM). iCCM is a strategy aiming to provide timely and effective treatment of malaria, pneumonia, and diarrheoa in areas with limited access to facility-based healthcare providers, especially in children under-five (Ministry of Health, 2017). In 2008, the Malawian Government initiated an iCCM strategy to reduce the child mortality rate. The programme entailed training HSAs to treat children at community level. However, this strategy faced a number of challenges, such as poor availability of and limited use of logistics data (low data visibility), and low motivation, among others (Shieshia et al., 2014). To address some of these challenges, the Ministry of Health in partnership with Supply Chain for Community Case Management (SC4CCM) designed a Cstock mHealth tool for community level-reporting of stock on hand data and resupply of 19 health products managed by CHWs (Shieshia et al., 2014).

Cstock mHealth is a rapid Short Message Service (SMS) used by HSAs to report stock data of medical supplies through mobile phones. The system calculates HASs to re-supply quantities of medical supplies and sends this information to health facility staff. The health facility staff receive this information so as to pick and pack products for HSA and notify them about collection date and time (Shieshia et al, 2014). Cstock mHealth has also a web-based accessible dashboard, which is simple and easy to use. It also generate reports, show stock levels, reporting rates, and alerts for central and district level managers. The dashboard provides visibility of HSA logistics data to district and central level managers. Recently, Cstock mHealth implemented in health facilities in 14 out of the possible 29 districts of Malawi (SC4CCM, 2018). Figure 1, illustrates how data and product flow in Cstock mHealth.

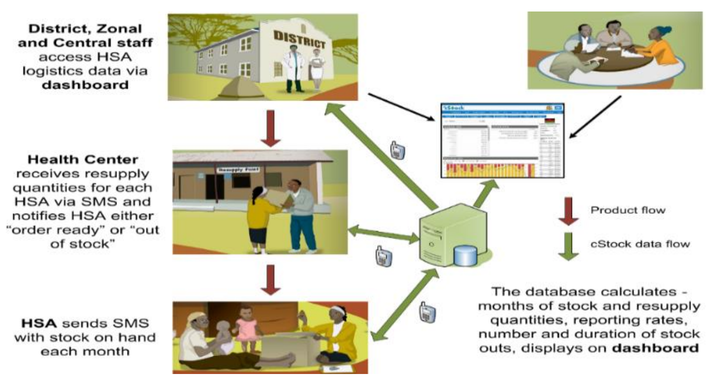


**Figure 1: Cstock mHealth Data and Product Flow (**SC4CCM, 2018)

## RESEARCH MODEL AND HYPOTHESIS DEVELOPMENT

The expectation confirmation model (ECM) as a based model includes four variables. Other variables were complimented from IS success model (DeLone & McLean, 2016), theory of social cognitive trust model (Meyer, Davis, & Schoorman, 1995), and unified theory of acceptance and use of technology model (Venkatesh et al., 2003), that offset for ECM theoretical limitations. These theories and models are briefly discussed, selected variables are justified, and proposed hypotheses presented herein. To define the boundary literature, the researchers limited the review of literature within the IS ranked journals that contained continuance intention as a criterion variable. Aside from this, it should be pointed out that the researchers did not aim to provide a complete model of users' expectations as determinants of continuance intention, but rather to contribute to the continuance stream by integrating salient user expectation beliefs likely to predict continuance intention to use mHealth (Osah, 2015).

### *Expectation Confirmation Model (ECM)*

Implementation of mHealth often fails to meet user expectations, leading to discontinued use (Ndazigayime & Maharaji, 2018). To sustain the use of such systems, IS ECM was developed (Battacherjee, 2001) to explain continued usage behaviour. ECM draws on expectation confirmation theory (ECT) (Oliver, 1980) and the technology acceptance model (TAM). Battacherjee (2001) integrates the selected constructs from ECT and TAM, and offers them as salient predictors of continuance intention with technology (Osah & Kyobe, 2017). ECM posits that individual's intention to continue using a given technology is dependent on three variables, namely: (i) level of user's confirmation of expectations, (iii) user's level of satisfaction, and (iii) post-adoption expectations, measured as post-usage usefulness (Osah &Kyobe, 2017; Battacherjee, 2008). ECM posits that users post-usage (Post-adoption expectations) of technology has a positive influence on their continuance intention to use technology. Likewise, post-usage usefulness has positive influence on user satisfaction with technology. Confirmation of expectation has positive influence on both post-usage usefulness and satisfaction with technology. On the other hand, user satisfaction is a strong predictor of continuance intention to use technology (Battacherjee, 2008, 2001). ECM has been widely used to study continuance behaviour, because it is: (i) supported by a growing empirical base in the marketing and IS usage literatures; (ii) parsimonious to predict continuance intention; and (iii) empirically testable in various contextual settings. Thus, this study poses the following hypotheses:

> ***H1:*** *A user's high level of satisfaction mHealth is positively associated with his or her continuance intention towards* Cstock *mHealth.*
>
> ***H2:*** *A user's perception of post-usage usefulness is positively associated with his or her continuance intention towards* Cstock *mHealth.*
>
> ***H3****: A user's perception of post-usage usefulness is positively associated with his or her satisfaction with* Cstock *mHealth.*
>
> ***H4:*** *A user's high level confirmation is positively associated with his or her satisfaction with* Cstock *mHealth.*
>
> ***H5:*** *A user's high level confirmation is positively associated with his or her post-usage usefulness with* Cstock *mHealth.*

### *Updated IS Success Model*

One of the weaknesses of ECM is that it only examines post-adoption expectations through the post usage usefulness variable ( Akter et al., 2013). However, the post-usage usefulness is not adequate to aggregate all the post-expectation beliefs such as control, attitudinal, and object-based beliefs that an individual user may hold towards the IS. Similarly, Battacherjee (2001) claims that pre-acceptance expectations are covered by satisfaction and confirmation constructs (Battacherjee, 2001), where the two variables do not capture all the pre-acceptance expectations that a user may hold towards the IS. In order to address these shortcomings, the study integrated quality triads (system quality, information quality, and service quality) from IS success model (DeLone & McLean, 2016). The IS success model is a generic model that is applied to study both pre-acceptance and IS continuance behaviours. In this study, the model is applied to conceptualise pre-acceptance expectations, which are quality triads.

System quality refers to user's perceptions about the technology, while information quality is defined as user's expectation about the technology output, such as relevance and accuracy. Service quality refers to the user's perceptions about the support from IS department or the vendor delivering the technology product or service. These quality triads have been validated in extant IS literature to have positive influence on user satisfaction with technology (Osah & Kyobe, 2017; DeLone & McLean, 2017). Likewise, it is assumed, that the same may apply to post-usage usefulness (Yakubu & Dasuki, 2018; Lai, 2016; DeLone & McLean, 2016). The relevance of the three quality triad variables to the present study is that quality is an important concept that users expect the IS artefact such as mHealth application to exhibit. Previous studies have also confirmed that quality is an object-based expectation belief or attribute that users possess as standards that an IS service or products should portray. Thus, it is hypothesised that:

> ***H6:*** *A user's perception of system quality is positively associated with his or her satisfaction with* Cstock *mHealth.*
> ***H7:*** *A user's perception of system quality is positively associated with his or her post-usage usefulness with* Cstock *mHealth.*
> ***H8:*** *A user's perception of information quality is positively associated with his or her satisfaction with* Cstock *mHealth.*
> ***H9:*** *A user's perception of system quality is positively associated with his or her post-usage usefulness with* Cstock *mHealth.*
> ***H10:*** *A user's perception of service quality is positively associated with his or her satisfaction with* Cstock *mHealth.*
> ***H11:*** *A user's perception of service quality is positively associated with his or her post-usage usefulness with* Cstock *mHealth.*

### *Theory Of Social Cognitive Trust (TSCT) Model*

Furthermore, trust was selected from the theory of social cognitive trust (TSCT) model (Meyer, Davis, & Schoorman, 1995). Trust is defined as the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party (Mayer et al., 1995). Similarly, trust is regarded as an expectation that others one chooses to trust will not behave opportunistically by taking advantage of the situation (Staub, Gefen, & Karahanna, 2003). Based on the two definitions, it is clear that trust can be conceptualised as an expectation belief a user can hold towards the IS artefact or from an actual provider/vendor of IS. The extant IS literature has applied trust to study mobile payments (Osah & Kyobe, 2017); e-government (Akkaya, Obermeier, Wolf, & Kramer, 2011); mobile banking (Kesharwani, & Bisht, 2012); and online shopping (Kim, 2012; Faqih, 2011).

The empirical findings show that trust has positive influence on satisfaction with technology. It also assumed that trust can also have positive influence on post-usage usefulness (post-adoption expectations) towards mHealth. Although the literature on role of trust on continuance usage of IS exists, relatively little research has examined the role of trust expectation in influencing users' continuance intention towards mHealth (Lankton, McKnight, & Thatcher, 2014). For this reason, extending the ECM to mHealth context by incorporating trust construct from TSCT model is of paramount importance to validate its explanatory power. Thus, it is hypothesised that:

> ***H12:*** *A user's high level of trust is positively associated with his or her satisfaction with* Cstock *mHealth.*
> ***H13:*** *A user's high level of trust is positively associated with his or her post-usage usefulness with* Cstock *mHealth.*

### *Unified Theory Of Acceptance And Use Of Technology (UTAUT) Model*

Effort expectancy is another variable that was conceptualised as user's pre-acceptance expectation. Effort expectancy relates to the degree of ease associated with the use of technology. This variable was selected from unified theory of acceptance and use of technology (UTAUT) model. The model postulates that effort expectance, performance expectancy, social influence, and facilitating conditions are constructs that influence users' intention to adopt an IS (Venkatesh et al., 2012). The effort expectancy construct is relevant to this study in the sense that users may have an expectation on how easy or difficult to use the mHealth application. This implies that, if the mHealth application does not meet the effort expectation of the users, they are likely to reject the technology and vice versa. The performance expectancy is left out because it is equivalent to perceived usefulness, which is already captured in ECM. Similarly, a facilitating condition variable was covered in IS success model, related to service quality expectation. Furthermore, social influence was removed from consideration, because it was deemed not an expectation factor. Thus, it is hypothesised that:

***H14****: A user's high level of effort expectancy is positively associated with his or her level of satisfaction with* Cstock *mHealth.*
***H15****: A user's high level of effort expectancy is positively associated with his or her level of post-usage usefulness with Cstock mHealth.*

Following the review of the theoretical models and the hypotheses development, Figure 2 shows a diagramme for the proposed research model.

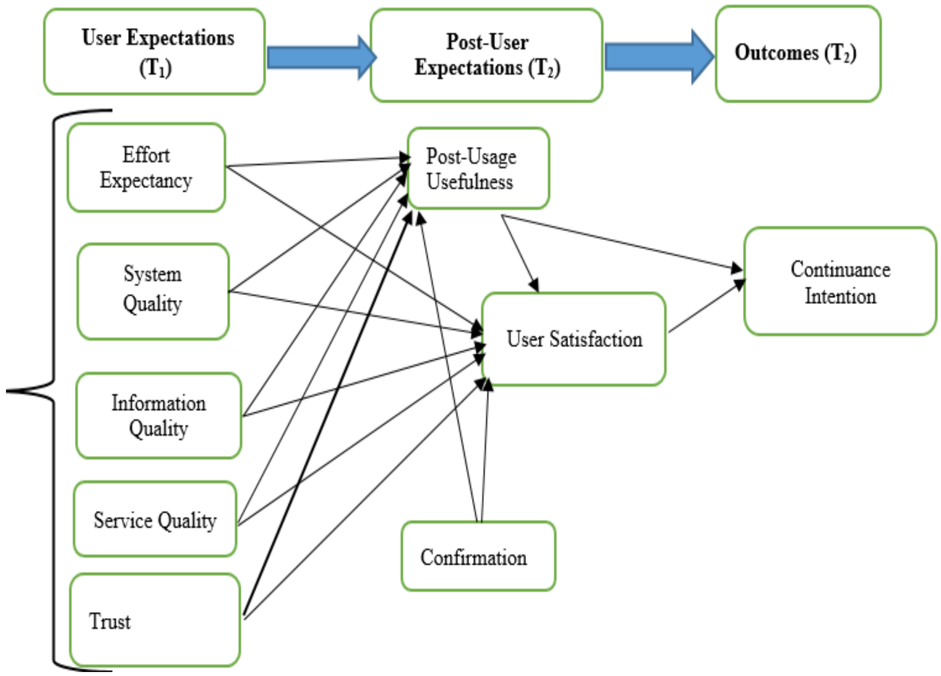


**Figure 2: Proposed research model**

The researchers were aware of the fact that some leading IS scholars have cautioned against the integration of IS acceptance theories in investigating continuance phenomena (Bhattacherjee & Barfar, 2011). These authors argue that the factors that predict initial adoption may not be suitable for explaining continuance, due to separate time-variants. However, other scholars have criticised this perspective, by arguing that relying only on post-adoption models or theories to study IS continuance provide an incomplete picture of the whole IS adoption process. Therefore, it is suggested that that merging both pre-acceptance and post-adoption models/theories in investigating IS continuance has the potential to improve the ECM explanatory power (Chiu & Wang, 2008; Limayem & Cheung, 2008). It is on this basis that this study merged both pre-acceptance and post-adoption theories so as to identify both pre-acceptance and post-adoption expectation beliefs as potential determinants of continuance intention towards use of Cstock mHealth in Malawi.

# METHODOLOGY

## *Research Design*

This study adopted a cross-sectional survey design (Babbie, 2009). The reasons for employing survey design were that it is popular and allows the collection of a large amount of data from a sizeable population (Creswell, 2014). We targeted a population of 308 CHWs, also known as Health Surveillance Assistants (HSAs), in the health facilities of three districts (Chitipa, Rumphi, and Nkhata-bay) in Northern Malawi. The study opted to use a census because it is effective if the population is small (Saunders et al., 2016; Babbie, 2009). The targeted research participants had access to Cstock mHealth. The district health facilities were purposively selected, because they were actively engaged in using Cstock, compared to the other districts in the region. The study utilised simple random sampling technique, because the researchers had accurate and easily accessible sample frame that listed the target population of HSAs (Creswell, 2014; Kumar, 2011). The researchers obtained the list of HSAs from the three district health facilities.

The study utilised a print survey questionnaire comprising two parts. Most of the targeted HSAs were working in hard-to-reach areas, where there was no access to the internet (Chipeta & Malanga, 2022; Malanga & Banda, 2021). For this reason, using print survey questionnaire was considered convenient and suitable. The first contained the demographic profile of respondents. The second comprised a standardised 27 closed-ended questions, with at least two scales, in order to measure nine constructs that were adapted from extant theories and literature (see Appendix 1). Furthermore, the questions in second part were subjected to a 7-point Likert scale (1=strongly disagree to 7=strongly agree).

### *Ethical Clearance*

This study is part of an on-going PhD thesis (Information Systems) registered at the University of Cape Town, South Africa. As such, permission to conduct the study was sought from the University of Cape Town, Faculty of Health Sciences (FHS) Human and Research Ethics Committee (HREC REF:553/2019). Furthermore, permission to collect data was sought from the three targeted district health facilities (Nkhata-Bay, Chitipa, and Rumphi). This process helped to assess the potential risk, such as psychological, physical, social and legal harm to participants (Creswell, 2014). Participation was voluntary, such that each participant was free to take part in or withdraw from the study at any time. Consent forms were also given to each respondent in order to sign his/her agreement or willingness of participation in the study.

### *Data Collection And Analysis*

Data collection took place between 10th July, 2019 to 30th May, 2020. Of 280 survey questionnaires that were randomly distributed to HSAs in the three district health facilities (Chitipa=90, Rumphi=120, and Nkhata-bay=70), 227 were successfully returned for data analysis, achieving a response rate of 81.07 percent. The study adopted two methods of data analysis. First, descriptive analysis using IBMSPSS version 25 was used to screen data and calculate the frequencies of respondents' demographics. Second, the study utilised a partial least square method to structural equation modelling (PLS-SEM) analysis using SmartPLS software tool version 3.8. PLS-SEM examines both the measurement and structural models simultaneously, consequently assessing factor analysis and hypothesis testing concurrently. For this reason, PLS-SEM approach was adopted over other SEM tools such as covariance-based SEM, where the aim of this study was exploratory in nature, prediction-oriented, and focused on model enhancement (Hair et al., 2017).

### *Data Screening Procedure*

Before data analysis, the researchers further screened all the 227 survey questionnaire missing data, outliers, data normality and common method bias. Outliers were detected through univariate and multivariate detection, in which cases with Z-scores of over 3 were removed as rules of thumb. Similarly, to test for data normality, the study adopted Skewness and Kurtosis tests in which threshold values (z-scores) of -3 to +3 for Kurtois and -2 to+2 for Skewness were respectively used as a rule of thumb (Azzalini, 2005). Furthermore, to test for common method bias, data was submitted to Haman's one factor method in IBM SPSS version 25. The results showed that the first factor accounted for 12.608percent, while the last factor was 5.058 percent. The results also indicated that all eight factors that were submitted to the Principal Component Analysis (PCA) accounted for 62.492 percent. Thus, a single factor was not accountable for more than 50 percent of variance in the data set, indicating absence of CMB (Barns & Barns, 2008). As a result, after screening the data, 51 cases were removed and only 176 cases were returned for data analysis.

## ANALYSIS OF FINDINGS

### *Demographic Profile*

The supplementary questions in the survey sought to gather respondents' demographics and other factors. The demographic profile of the respondents is summarised in Table 1.

| Variable(s) | Category(s) | Frequency(N=176) | Percent (%) |
|---|---|---|---|
| **Gender** | Male | 107 | 60.8 |
| | Female | 69 | 39.2 |
| **Age** | 20-25 | 1 | 0.6 |
| | 26-30 | 18 | 10.2 |
| | 31-35 | 66 | 37.5 |
| | 36-40 | 64 | 36.4 |
| | 41+ | 27 | 15.3 |
| **Education level** | Primary School Certificate of Education | 1 | 0.6 |
| | Malawi Junior Certificate of Education | 32 | 18.2 |
| | Malawi School Certificate of Education | 118 | 67.0 |
| | Professional Certificate | 15 | 8.5 |
| | Diploma Certificate | 8 | 4.5 |
| | Degree | 2 | 1.1 |
| **District health facility** | Chitipa | 67 | 38.1 |
| | Rumphi | 51 | 29.0 |
| | Nkhatabay | 58 | 33.0 |
| **Work experience** | 1-5 | 9 | 5.1 |
| | 6-10 | 47 | 26.7 |
| | 11-15 | 86 | 48.9 |
| | 16+ | 34 | 19.3 |
| | 1-5 | 9 | 5.1 |
| **Mobile Phone ownership** | Basic Phone | 76 | 43.2 |
| | Featured Phone | 85 | 48.3 |
| | Smart Phone | 15 | 8.5 |
| | Tablet | - | 0.0 |
| **Frequency usage of Cstock mHealth** | Daily | 14 | 8.0 |
| | Weekly | 35 | 19.9 |
| | Monthly | 126 | 71.6 |
| | Other | 1 | 0.6 |

**Table 1: Demographic profile of respondents**

### *Measurement Model Analysis*

The first stage in PLS-SEM analysis is to assess the measurement model (outer model). This involves the evaluation of reliability and validity of constructs in the conceptualised model (Henseler, Ringle, & Sinkovics, 2009). Using SMART-PLS 3.8, this study employed the following four steps to evaluate the reliability and validity of the research model: (i) indicator reliability; (ii) internal consistency, reliability; (iii) convergent validity; and (iv) discriminant validity.

Indicator reliability is a proportion of indicator variance that is explained by the latent variable (construct). In this study, indicator loadings of 0.50 and above were adopted (Hair et al., 2017) as cut-off. Secondly, in order to measure internal consistency reliability, Cronbach's alpha and a composite reliability were examined (Chin, 2010; Hamid, Sami & Sadek, 2017). Composite reliability measures the sum of the latent variable (LV)'s factor loadings relative to the sum of factor loadings plus error variance (Hair at al., 2017). Being exploratory in nature, the values of Cronbach's alpha and composite reliability between 0.60 and 0.70 were respectively accepted (Chin, 2010; Hamid, Sami & Sadek, 2017).

Convergent validity was assessed by examining the Average Variance Extracted (AVE) across all items associated with a particular construct. The AVE is calculated as the mean of the squared loadings of each indicator associated with a construct for standardised data. An acceptable threshold for the AVE is 0.50 or higher (Fornell-Lacker, 1981). These researchers examined the convergent validity. Convergent validity refers to the extent to which a construct converges in its indicators by explaining the item's variance (Sarstedt, Ringle & Hair, 2017). The results for examining reliability and convergent validity are presented in Table 2. The results show that all the measurement items that met the criteria were returned and those that failed were removed for further analysis.

| Construct (s) | Indicator(s) | No. of Indicator(s) | Indicator Loadings | Cronbach Alpha | Composite Reliability | Average Variance Extracted (AVE) |
|---|---|---|---|---|---|---|
| Continuance Intention | CONT1 | 2 | 0.75 | 0.67 | 0.76 | 0.61 |
| | | | 0.81 | | | |
| Satisfaction | SATISF1 | 2 | 0.80 | 0.65 | 0.78 | 0.69 |
| | SATISF2 | | 0.86 | | | |
| Post-Usage Usefulness | PUU1 | 3 | 0.63 | 0.67 | 0.78 | 0.54 |
| | PUU2 | | 0.82 | | | |
| | PUU3 | | 0.74 | | | |
| Confirmation | CONF1 | 2 | 0.96 | 0.63 | 0.73 | 0.59 |
| | CONF2 | | 0.51 | | | |
| System Quality | SYSQ1 | 3 | 0.76 | 0.71 | 0.83 | 0.62 |
| | SYSQ2 | | 0.82 | | | |
| | SYSQ3 | | 0.77 | | | |
| Service Quality | SERVQ1 | 2 | 0.89 | 0.69 | 0.72 | 0.57 |
| | SERVQ2 | | 0.58 | | | |
| Information Quality | INFQ1 | 2 | 0.67 | 0.67 | 0.77 | 0.61 |
| | INFQ2 | | 0.88 | | | |
| Trust | TRUST1 | 3 | 0.61 | 0.72 | 0.81 | 0.59 |
| | TRUST2 | | 0.81 | | | |
| | TRUST3 | | 0.86 | | | |
| Effort Expectancy | EEXP1 | 2 | 0.86 | 0.65 | 0.83 | 0.70 |
| | EEXP2 | | 0.82 | | | |

**Table 2: Results of reliability and convergent validity**

Discriminant validity measures the extent to which a construct is empirically distinct from other constructs both in terms of how much it correlates with other constructs and distinctly the indicators represent only the single construct (Hair et al., 2017; Sarstedt, Ringle & Hair, 2017). This means that the construct is unique and captures phenomena not represented by other constructs in the conceptual model (Hair et al., 2014). In order to establish discriminant validity, this study adopted Fornell and Lacker criterion and cross-loadings (Henseler at al., 2015). Fornell and Lacker criterion compares the square root of the Average Variance Extracted (AVE) with the latent variable (construct) correlations (Hair et al., 2014; Fornell-Lacker, 1981). This implies that the square root of each construct's AVE ought to be greater than its highest correlation with any other construct (Hair et al., 2014). Thus, this study examined the Fornell-Lacker criterion using SMART-PLS, and the results are presented in Table 3.

| CONF | CONT | EEXP | INFQ | PUU | SATIS | SERVQ | SYSQ | TRUST |
|---|---|---|---|---|---|---|---|---|
| **CONF** | | | | | | | | |
| **CONT** | 0,19 | | | | | | | |
| **EEXP** | 0,14 | 0,34 | | | | | | |
| **INFQ** | 0,29 | 0,21 | 0,35 | | | | | |
| **PUU** | 0,61 | 0,62 | 0,44 | 0,46 | | | | |
| **SATISF** | 0,54 | 0,59 | 0,35 | 0,34 | 0,45 | | | |
| **SERVQ** | 0,44 | 0,26 | 0,21 | 0,28 | 0,62 | 0,30 | | |
| **SYSQ** | 0,20 | 0,35 | 0,36 | 0,42 | 0,37 | 0,27 | 0,41 | |
| **TRUST** | 0,43 | 0,27 | 0,27 | 0,23 | 0,52 | 0,44 | 0,61 | 0,17 |

**Table 3: Results for Fornell-Lacker Criterion**

The results indicate that the square roots of each construct's AVE is greater than its highest correlation with any other construct, thereby indicating presence of discriminant validity. Another step was cross-loadings. Discriminant validity is shown when each measurement item correlates weakly with all other constructs, except for that to which it is theoretically associated. To establish discriminant validity in PLS-SEM analysis using cross-loadings, Chin (1998) suggests that each indicator loading should be greater than all of its cross-loadings. Likewise, as indicated in Table 4, the results show that all indicators have greater loadings than all of their cross-loadings, implying presence of discriminant validity.

| | CONF | CONT | EEXP | INFQ | PUU | SATIS | SERVQ | SYSQ | TRUST |
|---|---|---|---|---|---|---|---|---|---|
| **CONF1** | **0,94** | 0,03 | 0,03 | 0,16 | 0,33 | 0,32 | 0,07 | 0,08 | 0,33 |
| **CONF2** | **0,59** | 0,02 | 0,00 | 0,04 | 0,17 | 0,11 | 0,15 | -0,01 | 0,06 |
| **CONT1** | -0,04 | **0,78** | 0,14 | -0,02 | 0,22 | 0,40 | 0,02 | 0,19 | 0,06 |
| **CONT2** | -0,02 | **0,57** | 0,15 | 0,14 | 0,16 | 0,09 | 0,04 | 0,19 | 0,10 |
| **EEXP1** | 0,07 | 0,19 | **0,75** | 0,08 | 0,26 | 0,09 | 0,06 | 0,18 | 0,26 |
| **EEXP2** | 0,00 | 0,18 | **0,86** | 0,20 | 0,18 | 0,28 | -0,04 | 0,14 | 0,03 |
| **INFQ1** | 0,08 | 0,01 | 0,14 | **0,73** | 0,17 | 0,10 | 0,08 | 0,26 | 0,04 |
| **INFQ2** | 0,15 | 0,07 | 0,15 | **0,85** | 0,19 | 0,16 | 0,05 | 0,07 | 0,17 |
| **PUU1** | 0,10 | 0,24 | 0,19 | 0,09 | **0,61** | 0,14 | 0,15 | 0,27 | 0,03 |
| **PUU2** | 0,25 | 0,36 | 0,23 | 0,16 | **0,81** | 0,24 | 0,14 | 0,10 | 0,28 |
| **PUU3** | 0,34 | 0,24 | 0,14 | 0,22 | **0,73** | 0,15 | 0,26 | 0,08 | 0,39 |
| **SATISF1** | 0,16 | 0,23 | 0,15 | 0,10 | 0,07 | **0,55** | 0,03 | 0,09 | -0,07 |
| **SATISF2** | 0,36 | 0,24 | 0,23 | 0,17 | 0,25 | **0,87** | 0,01 | 0,14 | 0,31 |
| **SERVQ1** | 0,05 | 0,01 | -0,04 | 0,06 | 0,23 | 0,00 | **0,89** | 0,19 | 0,22 |
| **SERVQ2** | 0,15 | 0,16 | 0,04 | 0,08 | 0,13 | 0,15 | **0,58** | 0,08 | 0,32 |
| **SYSQ1** | -0,02 | 0,18 | 0,20 | 0,04 | 0,07 | 0,24 | 0,15 | **0,81** | 0,08 |
| **SYSQ2** | 0,07 | 0,14 | 0,16 | 0,10 | 0,13 | 0,09 | 0,15 | **0,82** | 0,07 |
| **SYSQ3** | 0,10 | 0,17 | 0,14 | 0,31 | 0,22 | 0,07 | 0,15 | **0,72** | 0,10 |
| **TRUST1** | 0,09 | 0,10 | 0,05 | 0,07 | 0,18 | 0,14 | 0,36 | 0,11 | **0,64** |
| **TRUST2** | 0,26 | 0,08 | 0,15 | 0,08 | 0,28 | 0,20 | 0,21 | 0,08 | **0,81** |
| **TRUST3** | 0,30 | 0,22 | 0,14 | 0,16 | 0,33 | 0,26 | 0,24 | 0,07 | **0,85** |

**Table 4: Results for cross-loadings**

## *Structural Path Model Analysis*

After the stage one of the measurement model was completed in PLS-SEM analysis, the second stage was to assess the proposed structural path model. The structural path model in PLS-SEM is assessed by examining the explanatory power of the structural model and the path coefficient (Sarstedt et al., 2019). To examine the structural model of the path coefficients, a bootstrapping method was run in SMART-PLS to obtain the t-values, p-values and standard errors to determine the statistical significance of the proposed hypotheses. To achieve this, a critical value of two-tailed tests was adopted as rules of thumb postulated in IS literature. Table 5 provides the results of structural model path coefficients, comprising 15 the hypotheses, path, path coefficient, t-values, p-values, significance results. The results indicate that nine hypothesized path relationships (H1, H2, H3, H7, H8, H9, H12, H14, and H15) found significance, while six path relationships (H4, H5, H6, H10, H11, H13) were found not to be significant. This implied that those path relationships that were significant had positive influence on continuance intention towards Cstock mHealth in Malawi.

| Hypotheses | Path | Path Coefficient (β) | T-values | P-values | Significance level | Conclusion |
|---|---|---|---|---|---|---|
| **H1** | CONF →PUU | 0.254 | 3.069 | 0.002 | *** | Supported |
| **H2** | CONF → SATIS | 0.176 | 1.924 | 0.055 | * | Supported |
| **H3** | EEXP → PUU | 0.172 | 1.707 | 0.088 | * | Supported |
| **H4** | EEXP →SATIS | 0.037 | 0.329 | 0.742 | NS | *Rejected* |
| **H5** | INFOQ → PUU | 0.061 | 0.907 | 0.365 | NS | *Rejected* |
| **H6** | INFOQ → SATIS | 0.039 | 0.580 | 0.562 | NS | *Rejected* |
| **H7** | PUU → CONT | 0.300 | 2.746 | 0.006 | *** | Supported |
| **H8** | PUU →SATIS | 0.139 | 1.698 | 0.209 | * | Supported |
| **H9** | SATIS → CONT | 0.339 | 3.190 | 0.002 | *** | Supported |
| **H10** | SERVQ →PUU | 0.084 | 0.953 | 0.341 | NS | *Rejected* |
| **H11** | SERVQ →SATIS | 0.046 | 0.307 | 0.759 | NS | *Rejected* |
| **H12** | SYSQ →PUU | 0.131 | 1.652 | 0.136 | * | Supported |
| **H13** | SYSQ →SATIS | 0.050 | 0.606 | 0.545 | NS | *Rejected* |
| **H14** | TRUST → PUU | 0.221 | 2.537 | 0.011 | ** | Supported |
| **H15** | TRUST → SATIS | 0.222 | 2.369 | 0.018 | ** | Supported |

*P< 0.10, **P<0.05, ***P<0.01, and Not Significant= NS

**Table 5: Results of the structural model path coefficients**

The study also used the coefficient of determination ($R^2$ value) to examine the structural path model. $R^2$ Value is a measure of the predictive power of the model, and calculated as the squared correlation between a specific endogenous construct's actual and predicted values (Hair et al. 2014). The rules of thumb acceptable for R values depend on the complexity of the research and discipline. In marketing literature, $R^2$ values of 0.75, 0.50 or 0.25 for criterion variables are considered as substantial, moderate, or weak respectively (Hair, Ring & Sarsdedt, 2011). However, in consumer behaviour, IS/IT adoption behaviour, and exploratory studies, the $R^2$ values of 0.25 and above for criterion variables are considered high (Hair et al, 2017). In this study, an $R^2$ of 0.271 was obtained from the criterion variable (criterion variable). As a result, it could be interpreted as higher, considering the fact that the research model was exploratory in nature, and focused on IS/IT pre-acceptance and post-adoption behaviour. Figure 3 illustrates the model, the outer loadings, path coefficients and the $R^2$ value explained by the conceptualised model.

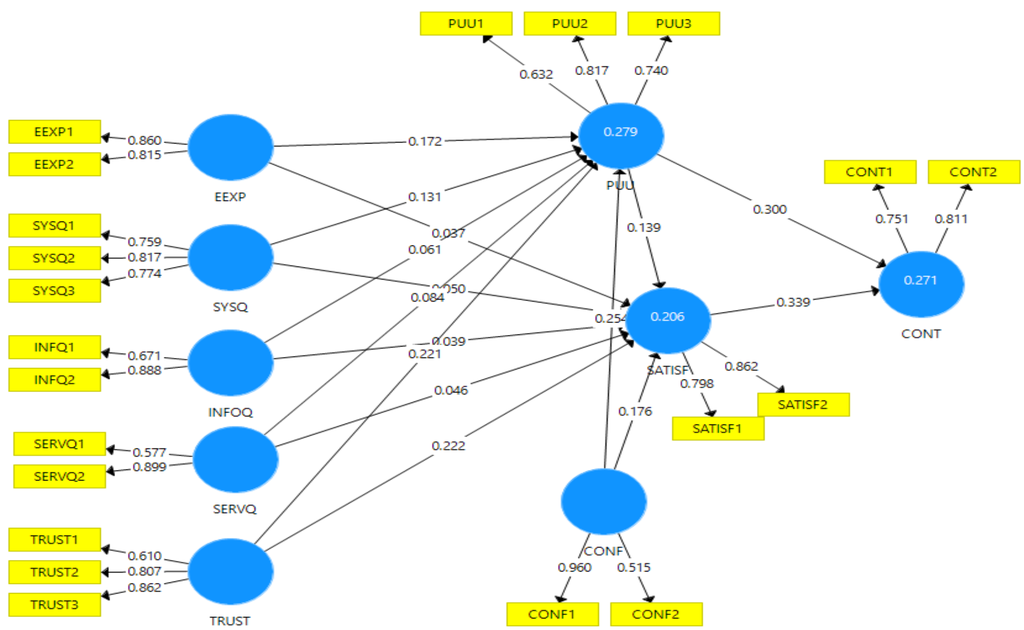


**Figure 3: Results of coefficient of determination ($R^2$)**

The study further evaluated the effect size ($f^2$), to assess the validity of the conceptualised structural path model (Chin, 2010; Cohen, 1992). Effect size measures the significant impact of a predictor variable on the criterion latent variable. In the structural model, the rules of thumb for $f^2$ values of 0.02, 0.015, and 0.35 indicating small, medium or large effect of exogenous latent variable on the endogenous latent variable in a structural model (Chin, 1998; Cohen, 1992). Table 6 show the results of effect size for the structural path model in SMART PLS.

| Predictor variable | Dependent (endogenous) variable | Effect size ($f^2$) | Remarks |
|---|---|---|---|
| PUU | SATIS | 0.00 | NS |
| PUU | CONT | 0.12 | medium |
| SATIS | CONT | 0.12 | medium |
| CONF | PUU | 0.07 | small |
| CONF | SATIS | 0.05 | small |
| EEXP | PUU | 0.04 | small |
| EEXP | SATIS | 0.03 | small |
| INFQ | PUU | 0.01 | NS |
| INFQ | SATIS | 0.00 | NS |
| SERVQ | PUU | 0.03 | small |
| SYSQ | PUU | 0.00 | NS |
| SYSQ | SATIS | 0.01 | NS |
| TRUST | PUU | 0.04 | small |
| TRUST | SATIS | 0.02 | small |

**Table 6: Results of $f^2$ for the structural model**

The study found that both post-usage usefulness (PUU) and satisfaction (SATIS) had medium effect on continuance intention (CONT), which is a direct criterion variable of the conceptual model for this study. However, PUU had no effects on SATIS, and information quality (INFQ) had no effect on either PUU, or SATIS. Likewise, system quality (SYSQ) had no effect on either PUU, or SATIS. Furthermore, Trust had mall effects on both PUU and SATIS, while effort expectancy (EEXP) had small effect on both PUU and SATIS.

# DISCUSSION AND CONCLUSION

This study aimed to identify user expectation beliefs as potential predictors of continuance intention towards mHealth in Malawi. To achieve this, the researchers conceptualised a research model from extant IS pre-acceptance and continuance literature comprising eight predictor variables (post-usage usefulness, satisfaction, confirmation, system quality, information quality, service quality, effort expectancy, and trust) and continuance intention as a criterion variable for the study. From the research model, fifteen hypotheses were formulated, tested, and validated empirically using a survey instrument from 176 community health workers who were using Cstock mHealth in Malawi.

### *Post-User Expectations And Continuance Intention Towards Cstock Mhealth*

From ECM, the study found that all five hypotheses had significant path relationships (Post-usage usefulness→ continuance intention (β=0.300), post-usage usefulness→satisfaction (β=0.139), satisfaction→continuance intention (β=0.339), confirmation→post-usage-usefulness (β=0.254), and confirmation→satisfaction (β=0.176)). These findings were consistent with previous studies (Osah & Kyobe, 2017; Brown et al., 2008; Battacherjee, 2001) that found that post-usage usefulness (which is an aggregated post-adoption expectation) positively influenced both continuance intention to use and satisfaction with technology. This also implies that post-adoption expectations impact positively on the continuance intention of HSAs to use Cstock mHealth. These benefits accrued through HSAs' experience (post-adoption expectations), may have increased their level of satisfaction with Cstock mHealth. This was further validated through the path relationships between confirmation and post-usage usefulness, as well as confirmation and satisfaction, which were found significant. This was consistent with existing literature (Osah & Kyobe, 2017 Brown et al., 2008). The study also found that satisfaction emerged as the strongest predictor of continuance intention with mHealth. This is also confirmed by previous studies (Brown et al., 2008; Min, 2007). This serves as an indication that users of Cstock mHealth valued high level of satisfaction as a salient determinant of continuance intention to use this technology.

### *User Expectations And Post-Usage Usefulness Of Cstock Mhealth*

The study also conceptualised five hypotheses to influence post-usage usefulness of mHealth (effort expectancy→ post-usage usefulness. The results showed that only three path relationships (effort expectancy→ post-usage usefulness (β=0.172), system quality → post-usage usefulness (β=0.131), and trust→ post-usage usefulness (β=0.221)) were found to be significant in influencing post-usage usefulness of Cstock mHealth. This implies that health workers viewed effort expectancy, system quality, and trust to have a positive influence on post-usage usefulness of Cstock mHealth. However, information quality and service quality were found not to be significant. This implies that health workers did not view these expectations as important in influencing their post-adoption expectations and continuance intention to use Cstock mHealth. The rejection of these hypotheses also implies that users' perceived information quality and service quality expectations were not met. This is consistent with previous study that have revealed that meeting service quality expectations remain a big challenge in IS implementation (Gürsel et al., 2015). Most mHealth projects do not have 24/7 call centers to offer user support, due to a combination of a lack of skilled personnel and lack of monitory motivation that users are expected to gain through training, seminars and workshops (Chipeta & Malanga, 2022; SC4CCM, 2018; Larsen-Cooper et al., 2016).

### *User Expectations And Satisfaction With Cstock Mhealth*

Five hypotheses were conceptualised as pre-acceptance expectations to influence user satisfaction with mHealth (effort expectancy→ satisfaction (β=0.037), system quality → satisfaction (β=0.050), information quality → satisfaction (β=0.039), service quality→ satisfaction (β=0.046), and trust→ satisfaction (β=0.222). However, only trust was found to be significant enough to influence user satisfaction with Cstock mHealth. Effort expectancy, systems quality, information quality, and service quality were found to be insignificant. These were unexpected findings, since previous studies have revealed that quality triads directly influence user satisfaction with technology (Osah & Kyobe, 2017; DeLone & McLean, 2016; DeLone & McLean, 2003).

In conclusion, the study found that effort expectancy, system quality, trust and confirmation have positive influence on continuance intentions towards mHealth mediated through post-usage usefulness and satisfaction. The findings both reinforce and contest the conventional way of explaining user expectations and continuance intention. The conventional views that user's continuance intention to use technology is dependent on user's level of satisfaction, the level of user's confirmation of expectations, and post-usage usefulness (post-adoption expectations) were validated (Osah & Kyobe, 2017; Brown et al., 2008; Battacherjee, 2001). However, the study found that system quality, information quality, and service quality did not have positive influence on user satisfaction with Cstock mHealth. This implies that the surveyed users of Cstock mHealth in Malawi harbour different expectation beliefs that may influence their level of satisfaction with technology, which stands as contrary to extant literature that understands quality triads as determinants of user satisfaction with technology and its continuance intention (DeLone and McLean, 2016). For this reason, the findings have both theoretical and practical implications.

### *Theoretical Implications*

The empirical findings from this study demonstrate the relevance of the proposed research model, which is based on ECM, with some additional expectation factors drawn from other theoretical models from extant IS pre-acceptance literature. The study also provided an explanation on the relationships between user pre-acceptance expectations and post-adoption expectations on continuance intention towards mHealth. Beyond this, the study confirmed that users' pre-acceptance expectations are mediated by post-usage usefulness and satisfaction to influence continuance intention towards use of mHealth. This means that having pre-acceptance expectations towards a system does not translate to or instigate actual intention to continue using it. Equally important is the fact that by integrating variables from pre-acceptance models to ECM, this study has refuted earlier assertions by scholars that it was impossible to integrate both pre-acceptance and continuance theories in a single study due to variant times. Further to this, the study has overcome the narrow and biased views that behavioural belief expectations are to be understood as the sole determinants of IS continuance. The integration of other expectation beliefs such as object-based expectation beliefs (system quality, service quality, information quality), control belief expectations (effort expectancy), and attitudinal expectation beliefs (trust), has advanced a new understanding of different expectation beliefs, their relationships, and strengths in influencing health workers' continuance intention to use mHealth in developing countries.

### *Practical Implications*

This research has demonstrated the policy and practical significance of taking into account user's expectation when deploying mHealth technologies to ensure their successful adoption in developing countries like Malawi. The study has also discovered that expectation factors that influence health workers in adopting mHealth developing countries may differ with those from developed world. The study found that all ECM variables were found to be consistent with conventional existing literature in influencing continuance intention towards mHealth. However, quality triads (service quality, system quality, and information quality) from IS success model (DeLone &McLean, 2016) demonstrated contrary results. In Malawian context, these quality triads were not significant, but rather, trust expectation was found to be a strong determinant of continuance intention towards mHealth, mediated by satisfaction and post-usage usefulness. The established wisdom is that quality triads have positive influence on user satisfaction (DeLone & McLean, 2016).

### *Limitations And Areas Of Future Research*

Despite theoretical and practical contributions, this study also has some limitations. The study used a parochial approach to identify potential user expectations as antecedents and determinants of continuance intention towards mHealth. Furthermore, research ought to integrate variables from other theories and models to increase ECM's explanatory power. Secondly, the study used a single theoretical underpinning, which was positivism. The use of mono-theoretical assumption has its weaknesses. For this reason, future study should include interpretivist or critical theoretical approaches to gain more insight into the study phenomenon. Third, this study was conducted as a cross-sectional survey design targeting only users of Cstock mHealth in three district health facilities. Consequently, it is important that future studies utilise a longitudinal approach, and replicate the study to other health facilities in the districts of Malawi, where Cstock mHealth is in use.

## REFERENCES

1. Akter, S., D'Ambra, J., Ray, P., & Hani, U. 2013. "Modelling the impact of mHealth service quality on satisfaction, continuance and quality of life." *Behaviour & Information Technology*, *32*(12), 1225-1241. https://doi.org/10.1080/0144929X.2012.745606
2. Azzalini, A. 200. "The skew-normal distribution and related multivariate families." *Scandinavian Journal of Statistics,* 159-188.
3. Battacherjee, A. 2001. "Understanding Information Systems Continuance: An Expectation Confirmation Model". *MIS Quarterly*, *25*(3), 351–370. https://doi.org/10.2307/3250921
4. Brown, S. A., Venkatesh, V., Kuruzovich, J., & Massey, A. P. 2008. "Expectation confirmation model: An examination of three competing models". *Organizational Behavior and Human Decision Processes*, *105*(1), 52–66. https://doi.org/10.1016/j.obhdp.2006.09.008

5. Chin, W. W. (2010). “How to write up and report PLS analyses.” In Handbook of partial least squares (pp.655-690). Springer Berlin Heidelberg.
6. Chin, W. W., & Newsted, P. R. 1999. “Structural equation modeling analysis with small samples using partial least squares”. *Statistical strategies for small sample research*, *1*(1), 307-341.
7. Chipeta, M., & Malanga, D. F. 2022. “The Impact of mHealth on Supply Chain Management of Medical Supplies in Village Clinics: A Case of Cstock mHealth in Malawi”. In *Building Resilient Healthcare Systems With ICTs* (pp. 125-152). IGI Global. https://doi.org/10.4018/978-1-7998-8915-1.ch006
8. Cohen, J. 1992. Quantitative methods in psychology: A power primer. In *Psychological bulletin*.112 (1).
9. *Creswell, J.W. 2014. Qualitative, Quantitative and Mixed Methods Approaches*. 4th ed. London: SAGE Publication.
10. DeLone, W. H., & McLean, E. R. 2003. “Measuring e-Commerce Success : Applying the DeLone & McLean Information Systems Success Model”. I*nternational Journal of Electronic Commerce*, *9*(1), 31–47. https://doi.org/10.1080/10864415.2004.11044317
11. DeLone, W. H., & McLean, E. R. 2016. “Information Systems Success Measurement.” *Foundations and Trends in Information Systems*, *2*(1), 1–116. doi:10.1561/2900000005
12. Fornell, C., & Cha, J. 1994. Partial least squares. *Advanced Methods of Marketing Research*, *407*, 52-78.
13. Fornell, C., & Larcker, D. F. 1981. Evaluating structural equation models with unobservable variables and measurement error.” *Journal of Marketing Research*, 39-50.
14. Gilani,M.S., Iranmanesh,M., Nikbin, D., & Zailani,S. 2016. “EMR Continuance usage intention of healthcare professionals.” *Health Informatics and Social Care.* http://dx.doi.org/10.3109/17538157.2016.1160245
15. Gürsel, G. 2015. “Perceived Importance of User Expectations from Healthcare Information Systems”. In *Healthcare Informatics and Analytics: Emerging Issues and Trends* (pp. 84-95). IGI Global. https://doi.org/10.4018/978-1-4666-6316-9.ch005.
16. Gürsel, G. 2016. “User expectations: Nurses’ perspective”. *Studies in Health Technology and Informatics*, *225*, 897–898. https://doi.org/10.3233/978-1-61499-658-3-897
17. Hair Jr, J., & Hult, M. G., Ringle, C., & Sarstedt, M. 2014. “A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM).

18. Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. 2017. "Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods." *Journal of the academy of marketing science*, *45*(5), 616-632.
19. Hair, J.F., Black, W.C., Babin, B.J., & Anderson, R.E. 2014. "Multivariate Data Analysis" 7th ed.Harlow: FT/Prentice Hall
20. Henseler, J., Ringle, C. M., & Sinkovics, R. R. 2009. "The use of partial least squares path modeling in international marketing." *Advances in International Marketing (AIM*), 20, 277-320.
21. Kadzandira, J. M., & Chilowa, W. 2001. "*The role of health surveillance assistants (HSAs) in the delivery of health services and immunisation in Malawi*." Government of Malawi, Ministry of Health and Population.
22. Larsen-Cooper, E., Bancroft, E., Rajagopal, S., O'Toole, M., & Levin, A. 2016. Scale Matters: A Cost-Outcome Analysis of an m-Health Intervention in Malawi. *Telemedicine and E-Health*, *22*(4), 317–324. https://doi.org/10.1089/tmj.2015.0060
23. Linda, S. L. 2012. "Managing User Expectations in Information Systems Development." *International Journal of Social, Behavioral, Educational, Economic, Business and Industrial Engineering*, *6*(12), 3710–3714. https://waset.org/Publication/managing-user-expectations-in-information-systems-development/14658
24. Malanga, D. F. 2017. "Implementation of Mobile Health Initiatives in Malawi: Current Status, Issues, and Challenges". *Health Information Systems and the Advancement of Medical Practice in Developing Countries*, 115-128. https://doi.org/10.4018/978-1-5225-2262-1.ch007.
25. Malanga, D. F., & Banda, M. J. 2021. The use of mobile phones by women microenterprises in Malawi: A sustainable livelihoods perspective. *Global Knowledge, Memory and Communication*. https://doi.org/10.1108/GKMC-09-2020-0143
26. Malanga, D. F., & Chigona, W. 2018. Mobile Health Initiatives in Malawi. Understanding Impact, Funding model and Challenges. *International Journal of Privacy and Health Information Management*, *6*(1), 49–60. https://doi.org/10.4018/IJPHIM.2018010104
27. Mayer, R.C., Davis, J.H. & Schoorman, F.D. 1995. An Integrated model of organizational Trust. *Academy of Management Review*, 1*5* (715**).**
28. Mburu, S. (2017). Application of structural equation modelling to predict acceptance and use of mHealth interventions at the design stage. *Journal of Health Informatics in Developing Countries*, *11*(2).
29. Min, Q. 2007. An Extended Expectation Confirmation Model for Information Systems Continuance, 3879–3882.

30. National Statistical Office 2017. Malawi Demographic and Health Survey. *National Statistics Office. The DHS Program*, 1–658. Retrieved from http://dhsprogram.com/pubs/pdf/FR319/FR319.pdf
31. Ndayizigamiye, P., & Maharaj, M. 2016. Mobile health adoption in Burundi: A UTAUT perspective. In *2016 IEEE Global Humanitarian Technology Conference (GHTC)* (pp. 613-623). IEEE.
32. Nyasulu, C., & Chawinga, W. D. (2018). The role of information and communication technologies in the delivery of health services in rural communities: Experiences from Malawi. *South African Journal of Information Management*, *20*(1), 1-10.
33. Nyemba-Mudenda, M., & Chigona, W. 2018. mHealth outcomes for pregnant mothers in Malawi: A capability perspective. *Information Technology for Development*, *24*(2), 245-278.
34. Ojasalo, J. 2006. Research and concepts Managing customer expectations in professional services. *Managing Service Quality: An International Journal*, Vol. 11 Issue: 3, pp.200-212, https://doi.org/10.1108/09604520110391379
35. Oliver, R. L. 1980. A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research,* 460-469.
36. Osah, O. 2015. *Determinants of User Continuance Intention towards Mobile Money Services: The Case of M-Pesa in Kenya.* PhD Thesis (Unpublished). University of Cape Town, Cape Town: South Africa. https://open.uct.ac.za/bitstream/handle/11427/16718/thesis_com_2015_osah_olam_oniso.pdf?sequence=1
37. Osah, O., & Kyobe, M. 2017. Predicting user continuance intention towards M-pesa in Kenya. *African Journal of Economic and Management Studies*, *8*(1), 36-50.
38. Petter, S. 2008. Managing user expectations on software projects: Lessons from the trenches. *International Journal of Project Management*, *26*(7), 700–712. https://doi.org/10.1016/j.ijproman.2008.05.014
39. Sarstedt, M., Ringle, C. M., & Hair, J. F. 2017. Partial least squares structural equation modeling. *Handbook of Market Research, 26*(1), 1-40.
40. Saunders, M., Lewis, P. & Thornhill, A. 2012. *Research Methods for Business Students.* 6th ed. London: Apprentice Hall
41. SC4CCM. 2018. *Emerging Lessons of Cstock.* http://sc4ccm.jsi.com/emerging-lessons/cstock/
42. Shieshia, M., Noel, M., Andersson, S., Felling, B., Alva, S., Agarwal, S., Lefevre, A., Misomali, A., Chimphanga, B., Nsona, H., Chandani, Y. 2014. Strengthening community health supply chain

performance through an integrated approach: Using mHealth technology and multilevel teams in Malawi. *Journal of Global Health*, *4*(2), 020406.

43. Straub, D., Boudreau, M. C., & Gefen, D. 2004. "Validation guidelines for IS positivist research: The Construction." In H. Reis & Judd, C. (Eds.), *Handbook of Research Methods in Social Psychology,* 339-369. New York: Cambridge University Press.
44. Szajna, B., & Scamell, R. W. 1993. The Effects of Information System User Expectations on Their Performance and Perceptions. *MIS Quarterly*, *17*(4), 493–516. https://doi.org/10.2307/249589
45. United Nations Development Programme [UNDP].2017. http://www.mw.undp.org/
46. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. 2003. User Acceptance of Information Technology. Toward a unified view. *MIS Quarterly*, 425-478.

Appendix 1: Measurement scales for the survey instrument

| Variable | Code | Measurement scales (indicators) | Ref. sources |
|---|---|---|---|
| System Quality (SYSQ) | SYSQ1 | I expected Cstock mHealth to quickly loads all text and images | DeLone &McLean (2016, 2003); Zhou (2013). |
| | SYSQ2 | I expected Cstock mHealth to be easy to use | |
| | SYSQ3 | I expected Cstock mHealth to be easy to navigate | |
| Information Quality (INFG) | INFQ1 | I expected Cstock mHealth to provide me with relevant medical information | DeLone &McLean (2016, 2003); Zhou (2013). |
| | INFQ2 | I expected Cstock mHealth to provide me with accurate medical information | |
| | INFQ3 | I expected Cstock mHealth to provide me with current medical information | |
| Service Quality(SERVQ) | SERVQ1 | I expected Cstock mHealth to provide me with services in a timely manner | DeLone &McLean (2016, 2003); Zhou (2013). |
| | SERVQ2 | I expected Cstock mHealth to provide quick responses to my transaction queries | |
| Trust (TRUST) | TRUST1 | I expected Cstock mHealth to be trustworthy | Osah & Kyobe (2017) |
| | TRUST2 | I expected Cstock mHealth provider to keep its promise | |
| | TRUST3 | I expected Cstock mHealth provider to keep my interest in mind | |
| Effort Expectancy (EEXP) | EEXP1 | I expected easy for me to become skillful at using Cstock mHealth | Venkatesh et al., (2003) |
| | EEXP2 | I expected Cstock mHealth to be user-friendly | |
| Post-Usage Usefulness (PUU) | PUU1 | Using Cstock mHealth has improved my performance | Kim (2012); Bhattacherjee at al. (2008) |
| | PUU2 | Using Cstock mHealth in my job has increased my productivity (such as saving my working time) | |
| | PUU3 | Overall, I find Cstock mHealth to be useful in my job. | |
| Confirmation (CONF) | CONF1 | My experience in using Cstock mHealth is better than what I expected before using it. | Osah & Kyobe (2017); Bhattacherjee et al., (2008) |
| | CONF 2 | Overall, most of my expectations from using Cstock mHealth are met. | |
| Satisfaction (SATIS) | SATISF1 | I feel satisfied using Cstock mHealth. | Bhattacherjee at al., (2008); McLean &DeLone (2016, 2003) |
| | SATISF3 | I feel pleased using Cstock mHealth. | |
| Continuance Intention (CONT) | CONT1 | I intend to continue using Cstock mHealth to send medical reports. | Osah & Kyobe, 2017; Kim (2012); (Bhattacherjee, 2001) |
| | CONT2 | My intentions are to continue using Cstock mHealth rather than use alternative means. | |