To Use or Not to Use. Investigating M-health Acceptance by Citizens in Malawi Using UTAUT and Trust

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Accepted: 10 April, 2020; Online: 19 April, 2020

DOI: https://doi.org/10.5281/zenodo.3756213

Abstract: Personal health management is a relatively new concept in Malawi which allows patients to manage health through mobile health (mHealth). Chipatala Cha Pa Foni (CCPF) project, translated from the Chichewa language to "health center by phone" is a hotline service that serves the general public. However, the use of this service in Malawi is considerably low and few studies have been carried out to investigate factors that influence acceptance and use. This study empirically investigates determinants of acceptance and use using a theoretical model founded on the Unified Theory of Acceptance and Use of Technology (UTAUT) and trust. Data was collected using a structured questionnaire from 379 respondents across 3 districts. Using Structural Equation Modeling (SEM) technique, data was analyzed and results showed that trust, effort expectancy, and performance expectancy positively influenced behavioral intentions. Findings also showed that four out of seven mediation effects between several variables including facilitating conditions and social influence were not supported. The results offer empirical support for several elements of the model used in the investigation in line with prior studies. The study offers novel insights into the mediating role of trust between UTAUT constructs and behavioral intentions. Since UTAUT is a fundamental theoretical model in technology acceptance research, modifying the model to suit the patients’ context contributes to growth in health research.

Key words: personal health management, technology acceptance, mHealth, UTAUT, trust, Malawi

INTRODUCTION

The 2030 agenda for sustainable development provides a chance for national and transnational bodies to renew their dedication to placing health at the center of growth. Goal 3 of the 17 SDGs particularly underscores the significance of universal health coverage (UHC) of access to excellent healthcare while easing financial burden (Tichenor & Sridhar, 2017). Nevertheless, healthcare access and reasonably priced health services still present an enormous challenge to attaining UHC
especially in low-middle income countries (LMICs) (Malanga & Chigona, 2018). According to the International Labour Organization (ILO), approximately 60-75% of rural inhabitants are deprived of crucial access to health services (International Labour Organization, 2015). Similar to other LMICs, Malawi’s health sector faces numerous challenges such as inadequate financing, a heavy burden of disease, poor infrastructure, and a dearth of healthcare workers (OXFAM, 2016). Malawi’s doctor-to-patient ratio currently falls at 0.018 per 1,000 which is suggestively below the World Health Organization’s (WHO) endorsed ratio of 2.28 per 1,000 patients. Furthermore, 84% of people live in rural and remote regions and although 85% of people reside within a 10-kilometer radius of a health facility, 24% do not reside within 5 kilometers of a health facility. Over 50% of women allude to the distance to health facilities as a significant obstacle to accessing healthcare in case of illness (Ministry of Health, 2017).

It is, therefore, argued that strengthening health information systems leads to reinforcing all other health systems components (Ministry of Health, 2014, 2018; Nabyonga-Orem, 2017). This is why electronic health (eHealth) systems and mobile health (mHealth) systems, in particular, are a crucial component of health systems strengthening (Ministry of Health, 2018; World Health Organization, 2018a). Devised by Professor Robert Istepanian, mHealth generally refers to ‘the use of emergent mobile communications and network technologies for healthcare’ (Istepanian et al., 2006) and is considered a subset of eHealth (Betjeman et al., 2013; World Health Organization, 2018a). Implementation of mHealth in LMICs is prompted by the dwindling prices of mobile phones, fast expansion of mobile networks, and advances in the mobile technology industry (Nanyombi & Ejiri, 2016). It allows for the utilization of mobile devices such as mobile phones, smartphones, personal digital assistants (PDAs), tablets, and other remote devices (Folaranmi, 2014; Ministry of Health, 2014). Evidence shows that mHealth enables availability of healthcare services to rural populaces (Larocca et al., 2016; World Health Organization, 2016), improves patient attendance rates (Beratarrechea et al., 2014), saves time and resources for both guardians and healthcare professionals (Franke et al., 2018; Tomlinson et al., 2013), facilitates quicker management of diseases, eases data collection (Depolli et al., 2016; Schuttner et al., 2014), and allows patients to access health information on their own. The latter function ensures adherence to medication, receipt of lab results, and linkage to support groups. Groupe Speciale Mobile Association (2018) established that for a third of mNutrition users, it was the sole source of nutrition information emphasizing the significance of mobile technologies for healthcare.
Regardless, the concept of personal health management is still underdeveloped in Malawi. Of the 31 mHealth projects registered in the country, only *Chipatala Cha Pa Foni* (CCPF) project, translated from the Chichewa language to "health center by phone", targets the general public. CCPF is a hotline service that provides health services for free. Although it was established in 2011 and is now available nationwide, only 0.3% of the population have used CCPF (Blauvelt et al., 2018). Still, few investigations have been carried out to understand the factors that influence the acceptance and use of mHealth. Acceptance is the perceptible readiness surrounding a consumer group to take on ICT for the achievement of tasks and is a key feature in determining the success or failure of any new technology (Louho et al., 2006). Studies on mHealth initiatives in Malawi have focused primarily on user satisfaction (Reynolds, 2017), stakeholder analysis (Blauvelt et al., 2018), approaches to project design (Laidlaw et al., 2017), particular health areas like maternal, newborn, and child health (MNCH) (Watkins et al., 2013), cost-benefit analysis of CCPF (Larsen-Cooper et al., 2016), or general usage of mobile technologies for enhancing reporting systems (Moyo et al., 2015).

The limited insights into the determinants of acceptance and use of CCPF necessitated this investigation. This study posits that the acceptance of mHealth by the general public in Malawi would assist in overcoming some of the many health systems challenges facing the country. The Unified Theory of Acceptance and Use of Technology (UTAUT) is an extensively utilized model for predicting technology acceptance and use. UTAUT was modeled from studying eight previous models and proposes four predictors which are performance expectancy, effort expectancy, social influence, and facilitating conditions. Four moderators are also used including gender, age, experience, and voluntariness of use (Samaradiwakara & Gunawardena, 2014; Venkatesh et al., 2003). UTAUT is understood to be an advanced model compared to others with a higher percentage of variance (R2 of 70%) in explaining behavioral intentions and approximately 50% of the variance in technology use (Hoque & Sorwar, 2017; Venkatesh et al., 2012). Moreover, UTAUT focuses on interactive technologies and is, therefore, better positioned to explain the acceptance of such technologies like mHealth compared to generic models like the theory of planned behavior (TPB). Besides, UTAUT contains more determinants than generic models that mathematically result in higher explained variances (Samaradiwakara & Gunawardena, 2014). Nevertheless, its sufficiency to predict technology acceptance in healthcare is uncertain, particularly in LMICs. As a result, several researchers have integrated and extended UTAUT in
various forms. Accordingly, adding contextually precise determinants ought to be encouraged to enhance the predictability of UTAUT when applied to healthcare (Bawack & Kala Kamdjoug, 2018).

The study incorporates the concept of trust as a determinant of acceptance and use. Defined as “the subjective probability by which an individual, A, expects that another individual, B, performs a given action on which its welfare depends” (Castelfranchi & Falcone, 2005), several studies demonstrated the significance of trust in determining technology acceptance and use (Jucks & Thon, 2017; Meng et al., 2019; Vega et al., 2011; Zhang & Gupta, 2018). Scholars proposed that trust can be relocated from a trusted entity (healthcare workers or institutions) to an unknown entity (technological artifact) (Meng et al., 2019). Moreover, scholars proposed that in the application of trust to socio-technological systems which consist of humans as operatives, trust in the system’s operatives could not be assigned directly to the entire system. Diverse categories of trust are therefore required (Carter & Bélanger, 2005; Castelfranchi & Falcone, 2005; Tan & Theon, 2001). This study, therefore, empirically validates the applicability of the integration of trust and constructs of the UTAUT in determining acceptance and use of mHealth by patients. The study uncovers some fundamental contributors to acceptance of mHealth services and proposes solutions for future advancements in mHealth.

1. Hypothesis development and theoretical model

1.1. Behavioral intention to use (BI)

Fishbein and Ajzen (1975) developed the theory of reasoned action (TRA) which proposed that some primary beliefs concerning the possibility of particular conduct to lead to specific outcomes would ultimately result in behavioral intentions. Numerous investigators have since demonstrated a positive correlation between behavioral intentions and usage behavior (Bawack & Kala Kamdjoug, 2018; Venkatesh et al., 2003). In the context of e-government, Alshehri et al. (2012) and Kurfali et al. (2017) investigated determinants of use by citizens in Saudi Arabia and Turkey. Both studies concluded that merging behavioral intentions and usage behavior makes sense. This study investigates the effects of independent variables on intentions to use mHealth.
1.2. **Trust**

It is not surprising that trust receives a lot of attention since it plays a pivotal role in society. In healthcare relations, trust is equally important. A care receiver trusts their care provider to offer well-timed and suitable care. Healthcare professionals trust their clients to relate accurate information concerning their health condition. Healthcare professionals trust one another to work together for the benefit of patients (Vega et al., 2011). The growing usage of the internet, SMS, and call services forms an extra dimension to these associations.

The perceived trustworthiness of an entity is an imperative antecedent of trust encompassing some characteristics that a trustor deems useful for building trust (Lee & Turban, 2001). Mayer et al. (1995) proposition that in a liaison with a particular other entity, discernments of ability, benevolence, and integrity will direct the trusting individual’s evaluation of the entity’s trustworthiness. Ability is an entity’s capabilities to affect a particular domain. Thus, in the context of mHealth, it applies to the capabilities of the internet, SMS, and call services. Benevolence denotes the extent to which a trustor concludes that a trustee has good intentions for them. This may refer to call center agents or healthcare workers that operate the mHealth system. Integrity is the trustor’s view of the trustee’s honesty and respectability.

Tan and Theon (2001) proposed two forms of trust in technological artifacts: one is trust in the agent which delivers the service (e.g. website managers, call center staff), the other is trust in the mechanism that supports the service between an agent and consumer (e.g. internet, SMS, telephony). In a study conducted in the rural Chakaria sub-district in Bangladesh, Khatun et al. (2016) found that participants of the “Health Line 789” hotline service expressed apprehensions concerning the quality of mHealth service providers as patients were not able to see the doctor over the phone. They did not understand how qualified medical doctors could work in a mHealth service center instead of meeting patients face-to-face. It is essential to understand how people perceive a system to promote usage. Operatives of a system play an important role in facilitating perceptions and subsequent intentions. Guo et al. (2016) established that trust in mHealth service providers facilitated the decline of people’s confidentiality apprehensions and growth in adoption intentions. Zhou et al. (2016) showed that users of a location-based service had a diminished level of trust in service providers in the absence of proper management of information.

On the other hand, several studies showed that trust in the mHealth system played an important role in shaping people’s intentions. Deng et al. (2018) demonstrated that patients’ trust affected
intentions to use mHealth services while Meng et al. (2019) found similar results in an assessment of elderly users. Sillance et al. (2006) demonstrated the significance of trust in persuading patients to use eHealth websites. In Briggs et al.’s (2002) study, more than 2500 individuals indicated their willingness to trust a health website if the perceived risk was minimal. Nhavoto et al. (2017) revealed that the design of an SMS system enabled reciprocal communication which enhanced trust. Similarly, it is anticipated that mHealth users' level of trust in service providers and the hotline service will positively affect behavioral intention to use the service.

**Hypothesis 1: The greater the trust, the greater the intentions to use mHealth services**

1.3. **Performance expectancy (PE)**

Performance expectancy is “the extent to which an individual believes that utilizing the technology will assist him or her to realize benefits in job performance” (Ahmad, 2014). The extent to which mHealth services provide useful contributions to an individual’s health is what makes it valuable. Such benefits may be expediency, contentment, financial rewards, and self-image (Hoque & Sorwar, 2017). Several studies confirm performance expectancy to be the strongest contributing factor to users’ behavioral intentions (Hoque & Sorwar, 2017; Schomakers et al., 2018; Y. Sun et al., 2013; Venkatesh et al., 2003). Results of Zhou et al.’s (2016) research indicated performance expectancy as an enabler for acceptance of mobile location-based services while Rahman and Hoque (2018) found a positive correlation in telemedicine use. Users’ optimism toward a technology’s capability to achieve anticipated healthcare goals can encourage acceptance.

In several other contexts, researchers found that one’s expectation of a system’s performance affected trust in the system. Lee et al. (2011), and Fakhoury and Aubert (2015) discovered that people's positive offline experiences with the government increased their enthusiasm to adopt an online service medium (e-government). Gao & Waechter, (2017) demonstrated that a poor quality m-payment system reduced users’ appraisal of the trustworthiness of the system. If a system is slow, interrupted or unavailable, users might be required to wait for a while to receive a response from those that manage the system. As a result, these challenges will reduce users’ preliminary trust in the mHealth system.

Concerning trust in the internet, SMS, or call systems, users anticipate negligible technical faults (Ehrismann & Stegwee, 2015). Van Velsen et al. (2015) suggested that patients’ needs had to be addressed during the design of a trustworthy technology for rehabilitation. They showed that
relevant, useful, and impartial data played a vital role in influencing patients and healthcare professionals’ trust in telemedicine portals for rehabilitative care. Koufaris and Hampton-Sosa (2004) identified perceived security control as an important antecedent of trust while Mpinganjira (2018) showed information usefulness to be one of the three key antecedents of trust in virtual health communities. In this study, the following hypotheses are, therefore, proposed:

**Hypothesis 2: The higher the performance expectancy, the higher the likelihood of behavioral intentions to use mHealth services**

**Hypothesis 3: The higher the performance expectancy, the greater the trust**

1.4. **Social influence (SI)**

Social influence is “the extent to which an individual perceives that important others believe he or she should use the new system”. Users will probably have different opinions concerning the approval and support of important others such as family members, friends, and coworkers when using mHealth (Cohen et al., 2013). Studies by Bawack & Kala Kamdjoug (2018) and Alam et al., 2018) showed that social influence was the most powerful determinant of user intentions to adopt mHealth services. Brinkel et al. (2017) revealed that users felt more confident if the voice behind an automated voice system was someone acquainted with the community such as community leaders or assembly members. This enhanced trust in information provided and subsequent acceptance of the mHealth program. Thus, mHealth acceptance may be enhanced by external influences from significant others. The following hypotheses are proposed:

**Hypothesis 4: The greater the social influence, the higher the performance expectancy**

**Hypothesis 5: The greater the social influence, the greater the trust**

1.5. **Effort expectancy (EE)**

Effort Expectancy is “the extent of ease related to the system use” (Ahmad, 2014). Naturally, people want to use a system that requires minimal effort. Linking to a hotline service must be easy and must provide better worth than traditional methods. The expectation is that an effective mHealth system will offer a better equilibrium concerning the impact and effort needed. Dwivedi et al. (2016) discovered that for mHealth, a system’s precision and legitimacy are reliant on the
consumers’ capabilities to use the system remotely. Several studies have shown the value of effort expectancy as a determinant of behavioral intentions. Focusing on emerging nations, Alaiad et al. (2019) developed an integrative model to assess the acceptance and use of mHealth and found that effort expectancy significantly influenced behavioral intentions. McCanney and Kisekka (2017) found that Apps that required less effort were more appealing to patients which encouraged the use of mHealth.

Studies have also shown that effort expectancy influences users’ trust in mHealth. Guo et al. (2016) assessed the effects of privacy and personalization on acceptance and use of mHealth by different age groups. They found that these factors were stronger in the younger age group than the older age group with personalization having a significant effect on trust. In their study, mHealth users required services that met their individual needs and for older people, the main concern was the amount of effort required to use mHealth. The less effort that was required, the more the trust in the service. On the other hand, Deng et al. (2018) revealed that among patients, perceived ease of use did not have a significant effect on trust. Nevertheless, this study proposes the following:

**Hypothesis 6: The lower the effort expectancy, the higher the performance expectancy**

**Hypothesis 7: The lower the effort expectancy, the higher the likelihood of behavioral intentions to use mHealth services**

**Hypothesis 8: The lower the effort expectancy, the greater the trust**

1.6. **Facilitating conditions (FC)**

Facilitating Conditions means "the extent of belief an individual has in the existence of organizational and technical infrastructure to facilitate system use" (Ahmad, 2014). A person's awareness of resource accessibility acts as a behavioral control that influences their intention to use a technology (Cohen et al., 2013). Resources may include money for airtime, mobile phones, electricity, and training. In places where mobile coverage is unavailable or there are challenges with access to mobile devices, the utilization of technology may be impossible (Chib et al., 2015). For that reason, some academics suggest that mHealth services suitable for LMICs need to be appraised extensively (Beratarrechea et al., 2017). A study by Mbelwa et al. (2019) demonstrated that facilitating conditions considerably affect consumers' behavioral intentions to utilize mHealth.
applications in urban areas. Likewise, Alam et al. (2018) revealed that facilitating conditions influenced intentions to use mHealth services in Bangladesh. Moreover, it is anticipated that the availability of resources will influence users’ trust in the mHealth service in this study. The following hypotheses are, therefore, proposed:

**Hypothesis 9:** The more the facilitating conditions, the higher the performance expectancy

**Hypothesis 10:** The more the facilitating conditions, the greater the trust

Figure 1: Research model

![Research model diagram]

*p < 0.05, **p < 0.001, ***p < 0.001

2. Methodology

2.1. Questionnaire

The questionnaire comprised of items principally adapted from previous studies. It was initially drafted in English with a Chichewa language translation developed later. Chichewa is a national local language spoken across the country which made it unnecessary to translate it into several other languages. This translation procedure was essential as shown in comparable studies in other countries (Brinkel et al., 2017; Deng et al., 2018; Hoque & Sorwar, 2017; Weng, 2016). The first section of the questionnaire consisted of single response questions that collect general information about the respondents and mobile phone use. A screening question was added to safeguard the
collection of responses from individuals aged over 15 years. Another screening question was added to make sure participants had used CCPF before. The subsequent section comprised items measured using a five-point Likert-type scale. Anchors ranged from "strongly agree" to "strongly disagree." See Appendix 1.

2.2. Pilot test

The questionnaire was first tested to ensure content validity. 15 individuals were selected to respond to the questionnaire. Through this process, some questions were paraphrased and refined. The frequency with which they use their phones was replaced with a question ascertaining ownership of mobile phones. Previous studies in Malawi found that it is common in the country to share phones which provides a unique paradigm for investigation (Blauvelt et al., 2018; Laidlaw et al., 2017; Reynolds, 2017). By applying a Cronbach alpha analysis, the questionnaire's reliability was checked.

2.3. Sampling

Sampling involves selecting a satisfactory amount of elements from a particular population. By choosing the correct sample, one can apply the features of the elements to the population (Alvi, 2016). There are numerous types of sampling techniques including systematic, stratified, random, convenience, snowball, and purposive sampling (Etikan & Bala, 2017).

2.3.1. Population

National data indicate that Malawi’s population is approximately 17,563,749. 43.9% of this number is under 15 years of age with 18% of this proportion under 5 years. 52.3% are between 15 and 64 years. At the regional level, 44% of people reside in the southern region, 43% reside in the central region while 13% live in the northern region (National Statistical Office, 2018). Blauvelt et al. (2018) showed that since CCPF’s inception, approximately 58,000 people have used CCPF representing 0.3% of the population and 1.4% of Airtel’s mobile network subscriptions. CCPF is also gaining popularity among youths aged between 15 and 24 since youth services were introduced in 2017. Data for this study was therefore collected according to user information and distribution by districts was referenced from national data.
2.3.2. Sample size

There is a substantial difference in thoughts concerning the selection of the best sample size in diverse statistical analyses. For instance, Hair et al. (2014) suggested that 200 to 300 is a suitable sample range to examine a model using SEM. Hoelter (1983) recommended 200 as a ‘critical sample size’ that is adequate for any general statistical assessment process for effective outcomes. Regarding the population size of CCPF users which is 58,000, Hunter (2016) recommends that at a margin of error of 5% and a confidence level of 95%, the study required estimated sample size of 384. Therefore, the study aimed at collecting 384 responses.

2.3.3. Sampling technique

Since the program is now operating nationwide, one district from each of the three regions was purposively sampled. Balaka, Mchinji, and Mzimba districts in the southern, central, and northern regions respectively were selected because the districts were used in the initial phases of the project. Therefore, there are likely more users compared to other districts. Based on regional population data, 169 respondents were required from the southern region, 165 respondents were required from the central region, and 50 were required from the northern region. Through district project offices, researchers were assisted to recruit participants of the study.

2.4. Data Collection

Data collection was done through a face-to-face paper-based method. The first page of the questionnaire contained information about the study which defined the scope of mHealth, the research objectives, and the hotline service. Participants were advised that they could decline to participate or stop at any point in the study. Willing respondents were required to read through a consent form. Participants were also required to sign the consent form or have their thumbprint as a form of signature. Respondents were required to fill in the questionnaires or the researchers asked them questions and filled the questionnaire according to their responses. Birks and Malhotra (2006) suggested that in research interactions, going to meet the participants is more convenient especially in the context of LMICs. The study used a paper-based approach to ensure a complete number of responses.

2.5. Data analysis

Structural Equation Modeling (SEM) technique was used to analyze data. Amos v23 and SPSS v20 software were used to carry out a comprehensive data analysis.
3. Results and interpretation

3.1. Descriptive statistics

Of the 384 questionnaires collected, 379 were used because of their completeness. Table 1 shows that 59.10% of respondents were male. 34.82% of respondents were between 25 and 34 years of age while 37.73% were primary school leavers. 35% of respondents had part-time employment with 23.21% indicating that they were engaged in farming. 85.22% of respondents indicated that they owned a phone while 14.77% indicated that they borrowed a phone to access CCPF services.

<table>
<thead>
<tr>
<th>Demographics</th>
<th>Frequency</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>224</td>
<td>59.10%</td>
</tr>
<tr>
<td>Female</td>
<td>155</td>
<td>40.89%</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>15-24</td>
<td>98</td>
<td>25.85%</td>
</tr>
<tr>
<td>25-34</td>
<td>132</td>
<td>34.82%</td>
</tr>
<tr>
<td>35-44</td>
<td>65</td>
<td>17.15%</td>
</tr>
<tr>
<td>45-54</td>
<td>36</td>
<td>9.49%</td>
</tr>
<tr>
<td>55-64</td>
<td>42</td>
<td>11.08%</td>
</tr>
<tr>
<td>65+</td>
<td>6</td>
<td>1.58%</td>
</tr>
<tr>
<td><strong>Level of education</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>37</td>
<td>9.76%</td>
</tr>
<tr>
<td>Primary school</td>
<td>143</td>
<td>37.73%</td>
</tr>
<tr>
<td>Secondary Certificate</td>
<td>91</td>
<td>24.01%</td>
</tr>
<tr>
<td>Professional Diploma</td>
<td>49</td>
<td>12.92%</td>
</tr>
<tr>
<td>Bachelor’s degree</td>
<td>41</td>
<td>10.81%</td>
</tr>
<tr>
<td>Master's degree</td>
<td>16</td>
<td>4.22%</td>
</tr>
<tr>
<td>Doctorate</td>
<td>2</td>
<td>0.52%</td>
</tr>
<tr>
<td><strong>Occupation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployed</td>
<td>14</td>
<td>3.69%</td>
</tr>
<tr>
<td>Intern</td>
<td>13</td>
<td>3.43%</td>
</tr>
<tr>
<td>Part-time worker</td>
<td>133</td>
<td>35%</td>
</tr>
<tr>
<td>Full-time worker</td>
<td>74</td>
<td>19.52%</td>
</tr>
<tr>
<td>Business</td>
<td>19</td>
<td>5.01%</td>
</tr>
<tr>
<td>Farmer</td>
<td>88</td>
<td>23.21%</td>
</tr>
<tr>
<td>Student</td>
<td>38</td>
<td>10.02%</td>
</tr>
<tr>
<td><strong>Phone use</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Own phone</td>
<td>323</td>
<td>85.22%</td>
</tr>
<tr>
<td>Shared phone</td>
<td>43</td>
<td>11.34%</td>
</tr>
<tr>
<td>Borrowed phone</td>
<td>56</td>
<td>14.77%</td>
</tr>
</tbody>
</table>
3.2. Analysis of constructs

Table 2 presents the results of reliability and validity tests. Included in the table are factor loadings, Cronbach alpha test, composite reliability (CR), and average variance extracted (AVE). Four cut-off points are suggested for a Cronbach Alpha test that shows excellent to low results. Scores above 0.70 are good while scores above 0.90 are excellent (Kurfalı et al., 2017). The Cronbach alpha test shows both good and excellent results. confirmatory factor analysis (CFA) is applied when the model has an apparent hypothesis concerning the factor structure. In SEM, CFA is obligatory for the data in question thus making SEM a necessary procedure for two reasons. Firstly, the process obtains approximations of the model’s limits or factor loadings, the factor variances and covariances, and the remaining error variances of the variables in question. Secondly, SEM is carried out to check if the model offers a good fit to the data (Hox & Bechger, 2003). The results show that the factor loadings are within an acceptable range. CR scores are also acceptable since they go beyond the commended cut-off point of 0.7 (Kurfalı et al., 2017; Sarwar et al., 2019). AVE scores are acceptable since they are above the recommended cut-off point of 0.5. These results imply that the items in the questionnaire have good convergent validity (88,89).

Table 2: Results of Confirmatory Factor Analysis (CFA)

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Items</th>
<th>Cronbach’s alpha</th>
<th>Factor Loadings</th>
<th>Composite reliability</th>
<th>Average variance extracted (AVE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social influence</td>
<td>SI1</td>
<td>0.831</td>
<td>0.651 0.863</td>
<td>0.836</td>
<td>0.632</td>
</tr>
<tr>
<td></td>
<td>SI2</td>
<td></td>
<td>0.835</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SI3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effort expectancy</td>
<td>EE1</td>
<td>0.822</td>
<td>0.886 0.742</td>
<td>0.827</td>
<td>0.619</td>
</tr>
<tr>
<td></td>
<td>EE 2</td>
<td></td>
<td>0.706</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>EE 3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Performance expectancy</td>
<td>PE1</td>
<td>0.815</td>
<td>0.597 0.866</td>
<td>0.822</td>
<td>0.608</td>
</tr>
<tr>
<td></td>
<td>PE2</td>
<td></td>
<td>0.727</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PE3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Facilitating conditions</td>
<td>FC1</td>
<td>0.801</td>
<td>0.771 0.786</td>
<td>0.804</td>
<td>0.579</td>
</tr>
<tr>
<td></td>
<td>FC2</td>
<td></td>
<td>0.718</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>FC3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trust</td>
<td>TII1</td>
<td>0.755</td>
<td>0.676 0.713</td>
<td>0.757</td>
<td>0.511</td>
</tr>
<tr>
<td></td>
<td>TII2</td>
<td></td>
<td>0.694</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>TII3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Behavioral intention</td>
<td>BI1</td>
<td>0.922</td>
<td>0.848 0.868</td>
<td>0.922</td>
<td>0.798</td>
</tr>
<tr>
<td></td>
<td>BI2</td>
<td></td>
<td>0.824</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>BI3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Secondly, a discriminant validity test was carried out. In discriminant analysis, the variate is designed to generate scores for individual assessments that outstandingly distinguishes between clusters of assessments (Hair et al., 2014). Results demonstrate that a good discriminant validity ought to have scores of square roots of AVE higher than associations between constructs. Table 3 indicates good discriminant validity based on the defined criteria.

<table>
<thead>
<tr>
<th>Construct</th>
<th>1</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social influence</td>
<td>0.795</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effort expectancy</td>
<td>0.088</td>
<td>0.787</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Facilitating conditions</td>
<td>0.199</td>
<td>-0.184</td>
<td>0.780</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Performance expectancy</td>
<td>0.016</td>
<td>0.226</td>
<td>0.040</td>
<td>0.761</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trust</td>
<td>0.241</td>
<td>0.007</td>
<td>0.344</td>
<td>0.093</td>
<td>0.715</td>
<td></td>
</tr>
<tr>
<td>Behavioral intention</td>
<td>0.150</td>
<td>-0.071</td>
<td>0.523</td>
<td>0.236</td>
<td>0.382</td>
<td>0.893</td>
</tr>
</tbody>
</table>

### 3.3. Model fit testing

In SEM, a model must be specified before analysis. A combination of hypothetical and practical findings from prior studies guide this process. Approximations of factor loadings and (co)variances are made when the model is specified (Hox & Bechger, 2003), results, which have been demonstrated in Table 2. A statistical chi-square ($\chi^2$) test is then carried out to examine the fitness of the hypothesized model. A highly significant chi-square represents an unfit model which requires one to construct a more suitable model. Nevertheless, scholars point out the shortfalls of relying solely on chi-square measurements and propose dividing $\chi^2$ by the degrees of freedom (df) (46,88). The recommended acceptable ratio for $\chi^2$/df is one that falls below 5.0. Table 3 presents the goodness of fit indices including comparative fit index (CFI), standardized root mean square (RMR), and root mean square error of approximation (RMSEA). The recommended thresholds are also indicated in Table 3.
Table 4: Goodness of Fit Statistics

<table>
<thead>
<tr>
<th></th>
<th>CMIN</th>
<th>DF</th>
<th>CMIN/DF</th>
<th>CFI</th>
<th>RMR</th>
<th>RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measurement</td>
<td>226.414**</td>
<td>120</td>
<td>1.326</td>
<td>0.966</td>
<td>0.038</td>
<td>0.045</td>
</tr>
<tr>
<td>model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Final model</td>
<td>159.377*</td>
<td>122</td>
<td>1.306</td>
<td>0.971</td>
<td>0.038</td>
<td>0.044</td>
</tr>
<tr>
<td>Threshold</td>
<td>--</td>
<td>--</td>
<td>1-3</td>
<td>&gt;0.95</td>
<td>&lt;0.08</td>
<td>&lt;0.05</td>
</tr>
</tbody>
</table>

3.4. **Hypothesis testing**

Hypothesis testing was then conducted after model fit testing. Findings show that H1, H2, H3, H5, H7, and H9 are supported while H4, H6, H8, and H10 are not supported. Table 5 provides details of the results.

Table 5: Results of hypothesis testing

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Standardized Path Coefficient</th>
<th>Standard Error</th>
<th>t-value</th>
<th>Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>TII – BI</td>
<td>0.210*</td>
<td>0.134</td>
<td>2.316</td>
</tr>
<tr>
<td>H2</td>
<td>PE – BI</td>
<td>0.445***</td>
<td>0.100</td>
<td>4.955</td>
</tr>
<tr>
<td>H3</td>
<td>PE – TII</td>
<td>0.306**</td>
<td>0.136</td>
<td>2.989</td>
</tr>
<tr>
<td>H4</td>
<td>SI – PE</td>
<td>0.142</td>
<td>0.111</td>
<td>1.540</td>
</tr>
<tr>
<td>H5</td>
<td>SI – TII</td>
<td>0.248*</td>
<td>0.90</td>
<td>2.506</td>
</tr>
<tr>
<td>H6</td>
<td>EE – PE</td>
<td>0.058</td>
<td>0.132</td>
<td>0.622</td>
</tr>
<tr>
<td>H7</td>
<td>EE – BI</td>
<td>0.197*</td>
<td>0.126</td>
<td>2.460</td>
</tr>
<tr>
<td>H8</td>
<td>EE – TII</td>
<td>0.096</td>
<td>0.108</td>
<td>0.941</td>
</tr>
<tr>
<td>H9</td>
<td>FC – PE</td>
<td>0.215*</td>
<td>0.092</td>
<td>2.364</td>
</tr>
<tr>
<td>H10</td>
<td>FC – TII</td>
<td>-0.040</td>
<td>0.074</td>
<td>-0.407</td>
</tr>
</tbody>
</table>

Note: *** = P < 0.001; ** = P < 0.01; * = P < 0.05
4. Discussion

The construct of trust and the primary UTAUT constructs including performance expectancy, effort expectancy, social influence, and facilitating conditions are used in this study to investigate users’ behavioral intentions to accept and use mHealth services. Results of the analysis indicate mixed results with four out of the ten hypotheses not supported. Other hypotheses offer empirical support in line with the outcomes of earlier studies that applied UTAUT to investigate mHealth acceptance and use.

Trust (H1) shows a direct positive effect on behavioral intentions. Prior investigations also revealed a constructive correlation between trust and mHealth acceptance and use. Deng et al. (2018) found that trust was the highest predictor of intentions to use mHealth services in China. Alam et al. (2018) found that although other UTAUT constructs positively affected behavioral intentions to use mHealth services, the trust-based construct of perceived reliability also affected behavioral intentions. Consistent with these hypotheses, Ortega Egea and Roman Gonzalez (2011) demonstrated that trust and risk factors were strongly predictive of physicians' acceptance of Electronic Health Care Records (EHCR) systems. Saad et al. (2020) found that 29.4% of mobile medical application users were anxious about revealing their medical information. The results of H1 demonstrate that when a user perceives a mHealth service to be trustworthy, they are highly likely to accept the service. Previous evaluations of the user perceptions of CCPF showed that over
90% of users highly trusted the information provided through the hotline service and felt comfortable talking to hotline workers (Blauvelt et al., 2018; Reynolds, 2017).

Similar to many previous studies, performance expectancy is strongly associated with mHealth acceptance (H2). Cimperman et al. (2016) found performance expectancy to be the strongest predictor of home telehealth services for older users’ acceptance behavior. Maiga and Namagembe (2014), Wu et al. (2011), and Sun et al. (2016) established similar results in mHealth acceptance by healthcare workers. Cohen et al. (2013) also found performance expectancy in the context of e-prescribing to significantly predict use. In the context of Malawi where women are required to travel long distances for consultations on MNCH, they may be persuaded to use the hotline service instead to save time, energy, and costs. A growth in opinions that CCPF is expedient and can add to the extension of access to healthcare would bring about a growth in the competencies of mHealth. Therefore, designing a solution that is considered useful for users is necessary to reduce the prospects of people not accepting the service. The hypothesis that higher performance expectancy is associated with increased trust (H3) was also supported. Gao and Waechter (2017) showed that the provision of quality information on an m-payment system increased the probability of users’ perceiving the service provider as dependable, and subsequently the m-payment as trustworthy. Lee and Turban (2001) demonstrated that users’ trust in a system depends on the system’s technical competencies. Ehrismann and Stegwee (2015) further noted that technical failures were a considerable risk and affected user trust. Therefore, the performance of both operatives and system mechanisms is important for influencing user trust.

The results supported the hypothesis that the lower the effort expectancy, the higher the likelihood of behavioral intentions to use mHealth services (H7). This is in line with other studies in which users of hotline services found it easy to use. For instance, Reynolds (Reynolds, 2017) found that users complemented CCPF on the fact that it was user-friendly and required minimal effort. Naturally, people prefer a user-friendly system at the point of care. Users must perceive the system as requiring less effort and more convenience. The easier mHealth services become the more users would accept the service. Thus, a decent simple service needs to be used to maximize the prospective of mHealth. Moreover, mHealth initiatives that would add to healthcare access would be easily accepted. On the other hand, neither performance expectancy nor trust mediates the relationship between effort expectancy and behavioral intentions since H6 and H8 were rejected.
Similar to findings of H8, Deng et al. (2018) found that although perceived ease of use and perceived usefulness positively affected behavioral intentions, their effect declined through the mediation of trust. Similarly, in the context of m-payments, Zhou (2014) found that effort expectancy had a limited effect on initial trust. Descriptive statistics indicate that 11.34% shared a phone with a family member while 14% borrowed a phone to use the hotline service. This may result in perceptions of effort exertion in accessing the service which may diminish trust. Moreover, a study by Reynolds (2017) indicated that some users expressed dismay over delays in answering calls and dropped calls. This resulted in users calling the service repeatedly to access the service. Although this may not be a common occurrence, users may perceive this as extra effort and affect their perception of the overall performance of the system (H6). They may attribute these mishaps to network problems or feel like the operators do not prioritize their needs. Likewise, Zhou (2014) found that the influence of effort expectancy on performance expectancy was rejected. The hotline service needs to ensure mechanisms that address service delivery mishaps to improve people’s perceptions of mHealth.

The hypothesis that higher social influence would positively affect performance expectancy (H4) was not supported. Khatun et al. (2015) found that in rural Bangladesh, community members expressed great interest in using mHealth services but were hindered by a lack of capacity and knowledge. Malawi has a relatively low literacy rate at 61% which may contribute to people’s limited expectation of service performance (World Health Organization, 2018b). On the other hand, H5 was supported in which greater social influence positively affects trust. Compared to developed nations, countries such as Malawi can be classified as associative cultures in which value is placed on societal interactions. Communication in such cultures happens on a face-to-face basis and amongst people who share commonalities (Banda & Gombachika, 2012; Gombachika & Khangamwa, 2013; Scheraga et al., 2000). In rural areas, females’ mobile phone usage depends mostly on males including spouses, relatives, or community leaders. Moreover, 33% of women possess a mobile phone unlike 50% of men (Blauvelt et al., 2018). These dynamics have the potential to promote or hinder initiatives such as MNCH and immunization programs which are the backbone of CCPF. Thus, phone usage for reasons besides placing regular phone calls remains a relatively new notion in Malawi. CCPF introduced youth services in 2017 which focus mainly on sexual and reproductive health. Blauvelt et al. (2018) showed that the youth (aged 15-24) constituted 38% of calls to the service. Considering the sensitivity surrounding sexual and
reproductive health, one can deduce that the youth may encourage each other to use the service since it offers more privacy and anonymity. Therefore, other peoples’ thoughts and views are vital for forming trust in the service.

Prior investigations primarily concentrated on the direct effect of facilitating conditions on intentions (Ndayizigamiye & Maharaj, 2016; Nematollahi et al., 2017). However, this study examined the indirect influence of facilitating conditions through the mediation of performance expectancy. Findings show support for this relationship (H9). In the context of a resource-limited society such as is the case with Malawi, the availability of mobile phones to more individuals, mobile network access, and the opportunity to increase literacy are some of the crucial factors necessary to influence expectations of the system performance and ultimate intentions to use the service. Ndayizigamiye and Maharaj (Ndayizigamiye & Maharaj, 2016) concluded that language adaptation was a critical requirement for mHealth acceptance in Burundi. In Malawi, CCPF hosts several different major languages including English, Chichewa, Tumbuka, and Yao. Expansion to include other languages such as Lomwe, and Tonga may influence expectations of performance. It is expected that once the service is understood in people’s native language, prospective users would be more accommodating of it (Ndayizigamiye & Maharaj, 2016). However, the influence of facilitating conditions on trust (H10) was rejected. The study found that 11.34% share a phone with others while 14.77% borrowed a phone to access CCPF services. This means that there is a possibility for limiting personal access to the service since only those that own a phone have the assurance of privacy and security of information thus limiting trust (77,97).

5. Theoretical contributions

Various technology acceptance models are used to determine acceptance in numerous technological contexts. The model employed in this study integrates UTAUT and trust and provides an extended generalization of UTAUT from the context of organizations to that of care receivers. UTAUT has mainly been examined under organizational settings with performance expectancy proving to be the principal determinant of behavioral intentions (Cohen et al., 2013; Jewer, 2018; Liu et al., 2015). This study practically investigates the constructs to authenticate their appropriateness in mHealth from the perspective of the general public. It, therefore, provides an important contribution to literature since it is one of the few studies exploring the predictors of mHealth adoption applicable to the general public in a developing country. Moreover, patients’ use and healthcare workers’ use of mHealth services differ in that patients voluntarily use a service
while healthcare workers often use mHealth under mandatory circumstances (Jewer, 2018). Therefore, assessments may produce different results and implications.

The outcomes offer additional confirmation for using UTAUT with supplementary constructs to assess mHealth acceptance and use. Important modifications of the UTAUT in this study are the influences on behavioral intentions of social influence, effort expectancy, and facilitating conditions mediated by performance expectancy and trust. Findings show that the direct influences of performance expectancy, effort expectancy, and trust on behavioral intentions are greater than the mediating effects. It may be concluded that similar to organizational contexts, performance is a superior consideration for users compared to the effort required in accessing the service. Trust is also considered influential to decision-making as users interact with hotline operatives and form opinions based on services provided.

6. Practical contributions

Findings also provide applied inferences about the benefits of enhancing acceptance of mHealth under the framework of a developing country. Few studies have been undertaken in the context of mHealth, especially in LMICs. The majority of investigations have been carried out in developed countries that present contextually different implications LMICs (Betjeman et al., 2013; Feroz et al., 2019; Free et al., 2013; Were et al., 2019). Scholars contend that there lacks pragmatic and policy evidence concerning mHealth principally in LMICs. Works evaluating mHealth interventions typically miss the inclusion of risk assessment, intervention acceptability, and user approval. This is especially true in LMICs where mobile phones are often communal, significant privacy concerns should be considered when forming interventions (Marcolino et al., 2018).

Findings show that people will be convinced of using the hotline service if its performance is good. This performance, firstly, applies to the technical system usability in that users should be able to connect to the service. Secondly, professional performance in that operatives must be able to assist users with relevant information and in a respectful manner. These factors, in turn, will positively affect user trust in the service as users will perceive it as reliable. Furthermore, the service will be seen to be advantageous if it offers an opportunity to exert less effort both in access to the service and use of the service. Such advantages may include saving time, reduced costs, increased knowledge, and minimal movement. Since hotline services are mainly for consultative purposes, if it does not offer any substantial assistance, users may revert to traditional face-to-face methods simply to seek consultation. Results also show that significant others play an important
role in ensuring acceptance and use since they influence a person’s trust in the system. The availability of resources and knowledge are crucial for facilitating acceptance and use.

In light of these results, project implementers ought to ensure the accessibility of the service by linking with mobile network providers to establish relevant infrastructure and provide technical support where service is interrupted. This will ensure the reliability and stability of the system. Project designers must take into consideration local cultural factors such as gender dynamics, socio-cultural practices, and local belief systems. Appropriate health communication strategies must be formulated that work around these local factors to influence acceptance and use of the service. Furthermore, the consideration of expansion to more languages is essential for targeting more people that may feel excluded. Moreover, the study outcomes may easily be adapted to support other emerging nations in the preparation and adoption of mHealth facilities.

7. Limitations and future direction

Firstly, the study was purely quantitative which may have limitations in terms of having in-depth knowledge of influencing factors. Future studies may adopt a mixed-method approach to investigate the determinants of acceptance and use will provide more comprehensive insights into acceptable behavior. Nevertheless, the study is a good starting point for future studies which could undertake a longitudinal approach to data collection instead of cross-sectional studies. This will assist in uncovering the causative relationship between constructs and have the ability to get significant information more sufficiently. Secondly, the study was conducted in the context of Malawi which has contextually different implications compared to other countries in the region and beyond. The results of this study may not represent mHealth in other countries and should be generalized cautiously. Thirdly, moderating variables used in the original UTAUT model were excluded from this study. Moreover, other constructs related to adoption intentions may be used in future studies to better explain acceptance and use.

8. Conclusion

This study integrated UTAUT constructs and trust to examine factors that influence acceptance and use mHealth by the general public in Malawi. Performance expectancy and trust mediated the relationship between social influence, effort expectancy, facilitating conditions, and behavioral intentions while trust mediated the effect between performance expectancy and behavioral intentions. The investigation revealed that performance expectancy, effort expectancy, and trust
positively influenced behavioral intentions to use. Findings also showed that four out of seven mediation effects were not supported. The outcomes reflect the cultural and socioeconomic characteristics of the people concerning adoption intentions. Decisions to accept technology are influenced by multiple factors such as the usefulness of the technology, its easiness, people's opinions of it, and availability of human, infrastructural and monetary resources. The results offer useful evidence for strategy and policy development by mHealth service providers, policymakers, and managers. Moreover, the development of successful initiatives and the acceleration of the acceptance of mHealth amongst users is dependent on the determinants confirmed in this study.

Appendix

Table A: Survey questions

<table>
<thead>
<tr>
<th>Category</th>
<th>Number</th>
<th>Question</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Demographic information</strong></td>
<td>1</td>
<td>Gender</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Age</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Education</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>Occupation</td>
</tr>
<tr>
<td><strong>Mobile phone use</strong></td>
<td>5</td>
<td>How did you reach the hotline service (personally owned phone/shared phone/borrowed phone)</td>
</tr>
<tr>
<td><strong>Trust</strong></td>
<td>7</td>
<td>I think that the mHealth services’ technical and legal infrastructure protects enough personal information and data</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>In general, hotline service is a trusted tool I can use to interact with mHealth services</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>I trust online healthcare intermediaries’ abilities to provide mHealth services effectively and securely</td>
</tr>
<tr>
<td><strong>Performance expectancy</strong></td>
<td>10</td>
<td>Using the hotline service for health-related matters enables me to accomplish tasks more quickly</td>
</tr>
<tr>
<td></td>
<td>11</td>
<td>Using the hotline service improves my success about the subject of the health</td>
</tr>
</tbody>
</table>
If I use hotline service for health-related matters, I will increase my productivity

**Effort expectancy**

My interaction with the hotline service for health matters would be clear and understandable

It would be easy for me to become skillful at using the hotline service for health-related matters

I would find the hotline for health-related matters easy to use

**Social influence**

I will recommend others to use the hotline service

People who influence my behavior think that I should use mHealth services

People who are important to me think that I should use mHealth services

**Facilitating conditions**

I have the resources necessary to use the hotline to access mHealth services

I have the knowledge necessary to access mHealth services

Someone would be available to assist me when I experience technical difficulties

**Behavioral intention**

I plan to use the hotline services in a short time

I intend to use mHealth services in the future

I would use mHealth services

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*a* Adapted from Kurfali, et al. (2016)

*b* Adapted from Venkatesh, et al. (2003)

*c* Adapted from Cohen, et al (2013)
References


1–9.


**Acknowledgments**

I would like to thank Osman Jama for analyzing and interpreting the data. I would also like to thank the enumerators who collected the data and all respondents for sparing time to respond to the questionnaire.

**Dedication**

Thank God.

**Conflicts of Interest**

There are no conflicts to declare.

**Author Biography**

AG has a Bachelor’s degree in Public Administration and is studying for a Master’s degree in Public Administration at the University of Science and Technology of China.