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► **To cite this version:**

Macire Kante, Patrick Ndayizigamiye. Adoption of Mobile Applications for Self-healthcare Monitoring by the Youth in South Africa. José Abdelnour-Nocera; Elisha Ondieki Makori; Jose Antonio Robles-Flores; Constance Bitso. Innovation Practices for Digital Transformation in the Global South IFIP WG 13.8, 9.4, Invited Selection, AICT-645, Springer International Publishing, pp.79-96, 2022, Innovation Practices for Digital Transformation in the Global South, 978-3-031-12824-0. 10.1007/978-3-031-12825-7\_5. hal-04299516

**HAL Id: hal-04299516**

**<https://inria.hal.science/hal-04299516v1>**

Submitted on 22 Nov 2023

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# Adoption of Mobile Applications for Self-healthcare Monitoring by the Youth in South Africa

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**Abstract.** Despite growing recognition of the contribution and availability of mobile applications for self-healthcare monitoring to prevent non-communicable diseases (NCDs), NCDs remain a rising concern amongst the youth in sub-Saharan Africa and South Africa in particular. Indeed, self-healthcare monitoring mobile applications can be used to continuously educate and sensitize people about the need to adopt healthy lifestyles to prevent such diseases. However, the adoption of such applications is influenced by many factors which need to be identified in order to devise strategies to encourage people to adopt such applications. Thus, this study investigated the potential adoption of self-healthcare monitoring mobile applications by the youth in South Africa, using the Unified Theory of Acceptance and Use of Technology (UTAUT) as the theoretical lens. Data, gathered from a convenient sample size of 280 participants, were analysed using the Partial Least Square Structural Equation Modelling. The results revealed that performance expectancy and social influence explained 20.3% of the variance of youth's behavioural intention to adopt self-healthcare monitoring mobile applications in the South African context, while effort expectancy and facilitating conditions did not have a significant effect. Taking the resulting model into account could lead to an increase in the adoption of self-healthcare monitoring applications in South Africa which could assist in the prevention of NCDs. It is recommended that further studies should test the established factors from this study in other contexts.

**Keywords:** Adoption, Mobile Applications, Self-healthcare Monitoring, South Africa, Youth, UTAUT, PLS-SEM.

## 1 Introduction and Background

The surge of Non-Communicable Diseases (NCDs) has been widely recognized. More than seventy-five per cent of deaths linked to NCDs worldwide occur in Low and Middle-income countries [1]. In South Africa, it has been argued that youth are the most exposed to NCDs. For instance, De Wet and Frade [2] reported that a considerable

percentage of youth suffer from hypertension, diabetes, and obesity amongst other NCDs. These authors also concluded that NCDs were the predominant cause of mortality. Thus, attention should be paid to the prevention of NCDs amongst the youth in South Africa in particular, as NCDs are no longer attributed to “old age” only [3]. Unhealthy lifestyles such as smoking, excess liquor consumption, lack of physical exercise and skipping breakfast are some of the causes of NCDs in South Africa and globally [4]. One of the ways to prevent NCDs is to sensitize the youth to adopt a healthy lifestyle.

In addition, research has shown that self-healthcare monitoring and the provision of relevant information to the youth amongst others can prevent more than 40% of NCDs-related deaths [5]. Furthermore, Kim et al. [6] argue that healthcare monitoring is crucial in preventing NCDs such as asthma, diabetes and other diseases. Hence, there is a need to foster self-healthcare monitoring with the aim of changing people’s unhealthy behaviour, and therefore, lower the risk of NCDs. On the other hand, it has been argued that mobile technology can be used to change people’s unhealthy behaviour. Particularly, there is evidence that mobile applications with educational content on healthy lifestyle and self-healthcare monitoring can contribute to the adoption of healthy lifestyles. For instance, a systematic review by Zhao, Freeman and Li [5] has identified studies that link mobile health applications to the improvement of lifestyle, increasing physical activity, weight control, diet control and self-medication management.

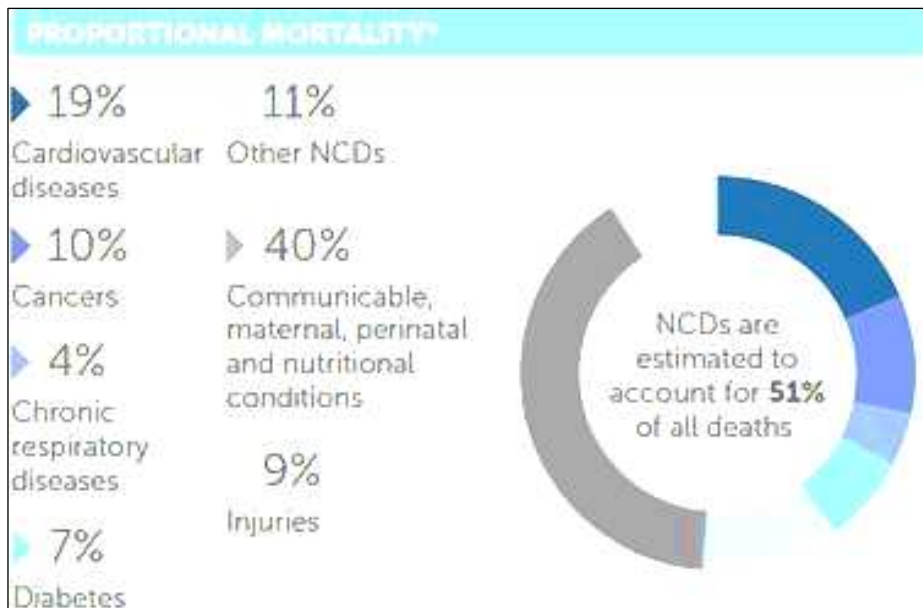
In South Africa, Petersen et al. [7] have found that people who suffer from NCDs such as diabetes demonstrate a positive behavioural intention to adopt mobile applications for diabetes self- management. Moreover, mobile phone usage is increasing among South African youth, who are more adept at utilizing technologies than older people [7]. Despite this increase in the use of mobile phones by the youth, recent literature suggests that the adoption of mHealth, including self-healthcare mobile applications is still scanty in South Africa [7,8] and in developing countries [9,10]. There are still factors that affect the adoption of mobile applications for self-healthcare monitoring purposes [11] which need to be clearly established. Moreover, there is also a need to establish the effects of these factors on the youth’s adoption of mobile applications that may assist them to monitor their health.

The aim of this paper was to investigate the youth’s adoption of mobile applications for self-healthcare monitoring purposes in South Africa. The specific objectives of this study were to: establish the factors that could influence the adoption of self-healthcare monitoring mobile applications; and identify the effects of these factors on the adoption of self-healthcare monitoring mobile applications.

## 2 Literature Review

### 2.1 Non-Communicable Diseases in South Africa

Non-Communicable Diseases are the main causes of deaths in South Africa. The World Health Organization reports that NCDs are estimated to account for 51% of all deaths in the country [1]. Addressing NCDs is critical to improving public healthcare. Researchers have argued that prevention and monitoring of NCDs are some of the best ways to address these diseases. For instance, Hofman [4] highlighted the need for monitoring interventions to effectively prevent premature deaths caused by NCDs. NCDs surveillance needs to be strengthened to provide reliable and robust information for planning and monitoring of health policy [12]. Additionally, the South African National Strategy commission [13] indicates that the South Africa's healthcare system has failed to address the leading diseases such as HIV/AIDS, tuberculosis, hypertension and diabetes. Figure 1 provides an overview of NCDs deaths in South Africa.



**Fig. 1.** NCDs proportional mortality source: world health organization (World Health Organization, 2018)

### 2.2 Mobile Health (mHealth)

Over the past decade, many researchers have investigated mHealth in developing countries [14, 15, 16, 17, 18, 19]. Mechael [20] reports that the health community debates

whether a specialized field of “mHealth” exists and how to define it. The World Health Organization described mHealth as the utilisation of mobile technologies such as mobile-based applications to realise health objectives [21]. By the end of the year 2021, there were more than 350 000 mHealth applications covering a broad scope of health issues ranging from managing chronic illness to tracking personal fitness [22]. Unsurprisingly, it is often argued that mHealth has the potential to transform healthcare by supporting citizen-centric care which is heralded to result in better care for patients at lower costs and with greater efficiency [23].

On a practical level, mHealth solutions can encourage the adopters to commit to a healthy behaviour and equip them with the information they need to manage their health conditions [21, 24]. In South Africa, it has been reported that over one hundred mHealth applications have been in use [25]. The use of mHealth in developing countries can help foster efficiency and effectiveness in the provision of healthcare [26]. In the same vein, Ndayizigamiye [27] investigated the potential adoption of mobile health technologies for public healthcare in Burundi. He found that mHealth adoption can contribute to disease prevention, disease management and the provision of quality healthcare in Burundi. Thus, mHealth applications, especially self-healthcare monitoring applications, present an opportunity for improving people’s health.

However, the benefits of mHealth cannot be realized without its adoption and use. Challenges pertaining to the adoption and use of mHealth have been reported as in developing countries. For instance, a review of 64 mHealth projects in developing countries revealed various factors and challenges that affect mHealth adoption [26]. Ndayizigamiye and Maharaj [28] investigated challenges to the adoption of mHealth. They found that the challenges are: physical access to mobile technology; human capacity and training; socio-cultural factors; trust in technology; local economic environment; macro- economic environment; political will and public support; budget and donors/partners funding; and organisational barriers. Furthermore, another study [29] revealed that two-thirds of the identified mHealth initiatives were abandoned prematurely. Therefore, factors that influence the adoption and use of mHealth in developing countries such as South Africa need to be investigated further.

The adoption of mHealth has attracted the attention of researchers in developed as well as developing countries. In China for instance, Deng et al. [30] examined and reported the determinants of the adoption of a mobile health service. Their study developed and validated a comprehensive mHealth adoption model in China. Similarly, other studies investigated mHealth adoption in Kenya [31], in South Africa [32, 33], in Burundi [34], in Uganda [35], in Tanzania [36], in Malawi [26], in the Democratic Republic of Congo [37] amongst others. These studies identified contextual factors that needed to be considered for the adoption of mHealth in these countries. Countries have different contextual factors (including culture) that needed to be taken into account

[38]. Thus, this study attempts to identify such factors within the context of the youth's adoption of mHealth in South Africa.

### **2.3 Adoption of Mobile Self-Healthcare Monitoring Applications**

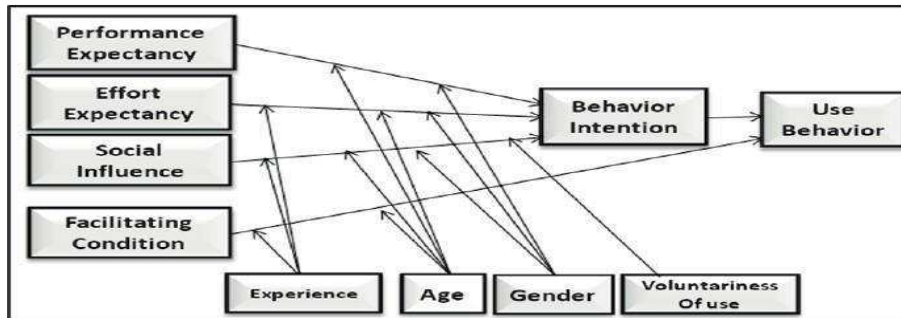
The choices people make, such as diet, socialization and exercise patterns, have a considerable impact on their health. It has been argued that exercise patterns have an impact on health-related issues such as anxiety, high blood pressure, stress and depression [39]. However, generally, people have little knowledge of these health-related issues. Hence, without adequate knowledge of preventative measures against NCDs, people's unhealthy lifestyles remain unchanged which increase the NCDs-related mortality. On the other hand, mHealth can empower individuals to manage and monitor their personal health [21]. An investigation of the challenges that affect the adoption of ICTs for diabetes self-management in South Africa was conducted by Petersen et al. [7]. The study was qualitative in nature, and hence, could not establish the effects of the factors (drivers and challenges) on the adoption of self-healthcare monitoring mobile applications in the South Africa's context. This points to a methodological gap, as there is a need to investigate the adoption of self-healthcare monitoring applications from a quantitative stance. Thus, this study aimed to fill this gap, to a certain extent, by investigating the adoption of self- healthcare monitoring applications from a quantitative point of view.

## **3 Theoretical Framework & Hypotheses Formulation**

Woosley and Ashia [40] argue that in health IT research, there are three commonly used theories/models: a) Technology Acceptance Model (TAM), b) Diffusion of Innovation Theory (DOI) and c) Unified Theory of Acceptance and Use of Technology (UTAUT). However, UTAUT is more comprehensive than the other theories of technology acceptance [41]. Additionally, UTAUT has been used in various studies pertaining to healthcare (mHealth, eHealth, health) in developing countries [31, 42, 43, 44]. It is for these reasons that, the Unified Theory of Acceptance and Use of Technology (UTAUT) [45] was adopted as the theoretical lens underpinning this study.

The UTAUT model aims to explain a user's intention to use an information system and the subsequent use behaviour. The following are the four constructs of UTAUT and their descriptions. Performance expectancy refers to the individual beliefs that a system will improve his/her job performance. Effort expectancy refers to the extent of ease of use of a system. Social influence refers to the extent an individual perceives that 'important others', including his peers, would recommend using a system. Facilitating conditions refer to the extent to which a person believes that technical and organisational infrastructure are available to support the use of a system. The UTAUT model has proved to be a comprehensive framework that can explain a user's intention to use

an information system [45]. Venkatesh et al. [45], when testing the model, concluded that other models such as TAM and TAM2 explained approximately 40% of technology acceptance while, on the other hand, the UTAUT model explained 69% of intention to use a technology.



**Figure 2.** The UTAUT model [45]

In the context of this study, the four constructs of the UTAUT framework were used to assess factors that may influence the youth to adopt self-healthcare monitoring mobile applications. A study conducted by Nanyombi and Habinka [46] on the factors affecting the adoption of mHealth in both developed and developing countries reported performance expectancy as a driver of mHealth adoption. Hence, this study hypothesizes that:

H1<sub>1</sub> Performance expectancy has a positive effect on behavioural intention to adopt self-healthcare monitoring mobile applications.

Jeon and Park [47] argued that training on using mobile health and technical support had a significant effect on the adoption of mHealth. This points to effort expectancy of the UTAUT. Thus, this study argues that:

H1<sub>2</sub> Effort expectancy has a positive effect on behavioural intention to adopt self-healthcare monitoring mobile applications.

Social influence was reported as having an effect on the adoption of mHealth applications in Burundi [43] and in South Africa [8]. Therefore, this study argues that:

H1<sub>3</sub> Social influence has an effect on behavioural intention to adopt self-healthcare monitoring mobile applications.

Albertain [48] suggest that the (high) cost associated with using mHealth applications is a challenge to its adoption. Cost factors are related to the price of the mobile phone, airtime, and data [48]. In the same vein, Petersen et al. [7] have identified the cost of mobile devices and Internet connection costs as the economic factors that affect the behavioural intention to adopt mobile applications for diabetes self-management in South Africa. Furthermore, language has been identified as one of the determinants to



mHealth adoption in developing countries [3]. These are facilitating conditions of the UTAUT framework. This study, therefore, hypothesizes that:

H1<sub>4</sub> Facilitating conditions have an effect on self-healthcare monitoring mobile applications use behaviour.

H1<sub>5</sub> Behavioural intention has an effect on self-healthcare monitoring mobile applications use behaviour.

## 4 Methodology

This quantitative research used a structured questionnaire with 23 items ranked on a 5-point Likert scale (ranging from (1) “Strongly disagree” to (5) “Strongly agree”) to collect data. As shown in Table 5 in Appendix A, all measures of the UTAUT constructs within the questionnaire were adopted from previously validated research instruments except facilitating conditions which were formulated by the authors, based on the context of the study. Data were collected from a convenient sample size of 280 students registered at one of the campuses of an institution of higher learning in South Africa. Based on the evidence from the literature [49, 50, 51], this sample size was deemed large enough to draw statistically sound conclusions. The sample comprised youth based on the South Africa’s classification of “youth” [52]. The South African National Youth Development Agency Act defines “youth” as people between the ages of 14 and 35.

Basic statistical analysis and data management techniques (frequency analysis, descriptive statistics and data distribution analysis) were performed, using the Statistical Package for Social Sciences (SPSS) software version 20. Thereafter, the authors applied the Partial Least Square Structural Equation Modelling (PLS-SEM) technique, using SMARTPLS version 3.2.9 software to assess the UTAUT model. The PLS-SEM helps to create path models to depict the causal sequence [53]. The PLS-SEM comprises two models, namely the inner or structural model and the measurement model. The inner model displays the relationships among the constructs while the outer model, also known as the measurement model, is used to evaluate the relationships among the indicator variables and their corresponding constructs. Table 1 provides the criteria used for PLS-SEM models assessment.

**Table 1.** Guidelines when using PLS-SEM  
[50,51, 53]

Assessment	Criterion	Description
Indicator reliability	Indicator loading > .600	Loadings represent the absolute contribution of the indicator to the definition of its latent variable.

Internal consistency reliability	Cronbach's $\alpha > 0.6$	Measures the degree to which the measured variables (MVs) load simultaneously when the latent variable (LV) increases.
Internal consistency reliability	Composite reliability $> 0.6$	Attempts to measure the sum of a latent variable (LV) factor loadings relative to the sum of the factor loadings plus error variance.
Content validity	Average Variance Extracted (AVE) $> 0.5$	The degree to which individual items reflecting a construct converge in comparison to items measuring different constructs.
Discriminant validity	Heterotrait-Menotrait Ratio (HTMT) $< 1$	In information Systems research, it is argued that discriminant validity should be assessed by the Heterotrait-Menotrait Ratio (HTMT).
Model predictability	Predictive relevance $Q^2 > 0.05$	By systematically assuming that a certain number of cases are missing from the sample, the model parameters are estimated and used to predict the omitted values.
Model validity	$R^2 > 0.100$	Coefficient of determination
Model validity	Path coefficients and critical t-values for a two-tailed test are 1.65 (significance level = 10 per cent), 1.96 (significance level = 5 per cent), and 2.58 (significance level = 1 per cent)	Structural path coefficients are the path weights connecting the factors to one another.

## 5 Findings

This study's results are reported in the light of the research objectives and compared with the current literature. This study collected 277 usable responses. Most of the respondents (87.73%) were between the ages of 18 and 24, followed by the age group of between 25 and 30 years. Respondents aged 31 and above were the least represented in

this study. In addition, 53.8 percent of the respondents were female while male respondents made up the remaining 46.2 percent.

### 5.1 Factors Influencing the Adoption of Self-Healthcare Monitoring Mobile Applications

The first objective of the study identified factors influencing the adoption of mobile applications for self-healthcare monitoring. The subsequent (measurement) model of PLS-SEM, as mentioned in the methodology section, is concerned with the validity of the model's constructs. This section assesses the convergent validity and discriminant validity of the latent variables. A latent variable that has convergent and discriminant validity implies that it can be incorporated into the model under study [51].

#### Convergent validity

The authors used the following measures to assess convergent validity: composite reliability (greater than 0.8), Cronbach's alpha (greater than 0.8), average variance extracted (AVE) (greater than 0.6) and indicator reliability (greater than 0.7). As depicted in Table 2, the convergent validity was established, as the values of Cronbach's alpha and composite reliability were above the threshold of 0.8 and the average value extracted and indicator reliability above the threshold of 0.6 and 0.7 respectively for all the constructs.

#### Discriminant validity

Discriminant validity represents the extent to which the construct is empirically distinct from other constructs; in other words, the extent to which the construct measures what it is intended to measure. There are three means of assessing the discriminant validity: the Fornell-Larcker criterion, the cross-loading criterion and the Heterotrait-Monotrait Ratio (HTMT) [50].

Although the assessment of cross-loadings and the use of the Fornell-Larcker criteria are accepted methods for assessing the discriminant validity of a PLS model, these methods have shortcomings [53]. This was noted by Hair et al. [50] who argued that the lack of discriminant validity was better detected by the Heterotrait-Monotrait Ratio (HTMT) assessment. Thus, we used the HTMT criterion to assess discriminant validity (see Table 3).

**Table 2. Convergent validity**

Construct	Item	Indicator reliability	Cronbach's alpha	Composite reliability	Average Variance Extracted (AVE)
-----------	------	-----------------------	------------------	-----------------------	----------------------------------

BI	BI1	0.936	0.885	0.945	0.896
	BI2	0.957	0.806	0.884	0.719
EE	EE1	0.834	0.907	0.954	0.911
	EE2	0.879	0.819	0.892	0.733
	EE3	0.830	0.876	0.922	0.798
FC	FC1	0.936	0.819	0.879	0.710
	FC2	0.973	N/A	N/A	N/A
PE	PE1	0.868	0.885	0.945	0.896
	PE2	0.889	0.806	0.884	0.719
	PE3	0.809	0.907	0.954	0.911
SI	SI1	0.860	0.819	0.892	0.733
	SI2	0.911	0.876	0.922	0.798
	SI3	0.908	N/A	N/A	N/A
AU	AU1	0.850	0.885	0.945	0.896
	AU2	0.916	N/A	N/A	N/A
	AU3	0.753	N/A	N/A	N/A

**Table 3. HTMT criterion**

	BI	EE	FC	PE	SI	AU
BI	N/A	N/A	N/A	N/A	N/A	N/A
EE	0.333	N/A	N/A	N/A	N/A	N/A
FC	0.093	0.114	N/A	N/A	N/A	N/A
PE	0.478	0.615	0.096	N/A	N/A	N/A
SI	0.300	0.335	0.220	0.343	N/A	N/A
AU	0.227	0.198	0.080	0.196	0.377	N/A

This study concluded that the convergent validity ( $AVE > 0.5$ ) and discriminant validity ( $HTMT < 1$ ) of the UTAUT constructs, as presented in this study, were established. Therefore, based on the UTAUT model, factors that could influence the youth's adoption of mobile applications for self-healthcare monitoring were performance expectancy, effort expectancy, facilitating conditions, social influence, behavioural intention and use behaviour. Therefore, the first research objective of this study was achieved.

## 5.2 Effects of the Factors on the Adoption of Self-Healthcare Monitoring Mobile Applications

The second research objective identified the effects of the factors identified through the first objective on the adoption of self-healthcare monitoring mobile applications. In PLS-SEM, the structural or inner model represents the causal model. The primary criterion for the evaluation of the causal model is the coefficient of determination ( $R^2$ ). The second criterion is the path coefficient ( $\beta$ ), the third is the predictive relevance ( $Q^2$ ), followed by the Standardized Root Mean Square Residual (SRMR) [50]. The last criterion is to test whether there are any moderating variables. The following sections present the results pertaining to the assessment of these criteria.

### Coefficient of Determination ( $R^2$ )

As shown in Figure 3, the variance of the first endogenous variable (behavioural intention) is 0.203. This means that performance expectancy, effort expectancy and social influence explain 20.3% of the variance in the behavioural intention to adopt self-healthcare monitoring mobile applications. Furthermore, this  $R^2$  value of 0.203 shows that the model derived from this study is good as it explains more clearly the youth's adoption of self-healthcare monitoring mobile applications.

### Path Coefficients ( $\beta$ )

Structural path coefficients are the path weights connecting the model factors to one another ( $\beta$ ). On the first endogenous variable, this study found that performance expectancy (PE) has the strongest effect on behavioural intention (0.355), followed by social influence (0.160). The effects size of effort expectancy and facilitating conditions on the behavioural intention to adopt self-healthcare monitoring mobile applications are 0.070 and 0.059 respectively. Moreover, behavioural intention has the second strongest effect in the model (0.229) on the endogenous variable (use behaviour). The path coefficients  $\beta$  of the model constructs are greater than 0.1 except for effort expectancy (0.070) and facilitating conditions (0.059). Thus, they can be considered as significant.

Using SMARTPLS version 3.2.9, we ran the bootstrapping function as suggested by [53] (Figure 3). The results of the bootstrapping are reported below in Table 4.

**Table 4. Path coefficients**

Hypothesis	$\beta$	T-statistics	P-values	Comments
PE -> BI	0.335	4.51 ***	<0.001	Supported

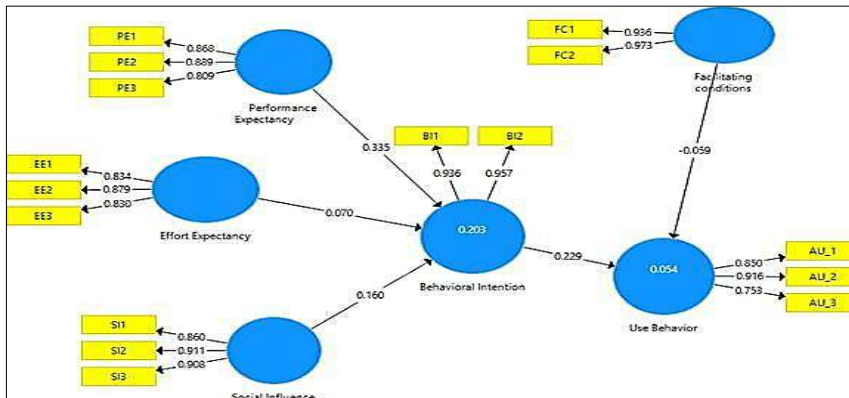
EE -> BI	0.070	0.88	0.38	Rejected
SI -> BI	0.160	2.95***	<0.001	Supported
FC -> AU	0.059	0.66	0.51	Rejected
BI -> AU	0.229	4***	<0.001	Supported

**Predictive relevance (Q<sup>2</sup>)**

The blindfolding function of SmartPLS 3.2.9 was run, following the recommended guidelines [51,53]. The results indicated that performance expectancy, effort expectancy and social influence were highly predictive of the behavioural intention to adopt mobile applications for self-healthcare monitoring with a high Q<sup>2</sup> (0.16). This assertion was based on the argument provided by Garson [53] who reported that a Q<sup>2</sup> value above 0 indicates that a model is relevant to predicting the set factor(s). Behavioural intention also predicted its endogenous latent variable (i.e. use behaviour with a high Q<sup>2</sup> of 0.03). These results for the model prediction were consistent with the threshold reported in the literature (see Table 1).

**Standardized Root Mean Square Residual (SRMR)**

The model fit function of SMARTPLS provided SRMR value of 0.04. An SRMR value of less than 0.08 is deemed adequate [53,54]. Therefore, the model passed the SRMR test.



**Figure 3.** Model results.

## 6 Discussion

This study was designed to establish the determinants of the adoption of self-healthcare monitoring mobile applications in South Africa. In the literature review, the authors found empirical evidence suggesting that performance expectancy, effort expectancy, social influence, facilitating conditions and behavioural intention constructs of the UTAUT framework were determinants of the adoption of mHealth [7, 55]. The results of this study confirmed these findings. As stated by Heeks [56], each (key) stakeholder's behaviour towards the adoption of an Information and Communication Technology for Development (ICT4D) project is important to the success of the project. In the context of healthcare, this means that the behaviour of each stakeholder (such as youth, patients, elders and so on) towards the adoption of mHealth need to be considered in order to convey information that will enable the stakeholder to make informed health-related decisions. In this study, the authors have provided the determinants for the adoption of self-healthcare monitoring mobile applications by the youth; hence, contributing to the understanding of the youth's behaviour towards mHealth adoption in the South African context. Another important finding with regard to the first specific research objective (to establish the factors that can influence the adoption of self-healthcare monitoring mobile applications) is the statistical power of these determinants. The authors argued in the literature review that there is a methodological gap, as a previous similar study conducted in South Africa has used qualitative methods and hence, could not provide statistical value (s) to support the findings. The authors of this paper have filled this gap by providing the Average Variance Extracted (AVE) of each one of the identified determinants. On a practical level, designers of mobile health in general and self-healthcare monitoring mobile applications in particular, should pay attention to these identified determinants.

The second research objective was to identify the effects of these factors on the adoption of self-healthcare monitoring mobile applications. The authors identified that performance expectancy (H1<sub>1</sub>) and social influence (H1<sub>3</sub>) have positive effect on behavioural intention to adopt self-healthcare monitoring mobile applications. Additionally, behavioural intention have a positive effect on use behaviour (H1<sub>5</sub>). However, hypotheses H1<sub>2</sub> (effort expectancy has a positive effect on behavioural intention to adopt self-healthcare monitoring mobile applications) and H1<sub>4</sub> (facilitation conditions have a positive effect on use behaviour) were rejected. The findings concurred with those of Karuri [31] who argued that, in the context of the adoption of District Health Information Systems 2 (DHIS2) in Kenya, performance expectancy and social influence positively affected the health workers' behavioural intention to adopt the DHIS2, and that behavioural intention positively affected the health workers' intention to use the system. Opoku, Scott and Quentin [57] also confirmed these findings in the context of the adoption of teleconsultations in Ghana.

In this study, effort expectancy did not exert a significant effect on behavioural intention to adopt self-healthcare mobile applications probably because the youth were generally conversant with the use of smartphones and mobile applications. Therefore, they generally did not have difficulty using mobile applications. Consequently, effort expectancy did not influence their decision to adopt self-healthcare monitoring applications.

For self-healthcare monitoring mobile applications designers and managers, it is important to concentrate on the content of their applications so that the youth will easily identify the benefits of using such applications. Additionally, it is important that designers and managers devise awareness interventions to encourage the youth to adopt such applications. These awareness programmes may be ran by youth peers who are regarded as role models, as the young people influence one another to adopt mHealth applications.

## **7 Conclusion**

The purpose of this study was to investigate the determinants of the youth's adoption of self-healthcare mobile applications. The study formulated five direct hypotheses, using the UTAUT framework as its underpinning theoretical foundation. The study firstly aimed at establishing the factors that could influence the adoption of self-healthcare monitoring mobile applications. In this regard, it was found that performance expectancy, effort expectancy, facilitating conditions, social influence and behavioural intention were factors that could influence the adoption of self-healthcare monitoring mobile applications. Secondly, this research proposed to determine the effects of the established factors. In this regard, the results suggested that performance expectancy and social influence have a positive and significant effect on behavioural intention while facilitating conditions and effort expectancy did not exert a significant effect. Lastly, the study proposed a model that explained 20.3% of the variance of use behaviour. The proposed model could be used as a guide for the adoption of self-healthcare monitoring mobile applications in South Africa.

All UTAUT factors evaluated in this study are contextual, as they are dependent on the specific context setup. Hence, further inquiries should be done to assess the established factors from this study in other contexts.

## **Acknowledgement**

The authors would like to thank Tom Cyprian Soni for his involvement in the collection of data for this study.



## Definition of Terms

**mHealth:** mHealth is a term that describes the use of wireless technology and mobile devices for medical care.

**Youth:** In this study, the term “youth” refers to people who are within the age range of 18 and 35.

**PLS-SEM:** The Partial Least Squares Structural Equation Modelling (PLS-SEM) is a statistical method that helps determine cause-effect relationships.

**UTAUT:** The unified theory of Acceptance and Use of Technology (UTAUT) is a theoretical framework used in the field of Information Systems (IS) to explain user intentions to use an information system and subsequent usage behaviour.

**Self-Healthcare Monitoring:** Self-Healthcare Monitoring refers to the use of mobile applications and wearable devices to monitor and manage one’s health.

**Heterotrait-Monotrait Ratio (HTMT):** HTMT is a statistical technique used to measure discriminant validity in Partial Least Squares-Structural Equation Modelling.

**Convergent validity:** Convergent validity helps determine whether measures of a construct are related.

**Discriminant validity:** Discriminant validity helps to determine whether measures that should not be related are indeed not related.

**Standardized Root Mean Square Residual (SRMR):** Root Mean Square Residual (SRMR) helps ascertain the mean size of residual correlations.

**The Coefficient of Determination ( $R^2$ ):**  $R^2$  helps determine the variation (s) within the dependent variable caused by independent variables.

**Average Variance Extracted (AVE):** The AVE helps to estimate, on average, the proportion of variation in a construct’s items can be explained by the construct or latent variable.

**Path coefficient ( $\beta$ ):** In PLS-SEM, path coefficient ( $\beta$ ) helps determine how an independent variable affects a dependent variable in the path model.

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