An adoption model of mHealth applications that promote physical activity

Patrick Ndayizigamiye¹, Macire Kante¹* and Shalati Shingwenyana¹

Abstract: Physical activity is one of the ways to promote a healthy and balanced life. There is growing evidence that physical activity can be promoted through the use of mHealth applications. However, the adoption of such applications is influenced by many factors. This study investigated these factors and the relationship among them to propose a model for the adoption of mHealth applications that promote physical activity. The study adopted two theoretical lenses as the guiding frameworks, namely the Diffusion of Innovation Theory and the Unified Theory of Acceptance and Use of Technology. Data were collected from a convenient sample of 140 respondents from South Africa, using a survey questionnaire. The Partial Least Square Structural Equation Modelling (PLS-SEM) was used to assess the proposed model. The results have revealed that awareness, effort expectancy, social influence and behavioural intention account for 35.3% of the variance of the use behaviour towards adopting mHealth applications that promote physical activity in South Africa. Hence, this study recommends that any intervention that...
seeks to promote the adoption of mobile applications to encourage physical activity should consider these factors.

**Subjects:** CAD CAE CAM - Computing & Information Technology; Adventure and Lifestyle Sports; Adoption and Fostering

**Keywords:** mHealth; South Africa; physical activity; UTAUT; DOI

### 1. Introduction

Mobile health (mHealth) applications are increasingly being considered as ways to promote physical activity (or exercise) to prevent non-communicable diseases (NCDs). NCDs are defined as chronic and acute diseases that emanate from a combination of physical, environmental and behavioural factors, constitute the primary causes of deaths in developing countries and account for 51% of all deaths in South Africa (World Health Organization, 2018). Additionally, the youth is increasingly at risk of contracting NCDs due to their unhealthy lifestyles such as smoking, heavy alcohol consumption and lack of regular physical exercise (physical activity) (World Health Organization, 2018).

The increase in the use of mobile phones by the youth globally and in South Africa provides an opportunity to devise interventions to promote healthy lifestyles such as engaging in regular physical exercise. Currently there are many mobile applications that can be used to promote healthy lifestyles among the youth. Such mobile health applications can help their users to exercise regularly or monitor their heart rate, among other things. However, the adoption of such mHealth applications is still limited (Kearney et al., 2012) due to many factors such as lack of awareness of mobile health applications (Kayeali et al., 2017; Krebs & Duncan, 2015), users’ perceptions, lack of or limited access to mobile phones, and lack of skills (Shyh-Chang et al., 2013). Other factors that affect the adoption of mHealth applications include lack of financial resources (Lee et al., 2018) and mHealth literacy (Lin & Bautista, 2017), peer influence (Van Woudenberg et al., 2018), rewards (Müller et al., 2016) and effort expectancy (Ndayizigamiye & Maharaj, 2016). Therefore, it is important to understand these factors and the relationships among them in order to find ways of encouraging the youth to adopt mHealth applications that promote physical activity.

The main objectives of this paper are:

(a) To identify factors that affect the youth’s adoption of mobile health applications that promote physical activity.

(b) To determine the effect of these factors on the adoption of mobile health applications that promote physical activity.

### 2. Conceptual framework and hypotheses development

#### 2.1. Factors affecting the adoption of mHealth applications that promote physical activity

mHealth applications can be classified into two categories: applications designed for disease management and those that support health behavioural change (Helbostad et al., 2017). mHealth applications that promote physical activity fall under the category of behavioural change.

Nevertheless, mHealth applications that promote physical activity have not been widely adopted. For instance, it is argued that the adoption of mHealth applications for physical fitness purposes in Germany is low (Canhoto & Arp, 2017) due to many factors. Canhoto & Arp (2017) explored the factors that support the adoption and sustained use of health and fitness wearables. These factors are context of use (technical infrastructure, observational learning and social expectations), technology user (personal characteristics, previous experience with technology, habits) and technology features and utility (perceived costs, features deemed most useful, utilitarian and
hedonic values). Similarly, Handayani et al. (2018) have identified ease of access, adequate and relevant information, service convenience and top management support as the factors that affect the implementation of mHealth in Indonesia. Additional factors identified in other contexts include perceived usefulness, perceived ease of use, enabling technology (battery lifespan) and compatibility (Dehghani, 2018); the cost (Schall et al., 2018); perceived usefulness and perceived ease of use (Kim & Chiu, 2019); self-efficacy, trust and adventure (Mencarini et al., 2019); awareness and perceptions (Sezgin et al., 2017; Xing et al., 2019) and functionality (Müller et al., 2016; Van Woudenberg et al., 2018).

2.2. Theoretical background

The Unified Theory of Acceptance and Use of Technology (UTAUT) is an information systems (IS) adoption framework with four constructs that influence a user’s behaviour or intention to use a technology (Venkatesh et al., 2003). The four constructs are performance expectancy, effort expectancy, social influence and facilitating conditions. In addition, the UTAUT model has four moderating variables, namely age, gender, experience and voluntariness of use.

The UTAUT model of Venkatesh et al. (2003) draws its constructs from different technology adoption models such as the Technology Acceptance Model (TAM), the social cognitive model and the innovation diffusion theory. Venkatesh et al. (2003) describe performance expectancy as the extent to which an individual believes that a technology will have a positive impact on his/her job. Effort expectancy is defined as the extent to which a technology is easy to use. Social influence is defined as the individual perceptions about what other people think about him/her using a technology. Facilitating conditions refer to the extent to which an individual believes that there is organisation or technical infrastructure to support the use of a technology.

In this study, the UTAUT constructs are defined as follows:

- Performance expectancy refers to the extent to which the youth believe that mobile applications that promote physical activity can assist them to achieve their health-related goals.
- Effort expectancy refers to the youth’s perceptions of the ease of use of mobile applications that promote physical activity.
- Social influence refers to the youth’s perceptions of how others may influence them to adopt mobile applications that promote physical activity.

![Figure 1. The UTAUT model (Venkatesh et al., 2003).](image-url)
Facilitating conditions refer to the extent to which the youth perceive that there are organisations and technical infrastructure to support their adoption of mobile applications that promote physical activity.

Table 1 below provides an overview of the identified empirical factors from the literature and their link to the UTAUT factors. However, the awareness factor could not be linked to the UTAUT model. We then looked at the Diffusion of Innovation Theory (DOI) of Rogers (1995). According to the DOI theory, the decision-making process to adopt an innovation comprises five phases: awareness, attitude formation, decision, implementation and confirmation. Awareness is defined as the extent to which a target population is conscious of an innovation and formulates a general perception of what it entails (Dinev & Hu, 2007; Rogers, 1995). During the awareness stage, the individual is exposed to the existence of the innovation, and is provided with information on how the innovation works and what its benefits are. Therefore, in the DOI theory, awareness is a determinant in the attitude formation phase in the diffusion of an innovation. Awareness was, therefore, extracted from the DOI model and adopted in this paper as depicted in the conceptual model in Figure 2.

The following hypotheses were formulated:

H1. Awareness has a significant positive effect on use behaviour.

H2. Performance expectancy has a significant positive effect on behavioural intention.

H3. Effort expectancy has a significant positive effect on behavioural intention.

H4. Social influence has a significant positive effect on behavioural intention.

H5. Facilitating conditions have a significant positive effect on use behaviour.

H6. Behavioural intention has a significant positive effect on use behaviour.

Figure 2. Conceptual framework.
3. Methods

A survey questionnaire was distributed to a sample of 310 young adults in the Gauteng province of South Africa. Hundred and Forty (140) usable questionnaires were returned which represented a 45% response. The reliability and validity of the research instrument were established through factor analysis. Data were analysed using descriptive statistics (frequency tables, means and standard deviations) using the SPSS Version 25. Thereafter, the Partial Least Square Structural Equation Modelling (PLS-SEM) method was used to assess the relationships among the constructs of the proposed model (conceptual framework) with the aid of the SMARTPLS Version 3.2.9 software. PLS-SEM is regarded as the most fully developed component of structural equation modelling (Henseler et al., 2016). Although the use of PLS-SEM was criticised by Rönkkö et al. (2015), the literature (Hair et al., 2018; Henseler et al., 2014; Henseler et al., 2016) addressed these critics and argued that PLS-SEM is a valid SEM statistical technique which could be used to test hypotheses. Moreover, the literature stated that PLS-SEM could handle small sample sizes such as 21 (Garson, 2016), 30 (Hair et al., 2011) and 100 observations (Kante et al., 2018). Thus, the choice to use PLS-SEM to assess the conceptual model was substantiated by current literature.

PLS-SEM helps to create path models to depict causal sequence (Garson, 2016). It consists of two subsequent models. The first model (inner model) is the structural model while the second model (the outer model) is the measurement model. The structural model displays the relationships among the constructs while the measurement model is used to evaluate the relationships among the indicator variables and their corresponding constructs. Table 1 provides the criteria used for the assessment of a PLS-SEM model.

4. Results

This section presents the research findings and the discussion thereof.

4.1. Demographic information

Most respondents were between the age of 18 to 23 (N = 84, 57.1%), followed by respondents between the age of 24 to 29 (N = 44, 29.9%) and lastly, respondents between the age of 30 to 35 (N = 11, 7.5%). Most of the respondents were females (N = 86, 58.5%) and the male participants were 53 (36.1%). In addition, 62.6% of respondents were students (N = 92), 19% were employed (N = 28), 8.2% were unemployed (N = 12) and 4.8% were self-employed (N = 7). Lastly, 93.2% of respondents indicated that they owned smartphones (N = 137) while 1.4% of respondents did not own smartphones (N = 2).
4.2. Factors that affect the adoption of mHealth applications that promote physical activity (Research objective 1)

The measurement model of PLS-SEM deals with the fundamental question of how one measures the constructs. The answers to this question are provided below through the assessment of the construct validity which is done through the evaluation of convergent validity and discriminant validity. Establishing the convergent and discriminant validity of a latent variable implies that the construct can be a determinant in the model under evaluation (Kante et al., 2018).

4.2.1. Convergent validity

A set of variables, presumed to measure the same construct, shows convergent validity if their inter-correlations are at least moderate in magnitude (Kline, 2013). The following measures have been used to assess the convergent validity: composite reliability (greater than 0.6), Cronbach’s alpha (greater than 0.6), Average Variance Extracted (greater than 0.6) and indicator reliability (greater than 0.6). Table 3 reveals that the constructs of the proposed conceptual framework (Figure 2) have passed these criteria, thus establishing their convergent validity.

4.2.2. Discriminant validity

Discriminant validity depicts the extent to which a construct is empirically distinct from other constructs (Garson, 2016). In other words, the extent to which the construct measures what it is intended to measure. Discriminant validity can be assessed using three methods: the Fornell-Larcker criterion, the cross-loading criterion and the Heterotrait-Menotrait ratio (HTMT) (Hair et al., 2014). However, although cross-loadings and the Fornell-Larcker criterion are accepted methods

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**Table 2. Guidelines for model assessment using PLS-SEM**

| Validity type            | Criterion                  | Description                                                                                   |
|--------------------------|----------------------------|-----------------------------------------------------------------------------------------------|
| Indicator reliability    | Indicator loading > 0.600  | Loadings represent the absolute contribution of the indicator to the definition of its latent variable. |
| Internal consistency reliability | Cronbach’s α > 0.6       | Measures the degree to which the MVs load simultaneously when the LV increases.                |
| Internal consistency reliability | Composite reliability > 0.6 | Attempts to measure the sum of an LV's 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 Q2 > 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           | R² > 0.100                 | Coefficient of determination                                                                 |
| Model validity           | Path coefficients’ critical t-values for a two-tailed test are 1.65 (significance level = 10 percent), 1.96 (significance level = 5 percent) and 2.58 (significance level = 1 percent). | Structural path coefficients are the path weights connecting the factors to one another. |

Adopted from Hair et al. (2019) and Kante et al. (2018).
for assessing the discriminant validity of a PLS model, these methods have shortcomings (Garson, 2016). This is noted by Hair et al. (2014) who argue that the lack of discriminant validity is better detected by the Heterotrait-Menotrait (HTMT) method. Thus, in this study, the HTMT criterion has been used to assess the discriminant validity as depicted in Table 4. The results of this assessment reveal that the discriminant validity of each one of the constructs of the proposed conceptual model is below the threshold value of 1. Hence, their discriminant validity has been established.

As the convergent and discriminant validity of the proposed model constructs have been established, we can argue that the construct validity of the proposed model has also been established. This implies that the awareness, performance expectancy, effort expectancy, social influence, facilitating conditions, behavioural intention and use behaviour constructs are appropriate variables that may have an effect on the adoption of mHealth applications that promote

| Construct        | Item                  | Indcator Reliability | Cronbach's Alpha | Composite Reliability | Average Variance Extracted (AVE) |
|------------------|-----------------------|----------------------|------------------|-----------------------|----------------------------------|
| Awareness        | AW1_Aheard            | 0.58                 | 0.794            | 0.873                 | 0.697                            |
|                  | AW2_Aseen             | 0.73                 |                  |                       |                                  |
|                  | AW3_Aused             | 0.78                 |                  |                       |                                  |
| Behavioural      | BI1_Bfrequent         | 0.64                 | 0.719            | 0.838                 | 0.633                            |
| intention        | BI2_Brecommend        | 0.71                 |                  |                       |                                  |
|                  | BI3_Bnecessary        | 0.55                 |                  |                       |                                  |
| Effort           | EE1_Elearning         | 0.82                 | 0.826            | 0.895                 | 0.741                            |
| expectancy       | EE2_Eusing            | 0.82                 |                  |                       |                                  |
|                  | EE3_Eunderstand       | 0.59                 |                  |                       |                                  |
| Facilitating     | FC3_Fhelp             | 0.76                 | 0.733            | 0.882                 | 0.788                            |
| conditions       | FC4_Ffinancialreso    | 0.82                 |                  |                       |                                  |
| Performance       | PE1_Passist           | 0.77                 | 0.787            | 0.876                 | 0.702                            |
| expectancy       | PE2_Pgoals            | 0.70                 |                  |                       |                                  |
|                  | PE3_Preduce           | 0.64                 |                  |                       |                                  |
| Social           | SI1_Speople           | 0.67                 | 0.838            | 0.891                 | 0.673                            |
| influence        | SI2_Speers            | 0.84                 |                  |                       |                                  |
|                  | SI3_Healthcarepros    | 0.67                 |                  |                       |                                  |
|                  | SI4_Relatives         | 0.52                 |                  |                       |                                  |

| Table 3. Convergent validity assessment results |
|------------------------------------------------|
| Construct                                      | Item                  | Indicator Reliability | Cronbach's Alpha | Composite Reliability | Average Variance Extracted (AVE) |
| Awareness                                     | AW1_Aheard            | 0.58                 | 0.794            | 0.873                 | 0.697                            |
|                                                | AW2_Aseen             | 0.73                 |                  |                       |                                  |
|                                                | AW3_Aused             | 0.78                 |                  |                       |                                  |
| Behavioural intention                        | BI1_Bfrequent         | 0.64                 | 0.719            | 0.838                 | 0.633                            |
|                                                | BI2_Brecommend        | 0.71                 |                  |                       |                                  |
|                                                | BI3_Bnecessary        | 0.55                 |                  |                       |                                  |
| Effort expectancy                             | EE1_Elearning         | 0.82                 | 0.826            | 0.895                 | 0.741                            |
|                                                | EE2_Eusing            | 0.82                 |                  |                       |                                  |
|                                                | EE3_Eunderstand       | 0.59                 |                  |                       |                                  |
| Facilitating conditions                      | FC3_Fhelp             | 0.76                 | 0.733            | 0.882                 | 0.788                            |
|                                                | FC4_Ffinancialreso    | 0.82                 |                  |                       |                                  |
| Performance expectancy                       | PE1_Passist           | 0.77                 | 0.787            | 0.876                 | 0.702                            |
|                                                | PE2_Pgoals            | 0.70                 |                  |                       |                                  |
|                                                | PE3_Preduce           | 0.64                 |                  |                       |                                  |
| Social influence                              | SI1_Speople           | 0.67                 | 0.838            | 0.891                 | 0.673                            |
|                                                | SI2_Speers            | 0.84                 |                  |                       |                                  |
|                                                | SI3_Healthcarepros    | 0.67                 |                  |                       |                                  |
|                                                | SI4_Relatives         | 0.52                 |                  |                       |                                  |

| Table 4. HTMT results                         |
|----------------------------------------------|
| Construct                                    | Aw   | BI   | EE   | FC   | PE   | SI   | UB   |
| Awareness                                    | 0.575|      |      |      |      |      |      |
| Behavioural intention                        | 0.63 | 0.671|      |      |      |      |      |
| Effort expectancy                            | 0.44 | 0.622| 0.496|      |      |      |      |
| Facilitating conditions                      | 0.585| 0.705| 0.738| 0.476|      |      |      |
| Performance expectancy                       | 0.599| 0.853| 0.594| 0.573| 0.756|      |      |
| Social influence                             | 0.583| 0.462| 0.464| 0.372| 0.381| 0.365|      |
physical activity. The following section depicts the extent to which the constructs affect the adoption of mHealth applications that promote physical activity.

4.3. Effects of the factors on the adoption of mHealth applications that promote physical activity

The structural model represents the causal model. The criteria for the evaluation of the model are the coefficient of determination ($R^2$), the path coefficient ($\beta$), the predictive relevance ($Q^2$) and the Standardized Root Mean Square Residual (SRMR). The assessment of these criteria are described in the following sections.

4.3.1. The coefficient of determination ($R^2$)

As shown in Figure 3, the variance of the first endogenous variable (behavioural intention) is 0.543. In other words, performance expectancy (PE), effort expectancy (EE) and social influence (SI) explain 54.3% of the variance in the behavioural intention (BI). Furthermore, behavioural intention, awareness and facilitating conditions (FC) explain 35.3% of the variance of use behaviour.

4.3.2. The path coefficient ($\beta$)

Structural path coefficients are the path weights connecting the factors to each other ($\beta$). On the first endogenous variable, Social Influence has the strongest effect on behavioural intention (0.49) to adopt mHealth applications that promote physical activity, followed by effort expectancy (0.232) and performance expectancy (0.135). On the second endogenous variable (use behaviour), the results reveal that awareness has the strongest effect in the model (0.459), followed by behavioural intention (0.173) and facilitating conditions (0.08). The path coefficient $\beta$ of our entire model’s construct was greater than 0.1 except for facilitating conditions (0.08). Using the SMARTPLS Version 3.2.9 software, we ran the bootstrapping function as suggested by Garson (2016). The results of the bootstrapping are reported in Table 5. As shown in Table 5, four hypotheses are supported while two are rejected.
4.3.3. Predictive relevance ($Q^2$)
The blindfolding function of SMARTPLS Version 3.2.9 software was run following the recommended guidelines. Performance expectancy, effort expectancy and social influence highly predict the behavioural intention to adopt mHealth applications that promote physical activity with a high $Q^2$ (0.315). Behavioural intention, awareness and facilitating conditions also predicted their endogenous latent variable (use behaviour) with a high $Q^2$ (0.326). This assertion was based on the argument provided by Garson (2016) and Kante et al. (2018) who reported that a $Q^2$ value above 0 indicated that a proposed model was relevant.

4.3.4. Standardised root mean square residual (SRMR)
The standardised root mean square residual (SRMR) was run using the SMARTPLS Version 3.2.9 software. The function model fit provided the SRMR value of 0.07. Our model passed this test. According to the literature, an SRMR value of less than 0.08 is deemed adequate (Garson, 2016; Kante et al, 2018).

5. Discussion
In line with the first research objective, it was found that the awareness, performance expectancy, effort expectancy, social influence, facilitating conditions, behavioural intention and use behaviour constructs were appropriate variables that might have an effect on the adoption of mHealth applications that promote physical activity. Prior studies in the same context have also found that awareness influenced the adoption of mHealth applications in Singapore (Wang et al., 2015). Moreover, performance expectancy, effort expectancy, social influence and facilitating conditions had an influence on the adoption of mHealth applications in Bangladesh (Dwivedi et al., 2016).

The second objective of this study was to determine the effect of the variables identified from the first research objective on the adoption of mHealth applications that promote physical activity. The first hypothesis ($H_1$: awareness has a significant positive effect on use behaviour) was supported. This finding was supported by the literature (Krebs & Duncan, 2015; Peng et al., 2016; Wang et al., 2015). Furthermore, the confirmed hypothesis provided a theoretical contribution as the UTAUT model was extended to include the awareness factor as a predictor of the adoption of mHealth applications that promote physical activity in the South African context. The second hypothesis ($H_2$: performance expectancy has a significant positive effect on behavioural intention

| Table 5. Path coefficient |
|-------------------------|
| **β** | **T-statistics** | **P-values** | **Comments** |
| Awareness -> Use behaviour | 0.454 | 6.263*** | 0.000 | Supported |
| Behavioral intention -> Use behaviour | 0.173 | 2.043** | 0.042 | Supported |
| Effort expectancy -> Behavioural intention | 0.232 | 3.364*** | 0.001 | Supported |
| Facilitating conditions -> Use behaviour | 0.082 | 1.023 | 0.307 | Rejected |
| Performance expectancy -> Behavioural intention | 0.135 | 1.535 | 0.125 | Rejected |
| Social influence -> Behavioural intention | 0.49 | 6.363*** | 0.000 | Supported |

Critical t-values for a two-tailed test are 1.65* (significance level = 10 percent), 1.96** (significance level = 5 percent) and 2.58*** (significance level = 1 percent).
to adopt mHealth applications that promote physical activity) was not supported. However, a previous study indicated that performance expectancy had a positive effect on behavioural intention (Hoque & Sorwar, 2017). The study by Hoque and Sorwar (2017) targeted elderly people while the study upon which this paper was based targeted the youth. Hence, an explanation of the fact that H2 was not supported could be that youth behavioural intention to adopt mHealth applications was different from that of the elderly.

The third hypothesis of this study (H3: effort expectancy has a significant positive effect on behavioural intention) was supported in accordance with previous studies (Alan et al., 2018; Dwivedi et al., 2016). The fourth hypothesis (H4: social influence has a significant positive effect on behavioural intention to adopt mHealth applications that promote physical activity) was also supported. Petersen et al. (2019) reported that the lack of social influence (support from family and peers) might be a potential challenge to mHealth adoption in South Africa. This reiterated the preponderant role of social influence in the adoption of mHealth applications in South Africa. The fifth hypothesis (H5: facilitating conditions have a significant positive effect on use behaviour) was not supported. The next hypothesis (H6: behavioural intention has a significant positive effect on use behaviour) was supported which was in accordance with previous studies (Ami-Narh & Williams, 2012; Hoque & Sorwar, 2017; Ndayizigamiye & Maharaj, 2016, 2017; Peng et al., 2016).

6. Conclusion

The primary objective of this paper was to propose a model for the adoption of mHealth applications that promote physical activity from a South African perspective. The paper further provided the determinants of the adoption of such applications. One unexpected finding was that awareness would have an effect on use behaviour in the context of this study.

This study recommends that any intervention that promotes the adoption of mobile applications to encourage physical activity should consider the identified factors.

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Correction

This article has been republished with minor changes. These changes do not impact the academic content of the article.

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