# Determinants of the Adoption of Mobile Applications that Help Induce Healthy Eating Habits

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**Abstract.** A healthy diet is a critical factor that affects long-term healthcare outcomes. One of the ways to induce healthy eating habits is through the use of mobile applications. To date, there has been little agreement on the determinants of the adoption of such mobile applications in the South African context. Hence, this study investigated the determinants of the adoption of mobile applications that help induce healthy eating habits in the South African context. The study adopted a survey research design and the UTAUT framework as the guiding theoretical framework. Data were collected and analysed using the Partial Least Square Structural Equation Modelling (PLS-SEM). Findings revealed that performance expectancy and social influence have a significant effect on the behavioural intention to adopt mobile applications that help induce healthy eating habits. However, effort expectancy does not significantly influence behavioural intention. Additionally, behavioural intention positively influences the use behaviour of such applications while facilitating conditions do not have a significant effect on the use behaviour. This study recommends that interventions geared towards encouraging the use of mobile applications to induce healthy eating habits should focus on the identified determinants.

**Keywords:** mHealth · Diet · Mobile applications · Youth · South Africa · Healthy eating habits · PLS-SEM

## 1 Introduction

A healthy diet is a critical factor that influence long term health outcomes. Claasen, Hoeven and Covic [1] found that the increased consumption of fatty food and food with high sugar content has become a concern among South Africans. Cooper, De Lannoy and Rule [2] further argued that such consumption is one of the major causes of diseases burden among the youth. A study that investigated the determinants of obesity revealed that South Africa has the second highest number of obese women amongst the 22 developing countries that were investigated [3]. In addition, Obesity and being overweight are majorly caused by unhealthy eating habits and can lead to high blood pressure and heart diseases [4]. Furthermore, it was reported that improving the wellness and health


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of the youth is not only important for their present well-being but for the South African economy as they constitute more than half of the South African population [5]. Hence, there is a need for interventions to induce healthy eating habits amongst the youth in South Africa. One of the ways to induce healthy eating habits amongst the youth is the use of mobile health applications. Kante and Ndayizigamiye [5] and Abraham [6] indicated that South Africa is one of the leading global adopters of smartphones, with 93% of South Africans having access to smartphones.

Literature suggests that mobile applications can be used to enhance public healthcare [7–11] and to induce healthy eating habits in particular [12, 13]. Ndayizigamiye and Maharaj [7] reported various mHealth interventions that have been piloted in East Africa. Ndayizigamiye et al. [8] on the other hand provided a proof of concept on how mobile applications can be used to support home-carers in South Africa. Ndayizigamiye and Maharaj [9] conducted a study that identified factors related to the Diffusion of Innovation theory (DOI) that have influence in the adoption of mHealth to provide healthcare services in Burundi. Ndayizigamiye [10] investigated the acceptance of mHealth capabilities in Burundi. Imaja, Ndayizigamiye and Maharaj [11] conducted a study that showed how mHealth can be used to combat Cholera in the Democratic Republic of Congo.

Coughlin et al. [13] studied innovative approaches to encourage healthy eating habits and physical activity in young people. They found that mobile diets and exercise applications can encourage young people to lose weight and keep a healthy diet. In addition, Shin [14] synthesized the literature by reviewing 193 papers on the use of smartphone applications for promoting healthy diet and nutrition. They found that smartphone users preferred quick and easy to run mobile applications that offered them better weight management and suggestions on healthy food intake. The review further identified that the use of mobile applications improved dietary intake of low fat, lower calories and high fibre foods, and also resulted in more physical activities. Moreover, Shin [14] found that having a dietitian support enhances the transition from having an intention to exert a certain behaviour, in this case adopting healthy eating habits, to the actual display of the behaviour, that is eating healthy food. The study concluded that the use of smartphones for photographic dietary tracking is not only convenient, but it increases user engagement as well as healthy eating behaviours.

On the other hand, there is a recognized need to focus on the wellbeing of the youth as they form the crust of the South African productive workforce. Particularly, there is a need to devise innovative interventions to encourage the youth to adopt healthy lifestyles in order to limit the burden of non-communicable diseases among the youth. Van den Berg et al. [15] investigated the lifestyles of South African students that are preparing to undertake a career in healthcare. They found that many of the surveyed students were at risk of getting non-communicable diseases. They also revealed that almost 20% of the surveyed students were obese or overweight. Moreover, they argued that the students had adopted bad eating habits as well as regular alcohol consumption. In the same vein, Van Rensburg and Surujlal [16] found that students (whom the majority are youth) are living unhealthy lifestyles and they have risky behaviours, which have consequences on their future health. The current increase in smartphone penetration amongst the youth in South Africa presents an opportunity to devise healthcare interventions targeting the youth. Particularly, encouraging youth to adopt mobile applications that help induce healthy eating habits could be one of the interventions geared towards inducing healthy lifestyles amongst the youth. Therefore, the objective of this study was to propose an adoption model of mobile applications that help induce healthy eating behaviour amongst the South African youth population.

The specific objectives of the study were to: identify factors that can influence the youth to adopt mobile applications that help induce healthy eating habits; determine the effect of these factors on the adoption of mobile applications that help induce healthy eating habits.

## 2 Literature Review

### 2.1 Determinants of the Adoption of Mobile Health Applications

There are a number of studies that have been conducted regarding the adoption of mobile applications in the healthcare context. For instance, a study by Zhao et al. [17] reviewed papers published between January 1, 2010, and June 1, 2015. They identified user-friendly design, real-time feedback, individualized elements, detailed information, and health professional involvement as the determinants of the adoption of mobile health applications. Similarly, Coughlin et al. [13] found that lack of awareness, negative perception, complexity, lack of customisation and feedback are some of the challenges that restrain young people to use mobile health applications. In addition, Kang [18] reported that mobile applications must be user-friendly so that they can serve their intended purposes. Furthermore, Cho, Park and Lee [19] identified factors related to health information-seeking behaviours that influence the adoption of mobile health applications. More specifically, they found that perceived usefulness and perceived ease of use affect the adoption of mobile health applications.

In the developing countries' context, Alam et al. [20] found that performance expectancy, social influence, effort expectancy, facilitating conditions and perceived reliability have an effect on the adoption of mobile health (mHealth) services in Bangladesh. Similarly, Hoque and Sorwar [21] reported that performance expectancy, effort expectancy, social influence, technology anxiety, and resistance to change also have an effect on the behavioural intention of users to adopt mHealth services in Bangladesh. They further found that facilitating conditions had no significant effect on the users' behavioural intention to adopt mHealth services. In Malaysia, Lan et al. [22] argued that performance expectancy, effort expectancy, social influence and facilitating conditions have a positive effect on the user's intention to adopt a mobile dietary intake monitoring application called vTracker. Moreover, Ndayizigamiye and Maharaj [23] found that effort expectancy, performance expectancy and facilitating conditions are significantly correlated with mHealth adoption in Burundi. In the South Africa's context, Ndayizigamiye et al. [5] found that awareness, effort expectancy and social influence have an effect on the adoption of mHealth applications that promote physical activity. In the same context, Soni, Ndayizigamiye and Kante [24] found that performance and social influence constructs of the UTAUT framework are the highest predictors of the youth's behavioural intention to adopt mobile applications for self-healthcare monitoring purposes. In addition, another qualitative study [25] indicated that results demonstrability; performance expectancy; savings; social aspects; awareness; connectivity; accessibility; ease of use and access; privacy; user satisfaction and affordability are factors that motivate South Africa's youth to adopt self-healthcare monitoring mobile applications.

### 2.2 Effects of mHealth Interventions on Food and Nutrient Intake

Soureti et al. [26] assessed the effects of automated web-based planning tools coupled with mobile text reminders on reducing intake of high-fat foods and food portion sizes in England. The primary outcomes revealed that participants in the intervention group were more likely to report eating balanced diet compared to others that did not partake in the intervention. Beasley et al. [27] on the other hand evaluated the capability of a Personal Digital Assistant (PDA)-based self-monitoring diet program (Diet-MatePro) in the United States of America. Participants in the control group were given a paper-based food diary to record their dietary intake while those in the intervention group were given the PDA-based program. The study recorded that diet adherence was higher among the DietMatePro group (43%) compared to the paper-based diary group (28%) ($p = 0.039$). Kerr et al. (2016) evaluated the effectiveness of tailored dietary text messaging for improving intake of fruit, vegetables and decreasing junk food (unhealthy food or drinks) over a 6-month period. The study findings revealed that men who received dietary feedback only, significantly reduced their energy-dense nutrient-poor (EDNP) intake (mean = 1.4 intake/day, $p = 0.02$) while women who received dietary feedback only, significantly reduced their intake of sugar-sweetened beverages (SSB) (mean = 0.2 intake/day, $p = 0.04$) compared with the participants in the control group. They concluded that the use of mobile technology has great potential for healthy diet and healthy weight promotion amongst young adults.

Vakili et al. [28] evaluated the impact of mobile phone short messaging system on healthy food choices among postmenopausal women in Iran. The study revealed that the consumption of vitamin A rich fruits and vegetables significantly increased in the intervention group compared to the control group ($P < 0.001$). Moreover, more women in the intervention group consumed fish after the intervention ($P = 0.02$). However, there was no significant increase in the consumption of dairy products within the intervention group. However, there was also a noticeable increase, although not significant, in the consumption of green leafy vegetable within the intervention group.

Atienza et al. [29] conducted a randomized study to evaluate the efficacy of using a Personal Digital Assistant (PDA) to increase the intake of whole-grain and vegetables intake in mid-life and older adults within an 8-week period. The study revealed that vegetables intake significantly increased within the participants in the intervention cluster (1.5–2.5 intake/day; $p = 0.02$). Furthermore, a trend towards greater intake of dietary fiber from grains was observed from the participants in the intervention cluster (3.7–4.5 intake/day; $p = 0.10$).

### 2.3 Effects of mHealth Interventions on Weight Loss

Fjeldsoe et al. [30] evaluated the effect of a text message-based (GHSH) intervention (as a follow up strategy) on people who participated in an intensive lifestyle coaching intervention. Two hundred and twenty-eight (228) participants were randomly selected to be either part of the intervention group or control group. Then, the participants were sent text messages for a period of 6 months based on each participant's preference. The outcomes revealed that participants in the intervention group recorded significant body weight loss (−0.89 kg), and a reduction in waist circumference (−1.34 cm). Weight loss was significantly greater in the intervention group than in the control group.

Haapala et al. [31] investigated the effectiveness of a mobile phone-enabled weight loss programme among overweight adults. One hundred and twenty-five overweight (BMI = 26 to 36 $kg/m^2$) adults (25- to 44-year-old) were randomly assigned either to an intervention (experimental) group or non-intervention group. Through text messages, participants in the intervention group (N = 62) who were self-directed dieters, were instructed to report their weight daily and received immediate tailored feedback. The outcomes revealed that participants in the intervention group recorded significant weight loss compared to the control (non-intervention group).

Lin et al. [32] investigated the effects of text messages to support a healthcare intervention for obese African Americans. The study used a randomized controlled trial of 124 adults of which 63 were assigned to the intervention while 61 were assigned to the control group. The intervention group received a standard care and daily tailored text messages for 6 months while the control group received only a standard care. They found that the extent of engagement with the text messages was correlated with weight loss. Participants in the intervention group recorded more weight loss (−2.5 kg after 3 months and −3.4 kg after 6 months) than the control group.

The above literature has revealed that mobile applications are currently used for healthcare purposes. In addition, the literature shows that these applications can help induce healthy habits. Thus, this study seeks to investigate the (potential) of the youth adopting mobile applications that can help induce healthy eating habits in the South Africa's context. The increasing use of smartphones by the youth in South Africa and their proficiency in the use of mobile devices make a good case for such an investigation.

## 3 Theoretical Framework

Ventkatesh et al. [33] developed the Unified Theory of Acceptance and Use of Technology (UTAUT) model by combining various factors from eight prominent technology acceptance theoretical frameworks based on their effectiveness in predicting anticipated and actual Information systems' use behaviour. The 8 theoretical frameworks that were combined to form the UTAUT were: a) the Theory of Reasoned Action (TRA) [34]; b) Davis' Technology Acceptance Model (TAM) and its extended version (TAM2) [35, 36]; c) the Motivation Model (MM) [37]; d) the Theory of Planned Behaviour (TPB) [38]; e) the Combined TAM and TPB [39] f) the Model of PC Utilization (MPCU) [40]; g) Roger's Innovation Diffusion Theory (IDT) [41] h) social Cognitive Theory [42]. The UTAUT framework holds that there are four key constructs that influence user's behavioural intention and use behaviour, namely, 1) performance expectancy, 2) effort expectancy, 3) social influence, and 4) facilitating conditions (see Fig. 1) [36].

### 3.1 Theoretical Propositions

Performance expectancy (PE) is defined as the degree to which an individual believes that using a system will help him or her to attain some gains in the job. In this study,

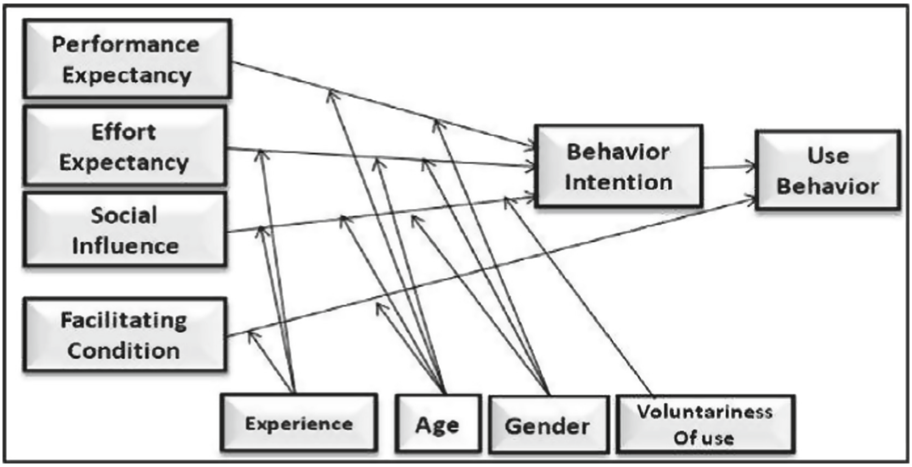


**Fig. 1.** UTAUT framework [36].

performance expectancy is defined as the degree to which an individual believes that using mobile applications will help him/her induce healthy eating habits. Thus, we hypothesized that:

H1$_1$. Performance expectancy positively influences the behavioural intention to adopt mobile applications that help induce healthy eating habits.

Effort expectancy (EE) is defined as the extent to which it is easy to use a system. In the context of this paper, effort expectancy is defined as the extent to which mobile applications that help induce healthy eating habits are easy to use. Hence, in this study we hypothesized that:

H1$_2$. Effort expectancy positively influences the behavioural intention to adopt mobile applications that help induce healthy eating habits.

Social influence (SI) is defined as the degree to which an individual perceives that 'important others' believe he or she should use a new system. This study defines social influence as the degree to which an individual perceives that 'important others' believe he or she should use mobile applications that help induce healthy eating habits. Hence, we hypothesised that:

H1$_3$. Social influence positively influences the behavioural intention to adopt mobile applications that help induce healthy eating habits.

Facilitating conditions (FC) are defined as the degree to which an individual believes that an organizational and technical infrastructure exist to support the use of a system. In this study, the 'facilitating conditions' construct is defined as the availability and access to the necessary resources and knowledge (skills) to support the use of mobile applications that help induce healthy eating habits. We, therefore, argued that:

H1$_4$. Facilitating conditions positively influences the behavioural intention to adopt mobile applications that help induce healthy eating habits.

Based on the relationship between behavioural intention and use behaviour in the UTAUT framework, we further hypothesized that:

$H1_5$. Behavioural intention positively influences the use of mobile applications that help induce healthy eating habits.

# 4 Material and Methods

Data were collected from 89 respondents conveniently sampled from an institution of higher learning in the Gauteng province of South Africa. The study adopted a 5-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree) survey questionnaire as the data collection instrument. Respondents were requested to fill the questionnaires and return them to enumerators. Data were analysed using the Partial Least Square Structural Equation Modelling (PLS-SEM). Partial Least Square Structural Equation Modelling (PLS-SEM) can be used to analyze a small sample size (20 or more respondents) [43–45].

Basic statistical analyses were conducted using SPSS version 20 to identify and deal with missing values and ascertain the multivariate normality. The analysis of missing values revealed that there were 5 questionnaires with a low response rate (missing values higher than 5%), and therefore they were excluded from further analysis as per Carter [46] suggestions. For those responses where the missing values were less than 5%, we applied the mean replacement technique [46]. The multivariate normality was tested through the skewness and kurtosis statistical tests as reported in Table 1. The values of skewness and kurtosis should be between ±1 [47]. However, the distribution of the data collected in this study was not within these acceptable values, indicating a non-normal distribution. However, it is possible to use PLS path modelling with highly skewed data [45] as all Structural Equation Modelling (SEM) techniques are quite robust against the skewness scenario [44].

Thereafter, we applied the Partial Least Square Structural Equation Modelling (PLS-SEM) technique using SMARTPLS 3.2.9 software to assess the UTAUT model. PLS-SEM helps to create path models to depict causal sequence [44]. PLS-SEM comprises two models, namely the inner model, or structural model, and the measurement model. The inner model displays the relationships between the constructs, while the outer model, also known as the measurement model, is used to evaluate the relationships between the indicator variables and their corresponding constructs [45]. Table 2 explains the criteria used for the PLS-SEM model assessment.

# 5 Results and Discussion

This section discusses the results of the study.

## 5.1 Demographics Information of the Participants

All participants were between the age of 18 and 35. Hence, they could be categorised as youth according to the South African National Youth Commission Act of 1996 which defines the South African youth as people who are aged between 14 years and 35 years [49]. Most of the participants were females (52.8%).

**Table 1.** Statistical analysis of the variables

| UTAUT constructs | Item | Mean | Std. deviation | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|---|
| | | | Statistic | Statistic | Std. error | Statistic | Std. error |
| Performance expectancy | Using mobile applications that help induce healthy eating habits will increase my chances of achieving my diet targets | 3.46 | 0.83 | −0.14 | 0.26 | 0.14 | 0.52 |
| | Using mobile applications that help induce healthy eating habits can help monitor my eating habits | 3.70 | 0.77 | −0.71 | 0.26 | 1.19 | 0.52 |
| | Using mobile applications that help induce healthy eating habits can improve my wellbeing | 3.75 | 0.80 | −0.51 | 0.26 | 0.75 | 0.52 |
| Effort expectancy | It is easy to learn how to use mobile applications that help induce healthy eating habits | 3.71 | 0.72 | −0.10 | 0.26 | −0.20 | 0.52 |
| | I understand how mobile applications that induce healthy diets work | 3.48 | 1.01 | −0.29 | 0.26 | −0.51 | 0.52 |
| | It is easy to use mobile applications that help induce healthy eating habits | 3.59 | 0.88 | −0.23 | 0.27 | −0.03 | 0.53 |
| Social influence | People who are important to me can influence me to use mobile applications that induce healthy eating habits | 3.32 | 1.09 | −0.10 | 0.26 | −0.80 | 0.52 |
| | People who influence my behaviour can influence me to use mobile applications that help induce healthy eating habits | 3.52 | 0.96 | −0.07 | 0.26 | −0.56 | 0.52 |
| | People whose opinions that I value can influence me to use mobile applications that help induce healthy eating habits | 3.68 | 0.91 | −0.40 | 0.26 | 0.38 | 0.52 |

(*continued*)

**Table 1.** (*continued*)

| UTAUT constructs | Item | Mean | Std. deviation | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|---|
| | | | Statistic | Statistic | Std. error | Statistic | Std. error |
| Facilitating conditions | I have the necessary resources to use applications that help induce healthy eating habits | 3.21 | 1.13 | −0.23 | 0.26 | −0.58 | 0.52 |
| | I have the required knowledge to use applications that induce healthy eating habits | 3.36 | 1.04 | −0.37 | 0.26 | −0.36 | 0.52 |
| | Applications that help induce healthy eating habits are compatible with the technologies I use | 3.45 | 0.88 | −0.28 | 0.26 | −0.24 | 0.52 |
| | I can get help from others when I have difficulties using mobile applications that help induce healthy eating habits | 3.54 | 0.83 | −0.38 | 0.26 | −0.43 | 0.52 |

## 5.2 Factors that Can Influence the Youth to Adopt Mobile Applications that Help Induce Healthy Eating Habits

Factors that can influence the youth's adoption of mobile applications that help induce healthy eating habits were identified using the measurement model of PLS-SEM. A latent variable can be a determinant only if its construct validity (convergent and discriminant validity) is established. Using, SMARTPLS software, we assessed the convergent and discriminant validity of the variables.

### 5.2.1 Convergent Validity

To establish convergent validity, a factor should be unidimensional [50]. A set of variables (factors) presumed to measure the same construct shows convergent validity if their inter-correlations are at least moderate (AVE > 0.5) in magnitude [44]. The Cronbach's Alpha (must be greater than 0.6), the Composite Reliability (must be greater than 0.6) and the Average Variance Extracted (AVE must be greater than 0.5) are reported below in Table 3. As reported in Table 3, all factors within each construct met the recommended threshold. Thus, the convergent validity was established for all the constructs.

### 5.2.2 Discriminant Validity

Discriminant validity represents the extent to which a construct is empirically distinct from other constructs [44, 45]. Although there are many ways to measure the discriminant validity, however, the Heterotrait-Menotrait (HTMT) Ratio is the recommended way to

**Table 2.** Guidelines for using PLS-SEM [44, 45, 48]

| Type of 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%),1.96 (significance level = 5%), and 2.58 (significance level = 1%) | Structural path coefficients are the path weights connecting the factors to one another |

validate the discriminant validity [44, 50, 51]. The results of the HTMT test are reported in Table 4. From Table 4, it can be concluded that the discriminant validity is established for all the UTAUT constructs (HTMT < 1).

**Table 3.** Results of the convergent validity assessment

| | Cronbach's alpha | Composite reliability | Average variance extracted (AVE) |
|---|---|---|---|
| Behavioural intention | 0.497 | 0.795 | 0.661 |
| Effort expectancy | 0.8 | 0.875 | 0.702 |
| Facilitating conditions | 0.544 | 0.814 | 0.686 |
| Performance expectancy | 0.796 | 0.877 | 0.706 |
| Social influence | 0.852 | 0.908 | 0.767 |
| Use behaviour | 1 | 1 | 1 |

**Table 4.** HTMT results

| | Behavioural intention | Effort expectancy | Facilitating conditions | Performance expectancy | Social influence | Use behavior |
|---|---|---|---|---|---|---|
| Behavioural intention | | | | | | |
| Effort expectancy | 0.42 | | | | | |
| Facilitating conditions | 0.29 | 0.64 | | | | |
| Performance expectancy | 0.56 | 0.62 | 0.43 | | | |
| Social influence | 0.71 | 0.33 | 0.56 | 0.42 | | |
| Use behaviour | 0.72 | 0.11 | 0.15 | 0.13 | 0.09 | |

Since the convergent validity and discriminant validity of effort expectancy, performance expectancy, social influence, facilitating conditions, behavioural intention and use behaviour were established, we can conclude that they constitute valid latent variables that can affect the adoption of mobile applications that help induce healthy eating habits.

### 5.3 Determinants of the Adoption of Mobile Applications that Help Induce Healthy Eating Habits

The coefficient of determination ($R^2$), the path coefficient (β), and the Predictive relevance ($Q^2$) are the criterion used to evaluate the causal model of the Structural Equation Model [45]. The results of the assessment of these criteria are reported below.

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

R-square ($R^2$), also known as the coefficient of determination is the overall effect size measure for the structural model. Figure 2 shows the model explains 27.4% of the variance of the behavioural intention (BI) to adopt mobile applications that help induce healthy eating habits. Garson [44] argues that an $R^2$ within the range of 0.67, 0.33 and 0.19 is "substantial", "moderate" and "weak" respectively. Hence, the $R^2$ of our model is considered to be of moderate strength.

### 5.3.2 Path Coefficient (β), and $Q^2$

Structural path coefficients (loadings), illustrated in the path diagram (Fig. 2), are the path weights connecting the factors to each other [45]. The path coefficients should be between 0 and 1 [44]. In our model, social influence has the strongest effect on the first endogenous variable (behavioural intention) with a value of 0.389, followed by performance expectancy (0.181) and effort expectancy (0.08). The effort expectancy construct, although it has the lowest effect in the model was maintained as its construct validity was established and is within the rage of 0 and 1. In addition, the behavioural intention construct has the strongest effect (0.522) on use behaviour. However, the 'facilitating conditions' construct did not have any significant effect on use behaviour.

We ran the blindfolding function of SmartPLS 3.2.9 and we determined that the $Q^2$ of the first dependent variable (behavioural intention) was 0.144 and hence greater than the threshold of 0. Additionally, the second dependent variable (use behaviour) had a $Q^2$ value of 0.249. As these values are all above 0, therefore, as recommended by Garson [44], we argued that our model predicted the adoption of mobile health applications that help induce healthy eating habits.

### 5.3.3 Hypotheses Validation and Discussion

The first hypothesis $H1_1$: Performance Expectancy -> Behavioural Intention was supported. This means that the degree to which an individual believes that using mobile applications will help him/her induce healthy eating habits influence the behavioural intention to adopt these applications. This finding concurs with Alan et al. [20] who found that performance expectancy had an impact on the behavioural intention towards the adoption of mobile health applications in Bangladesh. The second hypothesis $H1_2$: Effort Expectancy -> Behavioural Intention was rejected. This can be explained by the fact that youth are proficient in the use of smartphones. This means that effort expectancy may not have an influence on them as they will find it naturally easy to adopt mobile applications that help induce healthy eating habits. The third hypothesis $H1_3$: social Influence -> Behavioural Intention was supported, meaning that the degree to which an individual perceives that 'important others' believe he or she should use mobile applications that help induce healthy eating habits influence the behavioural intention to adopt these applications. This finding concurs with Neill et al. [52] who found that social influence affects the behavioural intention to adopt wearable technologies in healthcare. $H1_4$: Facilitating Conditions -> Use Behaviour was rejected. Similarly, Hoque and Sorwar [21] reported that facilitating conditions did not have a significant effect on the behavioural intention to adopt mobile health applications. Our last hypothesis argued that behavioural intention positively influences use behaviour, which was supported. In our model, behavioural intention affects significantly the adoption (use behaviour) of mobile applications that help induce healthy eating habits. Table 5 displays the confirmed and rejected hypotheses of the model.

**Table 5.** Hypotheses validation

| Hypothesis | Path coefficient (β) | T statistics | Model |
|---|---|---|---|
| **H1$_1$.** Performance expectancy -> behavioural intention | 0.181 | 1.753* | Supported |
| **H1$_2$.** Effort expectancy -> behavioural intentions | 0.079 | 0.79 | Rejected |
| **H1$_3$.** Social influence -> behavioural intentions | 0.389 | 3.514*** | Supported |
| **H1$_4$.** Facilitating conditions -> Use behaviour | 0.035 | 0.362 | Rejected |
| **H1$_5$.** Behavioral intentions -> Use behaviour | 0.522 | 6.096*** | Supported |

Critical t-values for a two-tailed test are 1.65* (significance level = 10%), 1.96** (significance level = 5%), and 2.58*** (significance level = 1%).

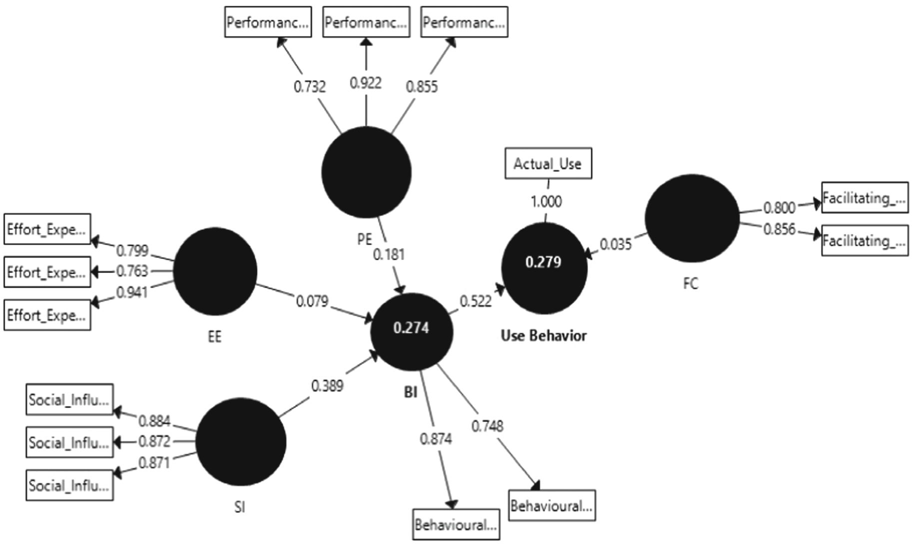


**Fig. 2.** Model results

## 6 Conclusion

This study identified factors that influence the adoption of mobile applications that help induce healthy eating habits. In addition, the study determined the effect of these factors on the adoption of these applications. The study concluded that performance expectancy and social influence have a positive and significant effect on the behavioural intention to adopt mobile applications that help induce healthy eating habits while effort expectancy does not exert a significant influence on behavioural intention. In addition, facilitating conditions do not have a significant effect on use behaviour of these applications. Behavioural intention on the other hand, has a significant and positive influence on use behaviour.

Hence, the study advocates that interventions geared towards encouraging the use of mobile applications to induce healthy eating habits should focus on the performance expectancy and social influence factors as this study determined that they exert a significant effect on the behavioural intention to adopt these mobile applications. However, these findings cannot be generalised due to the small sample size. Additionally, we did not test the moderating variables of the UTAUT model. Future research should investigate the adoption of mobile applications that help induce healthy eating habits using a much more representative sample. Moreover, it is suggested that an extended study should be carried out to identify the effect of the moderating variables of the UTAUT framework on the adoption of mobile applications that help induce healthy eating habits.

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