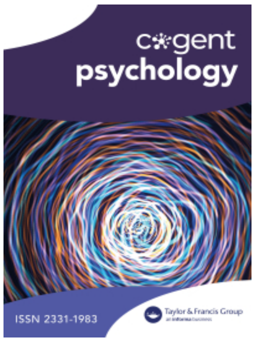

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Psychosocial predictors of downloading a mobile app promoting healthy and sustainable eating

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ABSTRACT

To reduce the environmental impact of food production has spurred the development of digital tools to promote sustainable eating, yet little research examined the psychosocial predictors of their adoption. This study addresses this gap by applying the Unified Theory of Acceptance and Use of Technology, including performance expectancy, effort expectancy, social influence, and facilitating conditions as predictors of technology use. To enhance the model's predictiveness, we included variables from the Model of Goal-Directed Behavior—attitude, anticipated emotions, and desire— as well as sociodemographic factors. 511 participants completed an online survey in which they evaluated a customized app designed to promote sustainable eating. Results showed that performance expectancy was the strongest predictor of attitude, anticipated emotions, and intention, whereas effort expectancy was not. Social influence and facilitating conditions predicted desire, which in turn predicted intention, and thus led to app download. Facilitating conditions and emotions were more influencial for women, older participants showed a higher desire despite high effort expectation, and those with higher education levels downloaded the app more due its perceived ease of use. These findings suggest that developers should focus on enhancing the emotional appeal and perceived value of the app while addressing the users' diverse needs based on gender, age, and education.

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1. Introduction

Current dietary habits, especially in Western societies, significantly impact the environment and health (Clark et al., 2020). Modern diets contribute to biodiversity loss, water scarcity, and climate change (Smith & Gregory, 2013). In addition, obesity and diet-related diseases represent a significant economic and social burden (Benthem de Grave et al., 2024). Despite these threats, sticking to a healthy and sustainable diet in the long term is challenging, especially without continuous and individualized support (Werner & Risius, 2021).

To overcome these challenges, experts have developed various digital tools, such as mobile apps for tracking dietary habits (Chen et al., 2017), which improve dietary interventions through quick access to information and interactivity (Benajiba et al., 2022). These tools can support healthy dietary choices by tailoring content to individual needs (Hebden et al., 2014) and presenting it in a meaningful way (David & Weinstein, 2024). While many studies have investigated the effectiveness of diet apps that focus on weight loss or healthy eating (Kay et al., 2022), there is a gap in research on apps designed to promote sustainable eating and there are no studies that have investigated user motivation to use them. In particular, there is a lack of a comprehensive model specifying the main antecedents and psychosocial processes explaining the choice to download and use an app aimed at promoting healthy and sustainable diets. To address this gap, we developed a customized app to promote healthy and sustainable eating, and then examined the key psychosocial predictors that determine users' initial engagement with the app, which is

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a crucial aspect for subsequent use (Delaney et al., 2021). Considering the lack of theoretical models specifically developed to explain technology acceptance in the field of pro-environmental behaviors, we integrated two theoretical approaches. To explore these psychosocial predictors, we referred to the UTAUT (Venkatesh et al., 2003), which is widely used in the field of technology acceptance, as our theoretical background. In addition, we integrated it with the Model of Goal-Directed Behaviour (MGB; Perugini & Bagozzi, 2001), which is used in the fields of health and environmental protection. This integration provides the opportunity to include both users' attitudes towards app use and two important measures of hedonic motivation, namely desire and anticipated emotions. This study is the first attempt to test this model integration to provide a theoretical framework that might be valuable for future study on the subject, by simultaneously investigating the role of technology-related (performance expectancy, effort expectancy) external (facilitating conditions and social influence) and individual factors (attitudes, hedonic motivation, emotions, desire) in predicting the mobile app download.

2. Theoretical background

2.1. The Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) is an important framework for understanding individuals' adoption and use of technologies. It is derived from the Technology Acceptance Model (TAM; Davis et al., 1989), which posits that perceived usefulness (i.e. the belief that using a technology will improve performance), and perceived ease of use (i.e. the belief that using a technology is effortless) influence people's intentions to use a technology, which in turn predicts actual use. The UTAUT builds on these constructs from the TAM and renames them *performance expectancy* and *effort expectancy*. In addition, two other variables: *social influence* and *facilitating conditions* (Kim & Lee, 2022), are introduced as predictors of behavioral intentions to use technology. Social influence refers to the perception that significant others believe they should use the technology (Venkatesh et al., 2003). Facilitating conditions represent perceptions of available internal and external resources that facilitate technology use (Venkatesh et al., 2003). A study using the UTAUT model found that performance expectancy explained most of the variance in technology adoption decisions (Tamilmani et al., 2019), with extrinsic motivation triggered by external benefits and practical advantages (Dwivedi et al., 2014). However, regardless of external rewards, intrinsic motivation, which involves engagement driven by hedonic motivation, was found to be crucial. This construct, defined as the fun or pleasure derived from using technology, directly influences technology adoption and use (e.g. Brown & Venkatesh, 2005; van der Heijden, 2004). Accordingly, Venkatesh et al. (2012) extended the UTAUT to include hedonic motivation. However, despite its importance, several scholars have not integrated hedonic motivation into their research. As the systematic review and meta-analysis by Tamilmani et al. (2019) shows, only 58% of the 79 UTAUT studies included this construct.

2.2. Integration of the goal-directed behaviour model

The Model of Goal-directed Behavior (MGB) is widely used to predict healthy and pro-environmental behavior and has been widely used in studies on healthy and sustainable eating (Chen, 2022; Nascimento & Loureiro, 2024). It has also been used in some technology acceptance studies (Schuster et al., 2013; Thomas-Francois et al., 2023). The integration of the MGB into the UTAUT can enrich it in two respects. The first advantage regards the inclusion of attitude, which is a psychological tendency expressed by evaluating a particular entity with some degree of favor or disfavor (Eagly & Chaiken, 1998). Analyzing attitudes toward app use enhances understanding of how beliefs, particularly performance expectancy and effort expectancy, influence intentions by considering how individuals evaluate the app as useful, positive and favorable for them. Therefore, we examined the impact of performance expectancy and effort expectancy on attitude towards the app (Kim & Kankanhalli, 2009; Thomas et al., 2013). The second advantage of integrating the MGB model into the UTAUT model regards the introduction of the concept of anticipated emotions, which are defined as the affective response that a person experiences when imagining or predicting future events or the consequences of possible actions (Baumgartner et al., 2008). These emotions influence a person's decision-making process regarding the performance of the behavior (in our case, the use of the app). In addition, anticipated emotions are particularly meaningful when it comes to the adoption of healthy and environmentally friendly behaviors, especially in the area of nutrition (Carfora et al., 2022a; Xu & Guo, 2019). These emotions are expected to influence desire and complement the variables that measure more rational and extrinsic aspects as well as intention. The MGB also includes desire, which is defined as a state of mind in which a person is personally motivated to perform an action or achieve a goal. In the MGB, desire is considered the most immediate determinant of intention, emphasizing its crucial role in the motivational hierarchy (Leone et al., 2004; Perugini & Bagozzi, 2001). In our study, we expected that desire would be a mediator between the predictors of intention (performance expectancy, effort expectancy, social influence, and facilitating conditions) and intention to use the app.

2.3. Controlling for the effect of sociodemographic variables

Finally, we examined the predictive role of sociodemographic factors (i.e. age, gender and education). Several studies highlight the importance of these factors for technology adoption (e.g. Acheampong et al., 2018; Chen et al., 2024). For example, older people find new technologies less useful compared to younger people (Vahdat et al., 2021). Younger individuals show greater satisfaction and perceived usefulness with mobile shopping apps than older adults (Natarajan et al., 2018). Several factors influence the acceptance of mobile healthcare technologies among older people (Murugesh-Warren et al., 2015). Men prefer fitness applications, while women prefer applications related to nutrition, self-care, and reproduction (Wang & Qi, 2021). In terms of education, higher educational attainment is positively related to technology friendly attitudes, favorability towards environmental considerations and collaborative consumption (Wali & Khattak, 2022). However, no study has systematically considered the effect of these sociodemographic variables on all predictors analyzed in this study. Specifically, there is a lack of research on how these sociodemographic predictors affect users' anticipated emotions and desire to use an app promoting healthy and sustainable eating.

3. The present study

Considering the above literature, we investigated whether the variables of the UTAUT model (i.e. performance expectancy, effort expectancy, social influence, and facilitating conditions) can be integrated with those of the MGB model (i.e. attitude, anticipated emotions and desire) to increase the predictive power of the model regarding the intention to use and download an app, while also controlling for sociodemographic factors. The integrated model tested is shown in Supplementary Materials (Figure 1).

Previous studies have found that performance expectancy and effort expectancy positively influence intention to use technology (e.g. Do Nam Hung et al., 2019; Fadzil, 2018; Venkatesh et al., 2003). In addition, several UTAUT studies found that social influences and facilitating conditions increase the intention to use technology (Kim & Lee, 2022; Palau-Saumell et al., 2019). Finally, several researchers have shown that people's intention to use an app determines its download (e.g. Palau-Saumell et al., 2019; Venkatesh et al., 2012).

On this basis, in the present study we expected that:

H1a: Performance expectancy is positively associated with intention to use an app.

H1b: Effort expectancy is positively associated with intention to use an app.

H1c: Social influence is positively associated with intention to use an app.

H1d: Facilitating conditions are positively associated with intentions to use an app.

H1e: Intention to download the app has a direct positive effect on app download.

In several previous studies, performance expectancy and effort expectancy have been shown to positively influence attitudes towards app use (Kim & Kankanhalli, 2009; Thomas et al., 2013). Furthermore, MGB studies have extensively confirmed that attitude influences desire (Nascimento & Loureiro, 2024; Qiao et al., 2021). Similarly, TAM, MGB, and UTAUT studies have shown that attitude predicts people's intention to engage in a particular behavior. Therefore, in this study we expected that:

H2a: Performance expectancy is positively associated with attitude towards using the app.

H2b: Effort expectancy is positively associated with attitude towards using the app.

H2c: Positive attitude towards using the app is positively associated with desire to use the app.

H2d: Positive attitude towards using the app is positively associated with intention to use the app.

So far, no study has explicitly investigated the effect of performance expectancy and effort expectancy on anticipated emotions. However, there is scientific evidence that the emotional dimensions

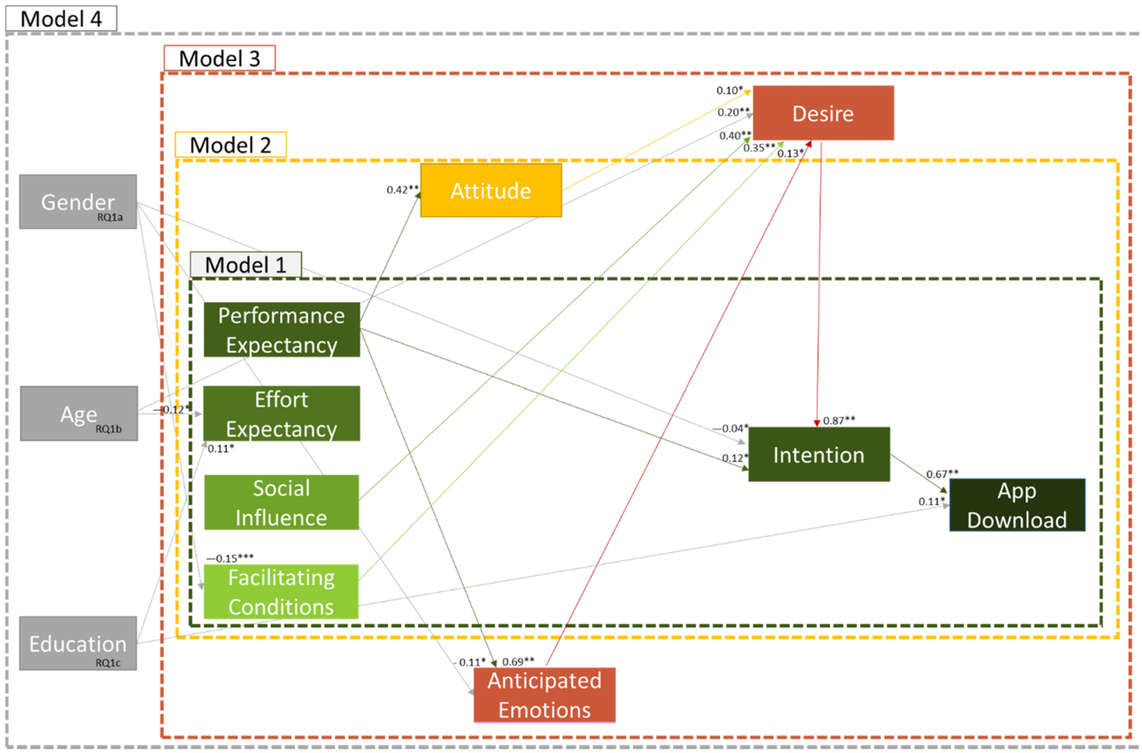

Figure 1. Results of the integrated UTAUT regarding App Download.

influence technology acceptance, such as perceived satisfaction (e.g. Singh, 2005).

H3a: Performance expectancy is positively associated with anticipated emotions related to using the app.

H3b: Effort expectancy is positively associated with anticipated emotions related to using the app.

Similarly, MGB studies have shown that social influences (defined as subjective norms in MGB) and facilitating conditions (defined as perceived behavioral control in MGB) predict desire to adopt recommended behaviors (Perugini & Bagozzi, 2001; Shiu et al., 2008). Therefore, we expected that:

H3c: Social influence is positively associated with desire to use the app.

H3d: Facilitating conditions are positively associated with users' desire to use the app.

According to MGB (Perugini & Bagozzi, 2001) and extended TPB models (Carfora et al., 2022a, 2022b, 2022c), anticipated emotions influence people's desire to perform a behavior and the associated intention. However, few studies have examined these relationships in the context of technology adoption and app download (Ding, 2018, Verkijika, 2020, 2021), although research on innovation adoption emphasizes the emotional role in the decision-making process (e.g. Loewenstein & Lerner, 2003; Valor et al., 2022). Therefore:

H3e: Anticipated emotions related to using the app are positively associated with desire.

H3f: Anticipated emotions related to using the app are positively associated with intention to use the app.

According to the MGB (Perugini & Bagozzi, 2001), a person's desire to engage in a behavior increases intention to perform it.

H3g: Desire to download the app is positively associated with intention to download the app.

We also tested the following mediating paths.

H1f: Perceived expectancy has an indirect positive effect on app download via attitude, then desire, and finally intention.

H1g: Perceived expectancy has an indirect positive effect on app download through anticipated emotions, then desire, and then intention.

H2e: Effort expectancy has an indirect positive effect on app download through attitude, then desire, and then intention.

H2f: Effort expectancy has an indirect positive effect on app download through anticipated emotions, then desire, and then intention.

H3g: Social influence has an indirect positive effect on app download via desire, and then intention.

H4c: Facilitating conditions have an indirect positive effect on app download through desire, and then intention.

H5c: Attitude has an indirect positive effect on app download through desire, and then intention.

H6c: Anticipated emotions have an indirect positive effect on app download through desire and then intention.

The final aim of our study was to determine whether the psychosocial factors considered to influence the app download were related to sociodemographic factors such as gender, age, and education. As there is little literature on the specific pathways from sociodemographic variables to the psychosocial factors considered, we did not make specific hypotheses but posed the following Research Question (RQ).

Are gender (**RQ1a**), age **(RQ1b)**, and education **(RQ1c)** associated with the psychosocial factors associated with the app use and its download?

4. Methods

4.1. Sample and procedure

This paper is part of a broader research project funded by European Union – NextGenerationEU, Ministero dell'Università e della Ricerca, Italiadomani – Piano nazionale di ripresa e resilienza (grant number CUPD53D23020480001), aimed at testing the effectiveness of digital tools in promoting adherence to healthy and sustainable diets, particularly the Mediterranean diet. Ethical approval for this study was obtained from the International University of Rome (ID 01/2024 – 18/04/2024). We first ran a statistical power analysis to determine the required sample size. Using A-priori Sample Size Calculator for Structural Equation Models (Soper, 2024), we conducted a sample size estimation considering an anticipated small effect size (ES = .20) (Cohen, 1988; Westland, 2010). With power = 0.80, number of latent variables = 8, number of observed variables = 30, and p = .05, the recommended minimum sample size was N = 444. We increased the sample size by at least 5%, resulting in an initial minimum sample of 466 participants, to account for the potential loss of subjects due to incomplete or incorrectly completed questionnaires.

A total of 511 participants completed the questionnaire correctly and completely (59.1% women; 39.3% men; 0% non-binary; 1.6% = preferred not to disclose this information; mean age = 28.92; SD = 12.80; age range = 18–76). Regarding the educational level of the participants, 4.5% had completed compulsory education, 61.6% had a high school diploma, and 33.5% had a university degree. The characteristics of our sample differed in part from those of the general Italian population. Compared to our sample, the national gender distribution is more balanced (51.1% women and 48.9% men), the national average age is higher (about 46.5 years) and the educational level is lower (37% had completed compulsory education; 42% had a high school degree, 21% had a university degree) (ISTAT, 2023).

The data were collected using the Prolific platform. Participants were informed that the study aimed to investigate the psychosocial factors related to the use of digital technologies. Participants were provided with privacy information and asked to sign an informed consent form if they intended to participate in the research. At the beginning of the questionnaire, all participants read a description of the app functionality ('This app provides information on the characteristics of a healthy and sustainable diet, a food diary to track food choices, goal setting for a healthy and sustainable eating style, and feedback on personal progress. The app can customize all this content to your preferences and characteristics'). In addition, participants were able to see some sample screenshots of the app's features to better visualize the features it offers and, in this way, provide a more valuable and realistic contribution to the research (see Supplementary Materials). A control question was included to check the reliability of participants' answers.

4.2. Measures

The measures of the study were taken from previous studies (Min et al., 2021; Perugini & Bagozzi, 2001; Wu et al., 2022). *Performance expectancy, effort expectancy, social influence, anticipated emotions, desire* and *intention* were measured with 3 items. *Facilitating conditions* were measured with 5 items. All were rated on a 7-point Likert scale ranging from 'Strongly disagree' (1) to 'Strongly agree' (7). *Attitude* was measured with 3 items using a bipolar 7-point matrix table. The *app download* was measured with the item 'After completing the questionnaire, I would like to be redirected to the app download page… no (0) – yes (1)'. Finally, participants indicate their gender (women = 1; men = 2; non-binary = 3; prefer not to specify = 4), age and level of education (compulsory schooling = 1; high school diploma =2; bachelor's degree = 3; master's degree = 4). The standardized factor loadings of each item, Cronbach's α, composite reliability, and average variance extracted (AVE), positive square root of the AVE are shown in Table 1.

4.3. Data analysis

In the preliminary analyses, we ran descriptive statistics on each study variable (Table 2).

Then, we used a mix of path analysis and confirmatory factor analysis, called a hybrid model (Hancock & Samuelsen, 2007), to test our H1- H6 and our RQs. This model includes a combination of latent and observed variables, with app download treated as a categorical observed variable (binary outcome). While the data follows a normal distribution, the complexity of the model, which incorporates both latent constructs and a binary outcome variable, led us to select the MLR (Maximum Likelihood with Robust standard errors) estimator. MLR is particularly suitable for handling such complex structural equation models with a mixture of variable types. To verify the internal consistency among the measurement items for each latent variable, we used composite reliability. We also tested convergent and discriminant validities of our data. The overall fit of the tested models was assessed using the following goodness-of-fit indices: comparative fit index (CFI), Tucker-Lewis fit index (TLI), and Root Mean Square Error of Approximation (RMSEA). CFI and TLI values greater than 0.90 are considered acceptable for the model, while a RMSEA value of less than 0.05 indicates a good fit (Byrne, 2001; Hu et al., 1992). Model 1 estimated the association between performance expectancy, effort expectancy, social influence, facilitating conditions, intention and app download. Model 2 tested the associations of Model 1 plus those related to attitude. Model 3 tested the associations of Model 2 plus those related to anticipated emotions and desire. Model 4 tested the associations among all considered psychosocial and sociodemographic factors (Figure 1). Comparisons between the models were conducted by considering the first model as a nested model of the subsequent models, with the regression weights of the paths involving the additional predictors gradually freed in each subsequent model. The acceptability of the extended models was evaluated using a corrected chi-square difference test ($\Delta\chi 2$) with MLR estimator. Model fit was further assessed using Akaike Information Criterion (AIC), Bayesian Information

Table 1. Standardized factor loadings, reliability, convergent and discriminant validity.

	Item	Cronbach's α	CR	AVE	√AVE	Highest correlation with any other latent variable	λ
Performance Expectancy (PE)		0.87	0.86	0.68	0.82	0.70 (DES)	
PE1	Using this app would help me protect my health						0.80
PE2	Using this app would improve my ability to manage healthy and sustainable food choices						0.82
PE3	Using this app would quickly monitor my progress						0.85
Effort Expectancy (EE)		0.87	0.89	0.73	0.85	0.29 (PE)	
EE1	I think I can easily learn how to use this app						0.94
EE2	I believe I can understand the information the app provides						0.76
EE3	I believe I can use this app with little effort						0.86
Social Influence (SI)		0.82	0.75	0.50	0.70	0.66 (FC)	
SI1	I would use this app if it was suggested by people who are significant to me (e.g. friends and relatives)						0.70
SI2	I would use this app if it was suggested by influencers who are food experts on social media (Instagram, Facebook…) or on the web						0.70
SI3	I would use this app if it was suggested by newspaper or magazine articles in print or digital media						0.73
Facilitating Conditions (FC)		0.84	0.85	0.53	0.73	0.66 (SI)	
FC1	I would be more willing to use this app if I had appropriate information about its use						0.78
FC2	I would be more willing to use this app if I had enough time to use it						0.63
FC3	I would be more willing to use this app if I knew there were people available to provide assistance						0.75
FC4	I would be more willing to use this app if I had the necessary technological resources						0.77
FC5	I would be more willing to use this app if it had similar functionality to the apps I already use						0.71
Attitude (ATT)		0.94	0.92	0.79	0.89	0.43 (AE)	
ATT1	Using this app is negative—positive						0.89
ATT2	Using this app is a bad idea—good idea						0.95
ATT3	Using this app is useless—useful						0.83
Anticipated Emotions (AE)		0.92	0.90	0.76	0.87	0.4 (ATT)	
AE1	If I use this app to make healthy, sustainable choices, I will feel proud of myself						0.92
AE2	If I use this app to make healthy, sustainable choices, I will feel satisfied						0.91
AE3	If I use this app to make healthy, sustainable choices, I will feel at peace with myself						0.78
Desire (DES)		0.96	0.96	0.88	0.94	0.85 (FUI)	
DES1	I would like to use such an app						0.93
DES2	I would like to be able to use this app as soon as possible						0.94
DES3	I would be excited to start using this app						0.95
Intention to Use the App (INT)		0.92	0.92	0.80	0.90	0.85 (DES)	
INT1	I am interested in downloading this app to explore its features						0.87
INT2	I intend to use this app to make healthy and sustainable food choices						0.90
INT3	I will most likely use this app						0.92

Note. λ= Standardized factor loading; CR = Composite Reliability; AVE = Average variance extracted; √AVE = Positive square root of the AVE.

Table 2. Means, Standard Deviations and Correlations of the Study Variables.

	M	*SD*	1	2	3	4	5	6	7	8	9
1. Performance Expectancy	5.03	1.20	1								
2. Effort Expectancy	5.80	1.01	0.27**	1							
3. Social Influence	3.75	1.32	0.52**	0.16**	1						
4. Facilitating Conditions	4.64	1.26	0.53**	0.15**	0.54**	1					
5. Attitude	4.80	1.66	0.39**	0.19**	0.30**	0.28**	1				
6. Anticipated Emotions	4.84	1.24	0.61**	0.19**	0.51**	0.47**	0.38**	1			
7. Desire	3.76	1.57	0.63**	0.19**	0.61**	0.65**	0.36**	0.53**	1		
8. Intention to Use the App	4.03	1.53	0.66**	0.21**	0.61**	0.65**	0.36**	0.54**	0.91**	1	
9. App Download	–	–	0.41**	0.13**	0.36**	0.41**	0.24**	0.32**	0.63**	0.68**	1

Note.
** $p < 0.001$.

Criterion (BIC) and Sample-size Adjusted Bayesian Information Criterion (SABIC), with lower values reflecting better fit and parsimony.

5. Results

Table 2 shows the means and standard deviations of the study variables. Overall, participants had medium high-performance expectancy and effort expectancy, which perceived the app as useful and easy to use. The descriptive statistics revealed varying levels of user perceptions regarding the smartphone app under investigation. Effort expectancy showed the highest mean score (M = 5.80, SD = 1.01), showing users' perception of the app as an easy tool. Performance expectancy also scored relatively high (M = 5.03, SD = 1.20), indicating positive expectations about the app's usefulness and functionality. Anticipated emotions (M = 4.84, SD = 1.24) and attitude (M = 4.80, SD = 1.66) both showed moderately positive scores. Facilitating conditions received a moderate score (M = 4.64, SD = 1.26). Interestingly, intention (M = 4.03, SD = 1.53) and desire (M = 3.76, SD = 1.57) showed lower mean scores. Social influence scored the lowest (M = 3.75, SD = 1.32). Additionally, of the 511 potential users, 218 downloaded the app. Analysis reveals a gender disparity: 62.7% of men downloaded the app, compared to 46.4% of women.

The results of the correlational analysis revealed several significant relationships among the study variables. Correlation showed that performance expectancy was particularly correlated to the hedonic components (anticipated emotions and desire). Effort expectancy had weak correlations with the other factors. Social influence was highly correlated with desire and intention. Facilitating conditions had strong correlations with desire and intention. Desire showed a strong correlation with intention. Finally, intention was highly correlated with app download.

5.1. Goodness-of-fit of the hypothesized integrated model

As shown in Table 1, the results revealed that all the composite reliability values ranged from 0.75 to 0.96, and were therefore greater than the minimum threshold of 0.60 (Bagozzi & Yi, 1988). Thus, the reliability of the measurement model was confirmed. The standardized item loadings of all observed variables on their corresponding latent constructs ranged from 0.63 to 0.95, thus being highly significant. Although the factor loading for the item FC2 of facilitating conditions was slightly low (λ = .63), it was retained due to its theoretical relevance in capturing the role of time availability. The AVE from latent constructs ranged from 0.50 to 0.88 (Table 1); thus equal or above the recommended threshold of 0.05 (Anderson & Gerbing, 1988; Fornell & Larcker, 1981). These findings showed that all measurement items presented a high convergent validity. Discriminant validity was confirmed using two approaches. First, following the Fornell-Larcker criterion, we tested whether the positive square root of the AVE for each latent variable was higher than the highest correlation with any other latent variable (Table 1; Fornell & Larcker, 1981). Second, we calculated the Heterotrait-Monotrait (HTMT) ratio for all pairs of constructs. The HTMT values for all construct pairs were below the recommended threshold of 0.85, (Henseler et al., 2015). However, the HTMT ratio between desire and intention (0.96) exceeded the recommended threshold, suggesting a potential issue with discriminant validity. Consequently, multicollinearity was tested and disconfirmed (VIF = 1.00, Condition Index = 4.9). This indicates that, despite being related, these constructs still capture distinct aspects of the decision-making process. Accordingly, both measures were retained because they align with the theoretical framework underpinning the study.

5.2. Model comparison

As shown in Table 3, the results supported the better fit of the extended models, with Model 4 showing the highest fit indices and the highest explanatory power. Model 3 achieved the lowest BIC value, indicating the best fit when penalizing model complexity. However, Model 4 had the lowest AIC and SABIC values, demonstrating the best overall balance between model fit and complexity, as well as the highest robustness in achieving this balance. Therefore, Model 4 was selected for its nuanced understanding of app download predictors and strong overall fit.

Regarding the intention to use the app, there was a direct effect of performance expectancy on intention, confirming H1a. Instead, the hypotheses about the direct effect of effort expectancy (H1b), social influence (H1c), and facilitating conditions (H1d) on intention were not confirmed. Furthermore, app download was significantly predicted by intention, confirming our H1e. Regarding the hypothesized relationship between the study variables (Figure 1 and Table 1 in Supplementary Materials), the results of the extended Model 4 showed that attitude towards app use was significantly predicted by performance expectancy. Thus, we confirmed H2a. However, it was not predicted by effort expectancy, which refutes our H2b. In addition, the hypothesis that attitude was a significant predictor of desire was confirmed (H2c); conversely, the hypothesis that intention to use the app was significantly predicted by attitude was disconfirmed (H2d).

Also, anticipated emotions were strongly predicted by performance expectancy, but not by effort expectancy. Therefore, we supported H3a but could not confirm H3b.

Desire to use the app was significantly predicted by social influence and facilitating conditions followed by anticipated emotions. Therefore, our results supported H3c, H3d, H3e. In addition, participants' intention to use the app was strongly predicted by desire, supporting H3g. In contrast, anticipated emotions did not emerge as a significant predictor of app download intention (H3f).

Performance expectancy influenced app download indirectly via attitude (H1f) and anticipated emotions (H1g), then desire, and finally intention. Effort expectancy did not indirectly influence app download, which did not support our H2e and H2. Furthermore, the paths from social influence (H3g) and facilitating conditions (H4c) to app download were mediated by desire and then intention. Finally, the paths from attitude (H5c) and anticipated emotions (H6c) to app download were also mediated by desire and then intention.

Model 4 also included the relationships of sociodemographic variables with the other study variables. Gender was negatively associated with facilitating conditions, suggesting that female participants perceive more conditions that facilitate app use than male participants. Gender was also related to anticipated emotions and intention, with females anticipating higher positive emotions and reporting slightly higher intention to use the app than males. Furthermore, gender had negative indirect effects on app download through facilitating conditions, desire, and intention and through anticipated positive emotions, desire, and intention. Age had a significant negative effect on effort expectancy but a positive effect on desire, meaning that older participants are less likely to find the app easy to use but have a stronger desire to use it. Additionally, the pathway from age to app download via desire and intention was significant. Education significantly predicted high effort expectancy (thus, higher-educated individuals perceived the app as ease to use) and app download, indicating that participants with a higher education level found the app less easy to use than those with a lower education level. However, they downloaded it more frequently. Education had no indirect effects on the on the other study variables.

Table 3. Goodness of fit statistics for the structural equation models.

Model	Chi-squared scaled	*RMSEA*	*CFI*	TLI	SRMR	AIC	BIC	SABIC
M1	1811.93	0.09	0.84	0.83	0.25	39456.42	39848.77	39559.94
M2	1736.71	0.09	0.85	0.83	0.24	39379.90	39771.67	39476.49
M3	754.8	0.05	0.95	0.95	0.05	38250.01	38679.70	38355.95
M 4	647.78	0.05	0.96	0.95	0.05	38186.90	38730.33	38320.87
	Model Comparison Scaled – Δχ(Δdf)	R^2 Attitude	R^2 Anticipated Emotions	R^2 Desire	R^2 Intention	R^2 App Download		
M1	M1 *vs* M2 = 65.89(2)*	–	–	–	0.68*	0.47*		
M2	M2 *vs* M3 = 890.04 (9)*	0.19*	–	–	0.68*	0.47*		
M3	M3 *vs* M4 = 115.08 (27)*	0.20*	0.49*	0.64*	0.93*	0.46*		
M 4		0.21*	0.50*	0.68*	0.93*	0.48*		

Notes: M = Model; χ^2 = goodness-of-fit statistics, df = degrees of freedom of chi-square statistics, p = p-value; RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index, TLI = Tucker-Lewis Index; SRMR = Standardized Root Mean Square residual index; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; SABIC = Sample-Size Adjusted BIC; *= $p < 0.001$.

6. Discussion

The aim of this study was to understand why people are interested in downloading a mobile app designed to promote healthy and sustainable eating. As far as we know, this is the first time such an application has been proposed. In addition, the model we used offers valuable insights for future research on the psychosocial predictors involved. We conducted a correlational study in which participants rated and had the opportunity to download a specially developed app. Specifically, we examined the key psychosocial factors associated with users' initial engagement. We referred to the widely used UTAUT model (Venkatesh et al., 2003), which includes performance expectancy, effort expectancy (technology-related factors), social influence, facilitating conditions (external factors), and intention as key factors, and integrated attitudinal and emotional predictors from the MGB (Perugini & Bagozzi, 2001)—namely attitude, desire, and anticipated emotions—while controlling for sociodemographic variables (gender, age, and education level). We integrated these two models because they provide a theoretical framework that reflects the increasingly strong correlation between public health, technology, and environmental sustainability. Moreover, this integrated model could serve as a reference for future studies seeking a validated framework to investigate the factors that drive people to use apps to promote healthy and sustainable eating.

Overall, our findings showed the role of technology-related (performance expectancy), external (social influence and facilitating conditions) and individual attitudinal and emotional factors in predicting the intentions to download and use the app. External factors represented the component of the model most strongly associated with the intention to use the app. As expected, intentions represented the most immediate antecedent of the decision to download the app. As for the technology-related factors, our results showed that new users rated the app positively when it was perceived as useful for health protection, nutrition management and progress monitoring. This confirms previous findings that performance expectancy is an important predictor of users' attitudes towards downloading the app (Thomas et al., 2013). Furthermore, our results confirmed that these perceptions reinforce expectations of future positive emotions, such as happiness, pride, and satisfaction when using the app (Singh, 2005). Both users' positive attitudes and anticipated emotions were associated with their intention to use and download the app, which is consistent with Fadzil's (2018) findings. Interestingly, performance expectancy had a greater impact on anticipated emotions than attitude, possibly because users are more attracted to the hedonic aspects of the app than its rational utility. This is consistent with the modern user's tendency to be more engaged by the hedonic experience of using technology rather than its functional benefits (Fang & Chiu, 2010). Furthermore, performance expectancy was found to have a direct effect on intention to use the app, as also shown in previous studies (e.g. Fadzil, 2018).

In terms of external factors, effort expectancy had no significant effect on attitude, anticipated emotions, or intention, although it was measured in a theoretically sound way and had a high mean (M=5.80), suggesting that ease of use is not an important predictor of engagement in an app. This is in line with previous studies (e.g. Hussein, 2017) and could be due to the fact that participants were interested in the app regardless of its difficulty. However, this result could be due to the specific operationalization used in the study, so future research should explore alternative measurements to better capture aspects of usability that influence adoption. In addition, our study showed that perceptions of social influence and facilitating conditions were related to intention to use the app and downloading it, but only when these factors reinforced the desire to use the app. This suggests that social support and the availability of resources that facilitate the use of the app are crucial in generating interest. This finding underscores the emotional dimension as a primary driver of user decision-making.

Concerning the individual factors, both users' positive attitudes and anticipated emotions were associated with their intention to use and download the app, consistent with Fadzil's findings (2018). Furthermore, the study showed that both attitude and anticipated emotions play an important role in the desire to use the app, although these effects are less pronounced compared to social influence and facilitating conditions (Shiu, 2008). This is because, in addition to attitudinal and affective motives, the performance of behavior is always linked to the social context, which provides varying degrees of social support and other facilitating factors. The presence of these conditions makes it easier for individuals to translate their motivation into actual behavior.

Our study has confirmed that desire has a strong influence on the intention to use the app, which is consistent with the findings of previous studies in different contexts (Leone et al., 2004; Shiu, 2008). This makes desire one of the strongest predictors of intention to perform a behavior. Our findings extend the literature on the role of desire, which has been studied primarily in the context of health-promoting behaviors such as reducing nicotine consumption (Shiu et al., 2008) or losing weight (Perugini & Bagozzi, 2001), but not in the adoption of technologies that promote healthy and sustainable behaviors. Intention to use the app, in turn, had a strong effect on app downloads, confirming that intention is a key indicator of actual behavior (Palau-Saumell et al., 2019; Tomczyk et al., 2021). This highlights that users initially engage through a hedonic evaluation of the app's utility, which refers to the sensory or emotional pleasure that goes beyond functional use (Van der Heijden, 2004). This evaluation is later followed by rational processing, which ensures that the app supports conscious, purposeful interactions (Venkatesh et al., 2016).

Our study also provided insights into the relation between sociodemographic variables and the psychosocial predictors of app adoption. Our data shows that men downloaded the app more frequently than women. This is in contrast to previous research that has shown a greater interest in nutrition apps among women (Wang & Qi, 2021). However, this result should be interpreted with caution as it could reflect the influence of other unmeasured variables, such as differences in dietary habits. In addition, our results showed that women perceived more facilitating conditions and anticipated more positive emotions than men, suggesting that they were more responsive to the benefits of the app. They also showed a slightly higher intention to use the app, especially when they reported more facilitating conditions and anticipated emotions, indicating a stronger predisposition to adopt apps promoting healthy and sustainable eating (Mortaş et al., 2023). Although older participants had higher effort expectancy, they expressed a stronger desire to use it than younger participants, possibly due to prioritizing health benefits over usability concerns. This reflects older adults' willingness to adopt health-related technologies for their direct benefits, as shown in previous studies (Cabrita et al., 2019; Sproul et al., 2023). Older adults tend to adopt health and nutrition technologies because of their personal health motivation, whereas environment-related technologies are less likely to be adopted if they are not embedded in this context (Hill et al., 2015). Finally, participants with higher levels of education found the app more ease to use, possibly indicating a more positive evaluation of usability. Accordingly, this group had a higher download rate of the app, suggesting a greater willingness to adopt an app promoting healthy and sustainable eating (Chen et al., 2024). Robust and user-friendly features may be critical to meet the expectations of this population.

6.1. Limitations of the study and future directions

Despite its significant contributions, our study has some important limitations. First, our sample was not representative of the entire Italian population, which is a limitation in terms of external validity. Women were slightly overrepresented compared to men, and the sample consisted mainly of younger people with a higher level of education than the national average. The generalization of our results should therefore be made with caution. Future research should aim to include a more balanced gender distribution, a wider age range and individuals with lower levels of education, who may have different decision-making patterns and levels of digital literacy. Future studies could investigate additional variables that were not considered in the present study to better understand the psychosocial factors that influence the decision to use healthy and sustainable eating apps. First, it would be interesting to investigate the influence of users' previous experiences with similar apps. Second, participants' knowledge of different diets and their values regarding healthy and sustainable food could influence their decision to download the app. The lack of data on dietary patterns limits the understanding of their interaction with variables such as gender in app adoption. Therefore, future studies should assess these to better investigate their impact on app engagement. Third, measuring other emotion-related variables such as excitement, curiosity and surprise—which have been shown to have significant effects in previous studies (Chekembayeva et al., 2023)—could provide new insights. Fourth, examining personality traits such as openness to change could help determine whether certain traits increase the likelihood of using such apps. In addition, future studies could test different descriptions of app features tailored to users' needs and expectations. A recent study found that describing app benefits based on users' regulatory focus significantly influenced actual downloads (Carfora et al., 2024). Fifth, future research could examine how sociodemographic factors interact to influence app downloading behavior to uncover patterns and relationships that remain hidden when these variables are considered independently. Finally, a longitudinal design could examine the stability of the observed relationships over time and determine whether users continue to use the app, which would provide a deeper understanding of the psychosocial mechanisms involved in the adoption of healthy and sustainable eating. Overall, this integrated model could serve as a reference for future studies seeking a validated framework to investigate the factors that drive people to use apps promoting healthy and sustainable diets.

6.2. Practical implications

Our findings have significant implications for the design and promotion of technologies to encourage healthy and sustainable eating. To increase the adoption of an app, it is important to focus on features that improve performance and enhance the user's hedonic experience. For example, an innovative app could include advanced features such as ingredient scanning for nutritional information, environmental impact assessments, and suggestions for sustainable alternatives. Incorporating gamification elements and social challenges could further motivate users. Marketing strategies should emphasize perceived facilitating conditions and create strong social support to increase interest and adoption. For example, the app could offer personalized support to help users overcome difficulties during use. The app should also be designed to meet the expectations of different population groups. For example, women are more likely to use the app if they feel that they have enough information, time, and technical resources (e.g. smartphone, tablet) to use it. If the app also has similar functionalities to the apps they have used before, this can increase adoption. Therefore, marketing campaigns targeting women should emphasize these facilitating conditions. As for the older population, previous studies (Schreurs et al., 2017) have shown that they tend to be less technologically literate. Therefore, it is crucial that the app provides continuous and personalized support to enhance their user experience. A demo version could also help older adults understand the app's features and potential difficulties before they download it.

7. Conclusion

The aim of this study was to understand the psychosocial factors that influence the intention to download a healthy and sustainable eating smartphone app, as well as the actual download. It represents the first attempt to investigate why people choose to download a smartphone application designed to promote sustainable eating. Although the predictive role of some psychosocial factors was confirmed, it remains to be seen whether future studies will provide comparable results and whether these results will help to identify optimal strategies for the development of highly engaging mobile applications. The study concludes that developers should focus on increasing the emotional appeal and perceived value of the app, taking into account the different needs of users based on gender, age, and education. Future research should explore these dynamics in different contexts to refine strategies to promote user engagement and technology adoption.

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Data availability statement

The data presented in this study are available from the corresponding author on request.

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