Assessment of nutrition-focused mobile apps' influence on consumers' healthy food behaviour and nutrition knowledge

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Abstract: The research explored if a nutrition-information app influences consumers' healthy food behavior and whether consumers improve their knowledge towards healthy food. Diet and nutrition apps are among the most popular health and fitness apps used by an increasing number of mobile device users. The analyzed app reads the product labels. Then it assesses the quality of ingredients and nutritional values based on user's personal data, such as age and physical activity level, and recommends healthier food alternatives. Scientific evidence of the effectiveness of nutrition-information apps for promoting consumers' healthy food behavior is still limited. The theoretical framework of the study is grounded in constructs from Health Belief Model (HBM) and Trans-theoretical Model (TTM) theories. Data were collected from consumers that spontaneously downloaded an existing nutrition-information app. Out of the 7000 consumers contacted, 143 respondents filled in both the baseline and follow-up questionnaires. The questionnaires included items deriving from the HBM and TTM theoretical constructs adopted, that is self-reported stage of change, susceptibility, severity, benefits, barriers, self-efficacy, cues to action, perceived and objective healthy food knowledge. The average age of respondents is 38 year-old and the sample of respondents is well distributed in terms of level of education, gender, income, working status, and geographical distribution. Findings of the study showed that nutrition-information apps can be effective in overcoming what consumers perceive as personal limitations in approaching healthy food. This is particularly evident among consumers that are building their motivation and concretely planning actions in favor of healthy eating. In particular, using a nutrition-information app decreases the perception of the barriers to healthy food eating. Users have a higher perceived personal strength and self-confidence in approaching healthy food. App users improved their objective and subjective knowledge of healthy food. The results confirmed the effectiveness of the theoretical framework. The results support that family members and friends play a specific role in healthy food behavior inclination. This suggests the inclusion of an additional theoretical construct, the social and family influence construct, when assessing the effectiveness of nutrition-information apps. To improve nutrition-information app effectiveness, the recommendation is that consumer behavior scientists, marketing researchers, nutritionists, and app developers cooperate in the apps design.

Highlights

- Nutrition-information apps use decreases barriers' perception towards healthy eating and improves nutrition knowledge
- Nutrition-information apps help consumers build motivation and promote actions in favor of healthy eating
- Consumers with high food purchasing involvement mostly benefit from nutrition-information apps
- Theoretical frameworks should include a 'social and family influence' construct to assess nutrition-information app effectiveness
- Nutrition-information apps may have a public health perspective addressing various socio-economic, religious, ethnic, cultural groups' dietary habits

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Abstract

The research explored if a nutrition-information app influences consumers' healthy food behavior and whether consumers improve their knowledge towards healthy food. Diet and nutrition apps are among the most popular health and fitness apps used by an increasing number of mobile device users. The analyzed app reads the product labels. Then it assesses the quality of ingredients and nutritional values based on user's personal data, such as age and physical activity level, and recommends healthier food alternatives. Scientific evidence of the effectiveness of nutrition-information apps for promoting consumers' healthy food behavior is still limited. The theoretical framework of the study is grounded in constructs from Health Belief Model (HBM) and Trans-theoretical Model (TTM) theories. Data were collected from consumers that spontaneously downloaded an existing nutrition-information app. Out of the 7000 consumers contacted, 143 respondents filled in both the baseline and follow-up questionnaires. The questionnaires included items deriving from the HBM and TTM theoretical constructs adopted, that is self-reported stage of change, susceptibility, severity, benefits, barriers, self-efficacy, cues to action, perceived and objective healthy food knowledge. The average age of respondents is 38 year-old and the sample of respondents is well distributed in terms of level of education, gender, income, working status, and geographical distribution. Findings of the study showed that nutrition-information apps can be effective in overcoming what consumers perceive as personal limitations in approaching healthy food. This is particularly evident among consumers that are building their motivation and concretely planning actions in favor of healthy eating. In particular, using a nutrition-information app decreases the perception of the barriers to healthy food eating. Users have a higher perceived personal strength and self-confidence in approaching healthy food. App users improved their objective and subjective knowledge of healthy food. The results confirmed the effectiveness of the theoretical framework. The results support that family members and friends play a specific role in healthy food behavior inclination. This suggests the inclusion of an additional theoretical construct, the social and family influence construct, when assessing the effectiveness of nutrition-information apps. To improve nutrition-information app effectiveness, the recommendation is that consumer behavior scientists, marketing researchers, nutritionists, and app developers cooperate in the apps design.

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1. Introduction

Obesity and associated non-communicable diseases (NCDs) such as cardiovascular disease, several forms of cancer, type-2 diabetes, account for 71 percent of all deaths globally (WHO 2018). Unhealthy diet and physical inactivity are the major behavioral risk factors. Experts recommend lifestyle changes, and encourage healthy diets and physical activity as preventions and treatments of NCDs (WHO 2018).

Nutrition and healthy lifestyle apps may provide a low-cost and efficient way to disseminate information about diet and nutrition to the general population. These apps also help provide targeted information to particular groups (e.g. overweight people, cancer survivors, heart disease risk group) (Okumus, Ali, Bilgihan, & Ozturk, 2018; Coughlin et al., 2015; Hebden, Cook, Van Der Ploeg, & Allman-Farinelli, 2012; Elbert, Dijkstra, & Oenema, 2016).

The number of mobile phone users worldwide is expected to reach 7.3 billion by 2023 (Statista 2019). Around 67 percent of the world's population is expected to use a mobile phone by the end of 2019 from 62.9 percent in 2016. Western Europe is the largest regional market, as almost 348 Million people will own a mobile phone by the end of 2019. Within North America, around 277 Million people will have a mobile phone by the end of 2019 (Statista 2018).

There has been an exponential rise in the availability of health and fitness apps (Schoeppe et al., 2016, 2017; Lowe, Fraser, & Souza-Monteiro, 2015; Allman-Farinelli & Gemming, 2017). Surveys have shown that nutrition-information and weight-loss apps are the most popular among the health apps (Accenture, 2016; Krebs & Duncan, 2015; Franco, Fallaize, Lovegrove, & Hwang, 2016; Statista 2012). Apps offer opportunities for consumers to monitor and manage their food purchasing and consumption (Lupton, 2018).

Previous research investigated the effectiveness of nutrition-information apps in app-based interventions for health behavior change (e.g. diet, physical activity), adopting a nutritionist and medical perspective. Thus, measured outcomes were app users' weight management (Wharton, Johnston, Cunningham, & Sterner, 2014; Breton et al., 2011; Hebden et al., 2012) and specific health conditions, such as obesity and diabetes (Mummah, Mathur, King, Gardner, & Sutton, 2016; Schoeppe et al., 2016; Flaherty, McCarthy, Collins, & McAuliffe, 2018). Few studies have examined app use in the context of food consumption and purchasing (Doub, Levin, Heath, & LeVangie, 2015; Gilliland et al., 2015; Flaherty et al., 2018). Others investigated how nutrition-information apps can support consumers' decision making when buying food (Okumus et al., 2016). These studies took into account that food service businesses play an important role in daily dietary habits (Penney, 2016) and how consumers may have particular dietary lifestyles, food intolerances, and food allergies. Another segment of the literature examined the theoretical foundations of past research, app design, input and output features, and the quality of nutritional information of nutrition-information apps (Chen, Cade, & Allmann-Farinelli, 2015; West et al., 2013; Direito et al., 2014; Schoeppe et al., 2017). Currently, there exists limited knowledge about the nutrition-information apps' potential on health behaviors from a consumer behavior perspective.

The wide use of mobile phones and the growing health and fitness app market are an opportunity to use the apps to prevent unhealthy lifestyle behavior (Covolo, Ceretti, Moneda, Castaldi, & Gelatti, 2017). Although mobile phones are increasingly used to provide health interventions, the scientific evidence of the effectiveness of health apps is incomplete. So far studies have widely favored a nutritionist and medical perspective, and largely ignored a consumers behavior perspective (Elbert et al., 2016). There is a need to investigate further the potential of nutrition-information apps for promoting healthy eating habits and adequate nutrition behaviors (Schoeppe et al., 2017; Coughlin et al., 2015). The objective of the present research is to assess whether the use of a nutrition-information app influences app users' healthy food behavior. In particular, it aims at exploring the influence on the level of readiness towards healthy food, whether the influence differs among various socio-demographic users, and whether app users improve their healthy food and nutrition knowledge.

1.1.Background

There is some evidence of the effectiveness of mobile phone app interventions on nutritional habits and medical care. Apps can be a useful and low-cost intervention strategy to improve diet and nutrition (Schoeppe et al., 2016; Coughlin et al., 2015; Covolo et al., 2017; Mummah et al., 2016; Rabbi, Pfammatter, Zhang, Spring, & Choudhury, 2014). The effectiveness of the mobile phone apps was positively assessed in intervention strategies that track diet and physical activity, like web-based, paper-based, and website and paper food diary (Gasser et al., 2006; Carter, Burley, Nykjaer, & Cade, 2013; Hutchesson, Roll, Callister, & Collins, 2015; Wharton et al., 2014), counseling (Allen, Stephens, Dennison Himmelfarb, Stewart, & Hauck, 2013), health education with health tips (Mendiola, Kalnicki, & Lindenauer, 2015), and Podcasts and interaction on Twitter (Turner-McGrievery & Tate, 2011). The app interventions measured changes in eating behaviors (e.g. self-reported dietary intake, calories, calories from fat, fruit and vegetable intake) and related health outcomes (e.g. body weight, fitness, blood pressure, glucose, cholesterol, quality of life) (Schoeppe et al, 2016; Covolo et al., 2017). Some interventions reported weight loss or reduction in BMI or body fat (Payne, Lister, West, & Bernhardt, 2015); however, only three studies reported significant results (Mattila et al., 2013; Turner-McGrievy et al., 2013; Thomas & Wing, 2013).

Studies reported high user acceptability of app-based interventions. Users found the apps convenient and easier to use as compared to other methods of diet tracking, especially when eating out of home (Payne et al., 2015; Schoeppe et al., 2016; Wharton et al., 2014; Mendiola et al., 2015). The manual process of food logging provided by nutrition-information apps might produce self-awareness and improve healthy food consumption (Rabbi et al., 2015).

Multi-component interventions that combine apps with other intervention strategies appear to be more effective than stand-alone app interventions (Schoeppe et al., 2016; Covolo et al., 2017; Allman-Farinelli & Gemming, 2017). One advantage of mobile phone apps is that they enable the use of different communication modes (e.g. text, video, audio) (Elbert et al., 2016). Interventions that focus on education alone often had limited success, because knowledge of healthy eating alone does not easily translate into adopting healthy behavior (Gilliland et al., 2015; West et al., 2013; Lowe et al., 2015). In fact, food information chains that guided users to healthy eating tips, recipes, and specific food vendors were the decisive element for improved awareness and consumption of healthy food (Gilliland et al., 2015).

Furthermore, numerous research papers and reviews evaluated the theoretical foundations incorporated into diet and nutrition apps' design. Most of the reviewers selected nutrition-information apps from Google Play and iTunes App Store (Franco et al., 2016; Chen et al., 2015; West et al., 2013; Direito et al., 2014). These papers show that there is a need to include more theoretical behavior change constructs into mobile phone apps for promotion of healthy dietary behavior (West et al., 2013; Chen et al., 2015; Allman-Farinelli & Gemming, 2017; Coughlin et al., 2015; Davis et al., 2016). Thus far the minimal integration of health behavior theory into the app design is considered an indicator for the low potential of apps to influence long-term behavior change (Davis et al., 2016). The studies that reviewed apps support that the theories adopted more frequently are the Health Belief Model and Theory of Planned Behavior.

Finally, past studies demonstrated that the behavior change techniques used in the app design influences the app effectiveness. The most effective techniques were self-monitoring, goal setting, and feedback (Schoeppe et al., 2016; Payne et al., 2015; Zhao et al., 2016; Schumer, Amadi, & Joshi, 2018). Additional common techniques were motivational messages, health education, reinforcement, gamification, exergames [1] , award and rewards, and social support (Coughlin et al. 2015).

2. Theoretical and methodological framework

2.1 Theoretical and methodological background of past studies

Past studies on the effectiveness of mobile phone apps on healthy food consumption are grounded in health behavior change theories (Gilliland et al., 2015; Coughlin et al., 2015; Schoeppe et al., 2016; Zhao et al., 2016; Michie & Johnston, 2012). The most common behavior change theories applied in app-based interventions were Self-determination Theory, Trans-theoretical Model, Social Cognitive Theory, Theory of Planned Behavior, Control Systems Theory of self-regulation, and the Behavior Change Wheel (Schoeppe et al., 2016; Payne et al., 2015). Michie and Johnston (2016) emphasize the importance of setting a consumer health behavior change perspective as the end-point of a behavioral intervention, in addition to evaluating the effectiveness of an intervention in terms of physical performance (e.g. weight, blood glucose level).

The methodological approach of past studies on app-based healthy food consumption interventions varied. Most studies using a mobile phone app in interventions on healthy diet, nutrition and physical activity were randomized- controlled trials (Coughlin et al., 2015; Schoeppe et al., 2016; Payne et al., 2015), targeted to adults (Coughlin et al. 2015; Schoeppe et al., 2016) and with higher rates of female participants (on average 64%) (Schoeppe et al., 2016). The majority of reviewed studies had a sample of less than 100 participants (Payne et al., 2015). The duration of interventions ranged from 1 to 24 weeks. The most common duration for follow-up assessments was at 12 weeks (Gilliland et al., 2015; Schoeppe et al., 2016; Mummah et al., 2016). For the app interventions researchers used commercially available apps or apps specifically developed for the purpose of the intervention (Gilliland et al., 2015; Mummah et al., 2016; Elbert et al., 2016; Rabbi et al., 2015; Hebden et al., 2012, 2014).

2.2 Theoretical and methodological background of the current study

The theoretical framework of the current research is based on the HBM and TTM theories. These theories are widely applied for studies on food consumer behavior and healthy food eating, and for the development and evaluation of diet and nutrition apps, as supported by the literature review carried out (Lee-Lin & Menon, 2005; Lee-Lin et al., 2013; Juniper, Oman, Hamm, & Kerby, 2004; Schoeppe et al., 2016; Mummah et al., 2016; Coughlin et al., 2015; Payne et al., 2015). Therefore, they are useful theoretical instruments to achieve the set research objectives. Table 1 presents the details of the two health consumer behavior models adopted and the relationship between them.

Under the HBM, an app user is more likely to adopt a healthy food consumption behavior if the user is susceptible to healthy food eating (susceptibility), believes that

1 Gamification is defined as using elements of game design in nongame contexts (Landers et al., 2018; Hamari, Koivisto, & Sarsa, 2014). Exergames are video games that are also a form of exercise. Exergaming relies on technology that tracks body movement or reaction. The genre has been credited with upending the stereotype of gaming as a sedentary activity, and promoting an active lifestyle.

eating healthy food prevents diseases and impacts on the body (benefits), perceives limited barriers to healthy food eating (barriers), has confidence in the ability to eat healthily (self-efficacy), and has adequate knowledge (knowledge) (Champion & Skinner, 2008). The TTM adds a time framework to explain healthy food behavior and sets a number of stages of readiness. An individual may progress from the unawareness of the problem and lack of interest about the healthy food behavior change to thinking about change, how to change, and to performing and maintaining the behavior change (Prochaska & Velicer, 1997).

The app user may start using the app when living different stages of the continuum. The use of the app may lead to a change in the stage of readiness, supporting the advancement or the step back in the stage of readiness. The TTM stage of readiness of the user is measured through the importance given to the HBM constructs collecting the relevant information during the data collection phases (Table 1).

Table 1. Integration of the TTM stage of readiness and HBM constructs

The two theories were extended with more constructs as suggested by previous studies (Orji, Vassileva & Mandryk, 2012; Glanz et al., 2008). Past research findings have shown that healthy food consumption behavior is driven by consumers' concern for appearance, attractiveness, and popularity (Nejad et al., 2004; Runfola et al., 2013). The society attaches a lot of importance on an individual's physical appearance. This is evident in the wide public, and even more so among younger generation, often attracted by the use of technologies to monitor and control their performance in healthy eating. Thus concern with appearance may be a motivating factor in preventive healthy eating behaviors. The other construct added to the model was the degree to which an individual is willing to try out any new mobile technology service (PIMs) (Rai et al., 2013). PIMs can be a predictor of consumer mobile technology usage intentions to try out mobile technology for health information searches. The propensity towards this technology may favor the effectiveness of a nutrition-information app in increasing healthy food behavior and food knowledge.

2.2.1Data gathering

Data gathering was carried out with a two-step approach, with a baseline and follow-up data collection steps (Table 2). Around 7000 app users were contacted as soon as they spontaneously downloaded the app and were invited to fill the baseline questionnaire The app is aimed at profiling food products from a nutritional point of view, by reading the product labels and assessing the quality of ingredients and the nutritional values. When the user scans the barcode, the app summarizes the main positive and negative characteristics of the product based on the user's information, and recommends healthier alternatives (See Appendix 1 for details on the nutrition-information app used).

App users were provided with a presentation letter describing the research aims. The app users that accepted to fill the questionnaire were re-contacted for follow-up after twelve weeks of app use. Both questionnaires were filled in on line with the support of Google-forms. Respondents consulted the app at least once a week, with a time average session of three minutes and twelve seconds, in line with average use of the app by common users. Data collection was carried out from October 2017 until March 2018. The participation was incentivized by sending two nutritional guidelines to respondents, one for each questionnaire filled in. The study was conducted in accordance with the privacy policy of the app company, that asked app users to fill the data privacy declaration and the study informed consent on line before proceeding with the first questionnaire.

The sample includes a good balance of respondents in terms of level of education, gender, income, working status, and geographical distribution. The age range is from 18 to 71 year-old, with an average age of 38-year-old (std. dev.: 14.49). Furthermore, around 30% have declared allergies, 25% have chronic diseases, and 55% use more than one health and fitness apps.

Table 2 – Data gathering and sample

2.2.2 Questionnaires

The research explored consumers' responses related to a number of constructs in both questionnaires to analyze possible changes in between t0 and t1 (Figure 1). Another set of questions was added in each questionnaire. Questions derive from the theoretical constructs adopted in TTM and BHM, in previous research studies on the evaluation of app users' behavior change, and in previous research studies and publications on healthy food behavior and healthy eating perception. The Figure 1 below provides details for each construct's theoretical references. App users had to rate their agreement with each item of the constructs. The research adopted a 1 to 5 Likert scale.

Figure 1. Questionnaire constructs

Baseline	– Perceived diet healthiness – Food purchasing habits – Socio-demographic information – Concern for appearance**** – Personal innovativeness toward mobile services (PIMs)*****
Follow-up	– App satisfaction
Baseline + Follow-up	– Self-reported stage of change* – Susceptibility** – Severity** – Benefits** – Barriers** – Self-efficacy** – Cues to action** – Perceived healthy food knowledge*** – Objective healthy food knowledge****

*Prochaska & DiClemente, 1983; Prochaska, DiClemente, & Norcross, 1992

**HBM: Becker, 1974; Champion & Skinner, 2008; Rosenstock, 1974

*** Gilliland et al., 2015; Weitzel et al., 2007

**** Gilliland et al., 2015; Orji et al, 2012; Su, A. Y. L., 2012; Samoggia et al., 2016; Samoggia & Castellini, 2018

***** Rai et al., 2013

2.2.3 Data elaboration

Data elaboration followed four phases. In the first phase, data elaboration aimed at identifying existing latent factors among theoretical constructs' items, with the support of factor analysis. This elaboration was carried out for baseline and follow-up results. It applied the principal components methods (PCA) and the Varimax rotation. Given the limited number of missing values in the variables included in the factor analysis, and so to strengthen the elaboration results, the listwise method was adopted. The Kaiser–Meyer–Olkin measure of sampling adequacy and the Bartlett's test of sphericity were calculated to assess the appropriateness of the data for factor analysis. The Kaiser–Meyer–Olkin index was 0.721 (baseline), and 0.734 (follow-up). The

Bartlett's test of sphericity was highly significant in both elaborations (0.000). These values supported the appropriateness of the data for the analysis. The factors had an eigenvalue criterion higher than 1, with a cumulated variance explained by the factors taken together. Cronbach alphas for each factor-construct ranged from 0.63 (family influence) to 0.77 (self-efficacy) in baseline factors, and from 0.62 (cues to action) to 0.81 (self-efficacy) in follow-up factors.

For baseline results, all initial 20 items had factor loadings above 0.52 and were grouped into 7 components. For follow-up results, all initial 18 items had factor loadings above 0.53 and were grouped into 6 components. Five factors load the same items in both questionnaires' results, and one factor (Self-Efficacy + Benefits-Appearance) in follow-up results loads items of two different factors (Benefits-Appearance, Self-Efficacy) in baseline result.

In the second phase, the elaboration aimed at calculating the value of each factor in baseline and follow-up. Therefore, the study calculated the average value of the items loading into the same factor. In order to compare values and possible changes of all items between t0 and t1, the average of t0 Self-Efficacy and Benefits-Appearance factors was calculated as mean of the means of both factors.

The third phase aimed at identifying changes in the values of HBM constructs in the different stages of the TTM model between t0 and t1. For each participant the research identified if there were advancements or step backs in the level of agreement of the constructs identified with the factor analysis. Variations in the different stages of readiness were cross-analyzed with socio-economic characteristics, including age, gender, level of education, employment status, income, geographical area of living, with a Chi-square analysis.

Finally, the research explored whether there was a relation between the effectiveness of the app, that is the most significant variations in constructs' values, and the app users' purchasing habits, perceived personal diet healthiness, app satisfaction and PIMs. The elaboration was based on a multivariate linear regression with the enter method. Correlation matrix of independent variables showed that VIF values are all in between 1 and 1.3 and Tolerance between .6 and .8. The low level of correlation supports that all independent variables are acceptable. Data elaboration was carried out with the support of SPSS (vers. 21.0 Chicago: SPSS Inc.).

3.Results

3.1 App users' evolution in stages of readiness towards healthy food behavior

Questionnaire items' loading in the factors identified in data elaboration is consistent. This confirms the validity of the theoretical models adopted. The factors identified in both t0 and t1 factor analyses are Barriers, Susceptibility, Severity, and Cue-to-Action. These factors confirm the HBM constructs. There are two further factors identified by the present research. These complete the framework of how to approach healthy food consumption behavior. They are Self-Efficacy-Benefit-Appearance, and Family Influence. App users merge construct items of self-determination with the perception of the benefits coming from disease prevention and body appearance. Consumers approach similarly these constructs, supporting that there is a conceptual overlap among physical health, appearance, and attractiveness. Moreover, app users consider the family influence as a specific construct. Family members and friends play a role in healthy food behavior inclination, which does not mix with other influencing elements.

Average values of app users' level of agreement on the constructs support that the most important impact of using a nutrition-information app is on the perceived barriers (-0,8) (see Appendix 2). After around twelve weeks of app usage, eating healthy food and adopting healthier food habits are less difficult, and the perceived personal strength in approaching healthy food is higher. All other constructs' relevance remains constant between t0 and t1. The use of an app does not contribute in varying the Self-Efficacy-Benefits-Appearance, that remains high (4.2-4.3), and the Severity and Cue to action that remain quite important (respectively 3.6 and 3.4). Moreover, app users keep on perceiving of having a medium susceptibility on unhealthy eating (2.8) and a low-medium influence coming from the social environment (2.1).

Research findings support that using a nutrition-information app brings the most significant changes in the barriers to healthy food eating. Table 3 shows the interrelation between the HBM construct factors' performance between t0 and t1 in the single TTM stages of readiness. Results support that using an app has very limited impact on the number of users in the Precontemplation and in the Maintenance constructs (from -0.7 to 0.7). The impacts are mainly on the HBM constructs of the Contemplation and Action stages, mainly the barriers (respectively -9.1 and 7.7); and in the Preparation stage, mainly the barriers (2.8), and self-efficacy (-3.5) (Table 3-b).

These findings support that if a user is in its early or advanced stages of readiness, the use of a nutrition-information app does not bring benefits. Whereas if the app users are developing their motivation, are thinking about intervening, or are actively planning actions, then the exposure to a nutrition-information app has a positive impact. It decreases the number of users that have concerns on the barriers, have low perception of self-efficacy, and perceive the likelihood of eating unhealthy food. Thus, there is a positive impact of the use of a nutrition-information app on overcoming what consumers may perceive as personal limitations and environmental difficulties.

Further results support the existence of the effects within the single TTM stage. This result comes from the sum of app users' variations in all HBM constructs in each TTM stages of readiness (Table 3-a). Besides Precontemplation, all stages of readiness have been positively affected with more positive than negative variations. The Contemplation is the most positively affected stage of readiness (30.8%). This confirms previous results. A nutrition-information app mostly affects app users that are in the process of developing their motivation and planning actions in favor of healthy eating. Moreover, the number of app users with positive variations is higher compared to the number of users encountering negative variations.

Table 3. Number of users that varied the perception level of HBM constructs in TTM stages of readiness

3.2 App effectiveness and app users' characteristics

The socio-demographic characteristics of the users are limitedly significant in explaining the nutrition-information app effectiveness. The level of education and the employment status are significant for the Action and Maintenance (respectively with Chi-square p-values between 0.044 and 0.076). Most of the nutrition-information app users that experienced a positive variation in the capability of intervening and maintaining their healthy dietary habits do not have an academic degree (69%).

Moreover, results support that most of the employed app users (80%) did not perceive an improvement in the capability of intervening and maintaining a healthy dietary habit. App users with an age above the average age, equivalent to 38 years, have more benefits in the Precontemplation stage (92%), compared to the younger ones (Chi-square p-value: 0.680). There is no significant difference among app users according to the gender or the presence of children in the household.

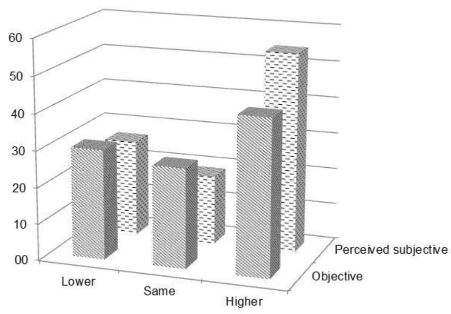
Finally, the research explored if the most significant identified effectiveness of the app, that is the change in the relevance of the barriers, has a relation with app users' purchasing habits, technology inclination, and satisfaction of their dietary lifestyle and technology (Table 4). The aim was to better understand the nutrition-information app impact in relation to the app users' characteristics. In particular, the research explored if the app has been more effective for the user highly involved in the food purchasing phase; for the user thinking to have a healthy diet; for the user that buys in a supermarket or discount; and for the user with a good level of PIMs. Results support that there is a relation with the high involvement in food purchasing (Sig. p-value: 0.006) and the app satisfaction (Sig. p-value: 0.069). If the app user is in charge of food purchasing, then the user will have benefits from the nutrition-information app use and will decrease the perceptions of the barriers to a healthy nutrition. Moreover, if the app user was satisfied by the app, then the barriers to healthy nutrition will decrease. The extent to which the user is technology driven or personally healthy food-oriented does not have a relation with the impact of using a nutrition-information app.

Table 4. Regression analysis on level change in barriers perception, technology propensity and purchasing habits

3.3 App users' nutrition knowledge

Findings support a change in the level of objective and subjective knowledge on healthy food when using a nutrition-information app (Figure 2). The exposure to an app increases the number of consumers with higher objective knowledge (39%). Yet, also one third of the users decrease their objective knowledge (27%). The number of users with higher subjective knowledge increases significantly (53%), compared to the number of users that decrease their subjective knowledge (23%). These results support that, despite the number of app users with higher objective and subjective knowledge increases, the impact on the perceived knowledge is higher than on the real objective knowledge. Therefore, there may be the risk that consumers overestimate their capability of approaching a nutritionally correct diet. The use of a nutrition-information app increases the consumers' self-confidence. However, their real competences need further consolidation to be consistent with the personal perception. These results are confirmed for consumers that use more than one nutrition and fitness app (non-significant Chi-square p-value: 0.561). Therefore, using one or more apps does not vary the objective knowledge of consumers.

Figure 2. Impact on nutrition knowledge (number of users)



4.Discussion

4.1 Effectiveness of nutrition-information apps

The present study found a positive impact of the use of a nutrition-information app on overcoming a number of consumers' perceived limitations to healthy food. In particular, using a nutrition-information app decreases the perception of the barriers to healthy food eating. After twelve weeks of app usage, the perceived personal strength in approaching healthy food was higher. This is consistent with previous research, which indicates that nutrition-information apps can change consumption habits by making healthy decisions easier (Gilliland et al., 2015; Mummah et al., 2016). Nutrition-information apps can also bring behavior change into real life situations, where consumers make decisions about their health (Schoeppe et al., 2016).

Food purchasing is critical in the food decision-making process and the adoption of a healthier eating behavior. Moreover, results of the present study indicate a positive relation between the impact of the app, high food purchasing involvement, and app satisfaction. If the app user is in charge of food purchasing, then the user will gain additional knowledge about healthy food. This may lead to healthier food purchasing behavior and dietary patterns, which may result in reducing the availability of unhealthier foods in the home (Flaherty et al., 2018).

To support the consumer's long-term use and positive exposure to a nutrition-information app, there is need to understand the users' app experience combined with their food purchasing habits. The availability of barcode scanners can assist in motivating consumers to continue to use the app because it reduces the burden on the user (Chen et al., 2015). This is especially important in routinized and low-involvement behavior, such as food purchasing (Flaherty et al., 2018). This is applicable in grocery shopping, at home, or during out-of-home food consumption in bars, cafeterias, fast-food, etc. The apps' function of nutritionally profiling single food products is mostly effective within few months. The present research show that the use of a nutrition-information app can help consumers increase their knowledge about the nutritional values of the food they purchase. However, once the user has identified possible alternatives to the initial unhealthy food choices, the motivation to use the app declines. This supports the need to design app functions that can maintain app users' interest and effectively respond to the consumers' needs. For example, added app services may include alerts on new products or promotional offers of food products similar to the ones scanned, but with better balanced nutritional profiles.

Past studies mostly profiled socio-economic consumer groups' familiarity towards mobile phone app use, rather than exploring possible different levels of effectiveness on the different socio-economic groups (Schoeppe et al., 2016). Higher app use is common among women and young people, who have positive attitudes towards apps (Sandholzer et al., 2015; Guertler et al., 2015). The present study's results shed some light on this aspect. The present research shows that there are some differences among various groups, depending on the socio-economic characteristics of app users. The impact is mostly effective among consumers that have lower level of education, are unemployed, and are middle-aged or older. Other socio-economic characteristics make limited contribution to the understanding of app users' different experience in using nutrition-information app. Results show that women and men have similar benefits and the impact on the app does not differ depending on the structure of the household. The results may suggest that although older age groups are usually less familiar with advanced technology tools, they benefit more from nutrition-information app. They are often more concerned about the nutritional values of food on their health, compared to younger consumers. The study also supports that a nutrition-information app is mostly effective among consumers with limited knowledge.

The present findings show positive changes in the consumers' objective and subjective level of knowledge on healthy food when using an app. This supports previous literature, suggesting that apps usage may increase nutrition knowledge and awareness of consumption practices (Lowe et al., 2015). On the other hand, the results show that consumers may become complacent with their knowledge and overestimate their familiarity of healthy food. Consumers' level of familiarity and capability to understand nutrition information varies, as well as their ability to define correctly the nutritional content of the combination of more than one food products. The promotion of the use of a nutrition-information app can provide a more comprehensive healthy food purchasing and consumption experience. The higher impact of multi-component interventions is widely supported by the literature (Schoeppe et al., 2016; Covolo et al., 2017; Allman-Farinelli & Gemming, 2017).

4.2 Theoretical and methodological considerations

The present study applied two widely tested behavior change theories, i.e. HBM and TTM, to study the impact of nutrition-information apps on consumers' healthy food behavior and nutrition knowledge. The aim was to apply them within a consumer behavior perspective. The research results confirm the effectiveness of the theoretical framework. Moreover, research findings suggest the inclusion of an additional theoretical construct when assessing the effectiveness of nutrition-information apps. This additional theoretical structure merges the items focused on the social and family influence. The inclusion of an additional construct focused on the social environment into the theoretical framework is innovative compared to previous studies' framework.

Past research mostly had a clinical and medical perspective. The analysis focused on the behavior change of the app user that was approached as a patient with limited consideration of the social environment. The suggestion is to put app users into a social and family context when evaluating app effectiveness. This perspective is consistent with past research theories and studies attributable to consumer behavior studies (Hartman et al., 2013; Menozzi, Sogari, & Mora, 2015; Samoggia et al., 2016; Villegas, Coba-Rodriguez, & Wiley, 2018).

Furthermore, the academic research is showing increasing interest towards user-generated food consumption data from nutrition-information apps. This new source of data could advance the research in consumer behavior theory, and healthy food consumer science (Maringer et al., 2018). This perspective must address issues related data availability and accessibility. Apps data are gathered by the apps' owners, which are mostly private companies with commercial interests. Therefore, there is a need to to coordinate to find mutual interests between researchers and the private sector. The app companies' cooperation is critical to help research projects based on commercial app data. The current research fits into this framework.

5.Limitations

The present study has some limitations. First, among the limitations of previous research on nutrition-information app effectiveness there were the small and convenient sample characteristics, and the limited study periods (Coughlin et al., 2015; Payne et al., 2015; Covolo et al., 2017). The current research is based on a fairly wide, but still convenient sample. Second, the study interviewed app users that spontaneously downloaded the app, thereby already expressing interest towards nutrition information provided by mobile phone apps. Third, the app effectiveness is evaluated focusing on the influence of the specific app without exploring other possible influencing factors, such as additional information sources, during the study period. In order to mitigate this limitation, the research tested whether the consumers' use of more than one app impacted on the effectiveness. Results showed there was no significant difference. Future research may consider using a control app. Fourth, the literature suggests to consult app usage statistics to understand the reasons for user's (dis)engagement with the apps during the study period (Schoeppe et al., 2016). In order to ensure a robust set of data, the current study addressed this aspect. In particular, the two-step data gathering ensured that interviewees were engaged with the app until the end of the data collection period. Moreover, the database cleaning excluded app users that did not use the app during the study period. Finally, the present research studied the impact of a nutrition-information app over a period of twelve-fourteen weeks. Past research observed that this is the most frequent length of time of app usage (Schoeppe et al., 2016; Mummah et al., 2016). Future studies may consider whether further retention in app usage is necessary to achieve a more significant long-term consumer behavior change, and actual healthy food consumption.

6.Conclusion and recommendations

Nutrition-information apps can be effective in overcoming what consumers may perceive as personal limitations in approaching healthy food. This is particularly evident among consumers that are building their motivation and concretely planning actions in favor of healthy eating. The exposure to the information and advice provided by a nutrition-information app improves app users' perceived self-efficacy and likelihood of eating unhealthy food. In particular, the perception of the barriers to healthy food eating decreases, and the subjective and objective knowledge on healthy eating increases. The impact of the app is stronger among consumers that have high food purchasing involvement, and are satisfied with the app.

Furthermore, the study leads to the definition of a number of conclusive recommendations. First, there is a need for cooperation in app development between consumer behavior scientists, nutritionists, marketing experts, and app developers to incorporate behavior change theories and techniques into the app development. This will improve the scientific quality and effectiveness of the apps. Second, nutrition apps should provide information and advice not only for the single app user, but for all family household components. The members of the family may have specific needs that the person responsible for food purchase or preparation may satisfy with the support of the app. Third, the background of different socio-economic groups, due to various religions, cultures, and countries, should be taken into account in the app development. Dietary habits may differ significantly among the various social groups' lifestyles. Fourth, nutrition-information apps may become an effective instrument within a public health perspective. App developers may cooperate with public health administrations, public canteens in schools, universities, and catering services. The consumer may receive useful information to correctly estimate the nutritional content of food, to know how many calories and what nutrients were consumed in a determined meal. It may include suggestions on what to consume in the other meals to obtain a nutritionally-balanced daily diet. This implies the promotion of a public-private cooperative environment, where app companies support the public institutions' aims of prevention of diseases and promotion of citizens' health.

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7. References

Abraham, C., & Michie, S. (2008). A taxonomy of behavior change techniques used in interventions. *Health Psychology*, *27*(3), 379–387. https://doi.org/10.1037/0278-6133.27.3.379.

Accenture Consulting (2016). Accenture 2016 consumer survey on patient engagement. https://www.accenture.com/_acnmedia/Accenture/Conversion-Assets/DotCom/Documents/Local/en-gb/PDF/Accenture-Patient-Engagement-Research-Recap-England.pdf#zoom=50 / Accessed 21 September 2018

Allen, J.K., Stephens, J., Dennison Himmelfarb, C.R., Stewart, K.J., & Hauck, S. (2013). Randomized controlled pilot study testing use of smartphone technology for obesity treatment. *Journal of Obesity*, 151597. https://doi.org/10.1155/2013/151597.

Allman-Farinelli, M., & Gemming, L. (2017). Technology interventions to manage food intake: Where are we now? *Current Diabetes Reports*, *17*(11), 1–8. https://doi.org/10.1007/s11892-017-0937-5.

Allman-Farinelli, M., Partridge, S. R., McGeechan, K., Balestracci, K., Hebden, L., Wong, … Bauman, A. (2016). A mobile health lifestyle program for prevention of weight gain in young adults (TXT2BFiT): Nine-month outcomes of a randomized controlled trial. *JMIR MHealth and UHealth*, *4*(2), e78. https://doi.org/10.2196/mhealth.5768.

Becker, G. (1974). A theory of social interactions. *Journal of Political Economy, 82*(6), 1063-1093. Retrieved from http://www.jstor.org/stable/1830662.

Breton, E. R., Fuemmeler, B. F., & Abroms, L. C. (2011). Weight loss - there is an app for that! But does it adhere to evidence-informed practices? *Translational Behavioral Medicine*, *1*(4), 523–529. https://doi.org/10.1007/s13142-011-0076-5.

Carter, M. C., Burley, V. J., Nykjaer, C., & Cade, J. E. (2013). Adherence to a smartphone application for weight loss compared to website and paper diary: Pilot randomized controlled trial. *Journal of Medical Internet Research*, *15*(4), 1–17. https://doi.org/10.2196/jmir.2283.

Champion, V.L., & Skinner, C.S. (2008). The health belief model. In Glanz, K., Rimer, B. K., & Viswanath, K. (Eds.). *Health behavior and health education. Theroy, research, and practice.* (pp. 45-62). (4th ed.). San Francisco: Jossey-Bass.

Chen, J., Cade, J. E., & Allman-Farinelli, M. (2015). The most popular smartphone apps for weight loss: A quality assessment. *JMIR MHealth and UHealth*, *3*(4), e104. https://doi.org/10.2196/mhealth.4334.

Coughlin S.S., Whitehead, M., Sheats, J.Q., Mastromonico, J., Hardy, D., & Smith, S. (2015). Smart- phone applications for promoting healthy diet and nutrition: A literature review. *Jacobs J Food Nutr* 2(3), 021. http://europepmc.org/abstract/MED/26819969.

Covolo, L., Ceretti, E., Moneda, M., Castaldi, S., & Gelatti, U. (2017). Does evidence support the use of mobile phone apps as a driver for promoting healthy lifestyles from a public health perspective? A systematic review of Randomized Control Trials, *Patient Educ. Couns.*, 100 (12), 2231-2243. https://doi.org/10.1016/j.pec.2017.07.032.

Davis, S. F., Ellsworth, M. A., Payne, H. E., Hall, S. M., West, J. H., & Nordhagen, A. L. (2016). Health behavior theory in popular calorie counting apps: A content analysis. *JMIR MHealth and UHealth*, *4*(1), e19. https://doi.org/10.2196/mhealth.4177.

Direito, A., Pfaeffli Dale, L., Shields, E., Dobson, R., Whittaker, R., & Maddison, R. (2014). Do physical activity and dietary smartphone applications incorporate evidence-based behaviour change techniques? *BMC Public Health*, *14*(1), 1–7. https://doi.org/10.1186/1471-2458-14-646.

Doub, A. E., Levin, A., Heath, C. E., & LeVangie, K. (2015). Mobile app-etite: Consumer attitudes towards and use of mobile technology in the context of eating behaviour. *Journal of Direct, Data and Digital Marketing Practice*, *17*(2), 114–129. https://doi.org/10.1057/dddmp.2015.44.

Elbert, S. P., Dijkstra, A., & Oenema, A. (2016). A mobile phone app intervention targeting fruit and vegetable consumption: The efficacy of textual and auditory tailored health information tested in a randomized controlled trial. *Journal of Medical Internet Research*, *18*(6), e147. https://doi.org/10.2196/jmir.5056.

Flaherty, S. J., McCarthy, M., Collins, A., & McAuliffe, F. (2018). Can existing mobile apps support healthier food purchasing behaviour? Content analysis of nutrition content, behaviour change theory and user quality integration. *Public Health Nutrition*, *21*(2), 288–298. https://doi.org/10.1017/S1368980017002889.

Franco, R. Z., Fallaize, R., Lovegrove, J. A., & Hwang, F. (2016). Popular nutrition-related mobile apps: A feature assessment. *JMIR MHealth and UHealth*, *4*(3), e85. https://doi.org/10.2196/mhealth.5846.

Gasser R., Brodbeck D., Degen M., Luthiger J., Wyss R., & Reichlin S. (2006) Persuasiveness of a mobile lifestyle coaching application using social facilitation. In IJsselsteijn W.A., de Kort Y.A.W., Midden C., Eggen B., & van den Hoven E. (Eds.), *Persuasive Technology. PERSUASIVE 2006. Lecture Notes in Computer Science,* vol. 3962. Springer, Berlin, Heidelberg. https://doi.org/10.1007/11755494_5.

Gilliland, J. A., Sadler, R., Clark, A. F., O'Connor, C., Milczarek, M., & Doherty, S. T. (2015). Using a smartphone application to promote healthy dietary behaviours and local food consumption. *BioMed Research International*, *2015(11)*, 1–11. https://doi.org/10.1155/2015/841368.

Glanz, K., Rimer, B. K., & Viswanath, K. (2008). *Health behavior and health education. Theroy, research, and practice.* (4th ed.). San Francisco: Jossey-Bass.

Glanz, K., & Bishop, D. B. (2010). The role of behavioral science theory in development and implementation of public health interventions. *Annual Review of Public Health*, *31*(1), 399–418. https://doi.org/10.1146/annurev.publhealth.012809.103604.

Guertler, D., Vandelanotte, C., Kirwan, M., & Duncan, MJ. (2015). Engagement and non-usage attrition with a free physical activity promotion program: The case of 10,000 steps Australia. *JMIR, 17, e176*. https://doi.org/10.2196/jmir.4339.

Hamari, J., Koivisto, J., & Sarsa, H. (2014, January). Does gamification work? A literature review of empirical studies on gamification. In Sprague Jr., R. H. (Ed.) *Proceedings of the 47th Hawaii International Conference on System Sciences (HICSS), Waikoloa, HI,* (pp. 3025-3034). IEEE. http://doi.org/10.1109/HICSS.2014.377.

Hartman, H., Wadsworth, D. P., Penny, S., van Assema, P., & Page, R. (2013). Psychosocial determinants of fruit and vegetable consumption among students in a New Zealand university. Results of focus group interviews. *Appetite*, 65, 35-42. https://doi.org/10.1016/j.appet.2013.02.005.

Hebden, L., Cook, A., Van Der Ploeg, H. P., & Allman-Farinelli, M. (2012). Development of smartphone applications for nutrition and physical activity behavior change. *Journal of Medical Internet Research*, *14*(4), 1–12.

Hebden, L., Cook, A., van der Ploeg, H. P., King, L., Bauman, A., & Allman-Farinelli, M. (2014). A mobile health intervention for weight management among young adults: A pilot randomised controlled trial. *Journal of Human Nutrition and Dietetics*, *27*(4), 322–332. https://doi.org/10.1111/jhn.12155.

Hutchesson, M.J., Rollo, M.E., Callister, R., & Collins, C.E. (2015). Self-monitoring of dietary intake by young women: Online food records completed on computer or smartphone are as accurate as paper-based food records but more acceptable. *J Acad Nutr Diet,* 115(1), 87–94. https://doi.org/10.1016/j.jand.2014.07.036.

Juniper, K. C., Oman, R. F., Hamm, R. M., & Kerby, D. S. (2004). The relationships among constructs in the health belief model and the transtheoretical model among African-American college women for physical activity. *American Journal of Health Promotion*, *18*(5), 354–357. https://doi.org/10.4278/0890-1171-18.5.354.

Krebs, P., & Duncan, D.T. (2015). Health app use among US mobile phone owners: A national survey. *JMIR Mhealth Uhealth*, 3(4), e101. https://doi.org/10.2196/mhealth.4924.

Landers, R. N., Auer, E. M., Collmus, A. B., & Armstrong, M. B. (2018). Gamification science, its history and future: Definitions and a research agenda. *Simulation and Gaming*, *49*(3), 315–337. https://doi.org/10.1177/1046878118774385.

Lee-Lin, F., Menon, U., Leo, M.C., & Pedhiwala, N. (2013). Feasibility of a targeted breast health education intervention for Chinese American immigrant women. *Oncology Nursing Forum* 40(4), 361-372. https://doi.org/10.1188/13.ONF.361-372.

Lee-Lin, F., & Menon, U. (2005). Breast and cervical cancer screening practices and inventions among Chinese, Japanese, and Vietnamese Americans. *Oncology Nursing Forum*, 32, 995–1003. doi:10.1188/05.ONF.995-1003.

Lowe, B., Fraser, I., & Souza-Monteiro, D.M. (2015). A change for the better? Digital health technologies and changing food consumption behaviors. *Psychol Mark* 32, 585–600. https://doi.org/10.1002/mar.20802.

Lupton, D. (2018). "I just want it to be done, done, done!" Food tracking apps, affects, and agential capacities. *Multimodal Technologies and Interaction*, *2*(2), 29. https://doi.org/10.3390/mti2020029.

Maringer, M., Van'T Veer, P., Klepacz, N., Verain, M. C. D., Normann, A., Ekman, … Geelen, A. (2018). User-documented food consumption data from publicly available apps: An analysis of opportunities and challenges for nutrition research. *Nutrition Journal*, *17*(1), 1–13. https://doi.org/10.1186/s12937-018-0366-6.

Mattila, E., Orsama, A.L., Ahtinen, A., Hopsu, L., Leino, T., & Korhonen, I. (2013). Personal health technologies in employee health promotion: usage activity, usefulness, and health-related outcomes in a 1-year randomized controlled trial. *JMIR Mhealth Uhealth*, 1(2), e16. https://doi.org/10.2196/mhealth.2557.

Mendiola, M. F., Kalnicki, M., & Lindenauer, S. (2015). Valuable features in mobile health apps for patients and consumers: Content analysis of apps and user ratings. *JMIR MHealth and UHealth*, *3*(2), e40. https://doi.org/10.2196/mhealth.4283.

Menozzi, D., Sogari, G., & Mora, C. (2015). Explaining vegetable consumption among young adults: An application of the theory of planned behaviour. *Nutrients*, 7 (9), 7633-7650. doi:10.3390/nu7095357.

Michie, S., Abraham, C., Whittington, C., McAteer, J., & Gupta S. (2009). Effective techniques in healthy eating and physical activity interventions: a meta-regression. *Health Psychol,* 28, 690–701. https://doi.org/10.1037/a0016136.

Michie, S., & Johnston, M. (2012). Theories and techniques of behaviour change: Developing a cumulative science of behaviour change, *Health Psychology Review*, 6(1), 1-6. http://dx.doi.org/10.1080/17437199.2012.654964.

Michie, S., Richardson, M. & Johnston, M., Abraham, C., Francis, J., Hardeman, W., … Wood, C.E. (2013). The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: building an international consensus for the reporting of behavior change interventions. *Annals of Behavioral Medicine*, 461(1), 81-95. https://doi.org/10.1007/s12160-013-9486-6.

Mummah, S. A., Mathur, M., King, A. C., Gardner, C. D., & Sutton, S. (2016). Mobile technology for vegetable consumption: A randomized controlled pilot study in overweight adults. *JMIR MHealth and UHealth*, *4*(2), e51. https://doi.org/10.2196/mhealth.5146.

Nejad, L. M., Wertheim, E. H., & Greenwood, K. M. (2004). Predicting dieting behavior by using, modifying, and extending the theory of planned behavior. Journal of Applied Social Psychology, 34(10), 2099–2131. http://doi.org/10.1111/j.1559-1816.2004.tb02692.x

Okumus, B., Ali, F., Bilgihan, A., & Ozturk, A. B. (2018). Psychological factors influencing customers' acceptance of smartphone diet apps when ordering food at restaurants. *International Journal of Hospitality Management*, *72*, 67–77. https://doi.org/10.1016/j.ijhm.2018.01.001.

Orji, R., Vassileva, J., & Mandryk, R (2012). Towards an effective health interventions design: An extension of the health belief model. *Online Journal of Public Health Informatics,* 4(3), ojphi.v4i3.4321. https://doi.org/10.5210/ojphi.v4i3.4321.

Payne, H. E., Lister, C., West, J. H., & Bernhardt, J. M. (2015). Behavioral functionality of mobile apps in health interventions: A systematic review of the literature. *JMIR MHealth and UHealth*, *3*(1), e20. https://doi.org/10.2196/mhealth.3335.

Penney, T.L., Jones, N., Adams, J., Maguire, E., Burgoine, T., & Monsivais, P. (2016). Are sit- down restaurant, fast food and café usage independently associated with diet and obesity? *Eur. J. Public Health, 26(suppl_1), 022-170.* https://doi.org/10.1093/eurpub/ckw170.022.

Prochaska, J., & DiClemente, C. (1983). Stages and processes of self-change in smoking: toward an integrative model of change. *Journal of Consulting and Clinical Psychology*, 5, 390–395. http://dx.doi.org/10.1037/0022-006X.51.3.390.

Prochaska, J. O., DiClemente, C. C., & Norcross, J. C. (1992). In search of how people change: Applications to addictive behaviors. *American Psychologist, 47*(9), 1102-1114. http://dx.doi.org/10.1037/0003-066X.47.9.1102.

Prochaska, J. O., & Velicer, W. F. (1997). The transtheoretical model of health behavior change. *American Journal of Health Promotion*, *12*(1), 38 48. https://doi.org/10.4278/0890-1171-12.1.38.

Rabbi, M., Pfammatter, A., Zhang, M., Spring, B., & Choudhury, T. (2015). Automated personalized feedback for physical activity and dietary behavior change with mobile phones: A randomized controlled trial on adults. *JMIR MHealth and UHealth*, *3*(2), e42. https://doi.org/10.2196/mhealth.4160.

Rai, A., Chen, L., Pye, J., & Baird, A. (2013). Understanding determinants of consumer mobile health usage intentions, assimilation, and channel preferences. *Journal of Medical Internet Research*, *15*(8), e149. https://doi.org/10.2196/jmir.2635.

Rosenstock, I. M. (1974). Historical origins of the health belief model. *Health Education Monographs*, 2, 328-335. https://doi.org/10.1177/109019817400200403.

Runfola, C. D., Von Holle, A., Trace, S. E., Brownley, K. A., Hofmeier, S. M., Gagne, D. A., & Bulik, C. M. (2013). Body dissatisfaction in women across the lifespan: Results of the UNC-SELF and gender and body image (GABI) studies. European Eating Disorders Review, 21(1), 52–59. http://doi.org/10.1002/erv.2201

Sandholzer, M., Deutsch, T., Frese, T., & Winter, A. (2015). Predictors of students' self-reported adoption of a smartphone application for medical education in general practice. *BMC Med Educ*, 15(91). https://doi.org/10.1186/s12909-015- 0377-3.

Samoggia, A., Bertazzoli, A., Hendrixson, V., Glibetic, M., & Arvola, A. (2016). Women's income and healthy eating perception. *Advances in Gender Research*, 22, 165-191. https://doi.org/ 10.1108/S1529-212620160000022018.

Samoggia, A., & Castellini, A. (2018). Health-orientation and socio-demographic characteristics as determinants of fish consumption. *Journal of International Food and Agribusiness Marketing*, 30 (3), 211-226. https://doi.org/10.1080/08974438.2017.1403986.

Schoeppe, S., Alley, S., Rebar, A. L., Hayman, M., Bray, N. A., Van Lippevelde, W., … Vandelanotte, C. (2017). Apps to improve diet, physical activity and sedentary behaviour in children and adolescents: A review of quality, features and behaviour change techniques. *International Journal of Behavioral Nutrition and Physical Activity*, *14*(1), 1–10. https://doi.org/10.1186/s12966-017-0538-3.

Schoeppe, S., Alley, S., Van Lippevelde, W., Bray, N. A., Williams, S. L., Duncan, M. J., & Vandelanotte, C. (2016). Efficacy of interventions that use apps to improve diet, physical activity and sedentary behaviour: A systematic review. *International Journal of Behavioral Nutrition and Physical Activity*, *13*(1), 127. https://doi.org/10.1186/s12966-016-0454-y.

Schumer, H., Amadi, C., & Joshi, A. (2018). Evaluating the dietary and nutritional apps in the google play store. *Healthcare Informatics Research*, *24*(1), 38–45. https://doi.org/10.4258/hir.2018.24.1.38.

Statista (2019). Forecast number of users worldwide from 2019 to 2023 (in billions). https://www.statista.com/statistics/218984/number-of-global-mobile-users-since-2010/ Accessed 12 July 2019

Statista (2018). Number of smartphone users worldwide from 2014 to 2020 (in billions). https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/ Accessed 17 October 2018

Statista (2012). Top preferences for health apps in the United States in 2012. 10/17/2018 https://www.statista.com/statistics/348731/preferences-for-health-apps-by-type-in-the-us/ Accessed 17 October 2018

Su, A. Y. L. (2012). Factors influencing the consumption of sugar-sweetened beverages by Taiwanese hospitality students. *Journal of Hospitality Marketing & Management*, 21(3), 295–310. https://doi.org/10.1080/19368623.2011.615019.

Thomas, J.G., & Wing, R.R. (2013). Health-e-call, a smartphone-assisted behavioral obesity treatment: pilot study. *JMIR Mhealth Uhealth*, 1(1), e3. https:/doi.org/10.2196/mhealth.2164.

Turner-McGrievy, G., & Tate, D. (2011). Tweets, apps, and pods: Results of the 6-month mobile pounds off digitally (mobile POD) randomized weight-loss intervention among adults. *Journal of Medical Internet Research*, 13(4), 1–14. https://doi.org/10.2196/jmir.1841.

Turner-McGrievy, G.M., Beets, M.W., Moore, J.B., Kaczynski, A.T., Barr-Anderson, D.J., & Tate, D.F (2013). Comparison of traditional versus mobile app self-monitoring of physical activity and dietary intake among overweight adults participating in an mHealth weight loss program. *Journal of the American Medical Informatics Association*, 20 (3), 513–518. https://doi.org/10.1136/amiajnl-2012-001510.

Villegas, E., Coba-Rodriguez, S., Wiley R., A. (2018). Continued barriers affecting Hispanic families' dietary patterns. *Family and Consumer Sciences Research Journal*, 46(4), 363-380. https://doi.org/10.1111/fcsr.12262.

West, J.H., Hall, P.C., Arredondo, V., Berrett, B., Guerra, B., & Farrell, J. (2013). Health behavior theories in diet apps. *Journal of Consumer Health on the Internet*, 17(1), 10-24. https://doi.org/10.1080/15398285.2013.756343.

Weitzel, J.A., Bernhardt, J.M., Usdan, S, Mays, D., & Glanz, K. (2007). Using wireless handheld computers and tailored text messaging to reduce negative consequences of drinking alcohol. *Journal of Studies on Alcohol & Drugs*, 68, 534–537. https://doi.org/10.15288/jsad.2007.68.534

Wharton, C. M., Johnston, C. S., Cunningham, B. K., & Sterner, D. (2014). Dietary self-monitoring, but not dietary quality, improves with use of smartphone app technology in an 8-week weight loss trial. *Journal of Nutrition Education and Behavior*, *46*(5), 440–444. https://doi.org/10.1016/j.jneb.2014.04.291.

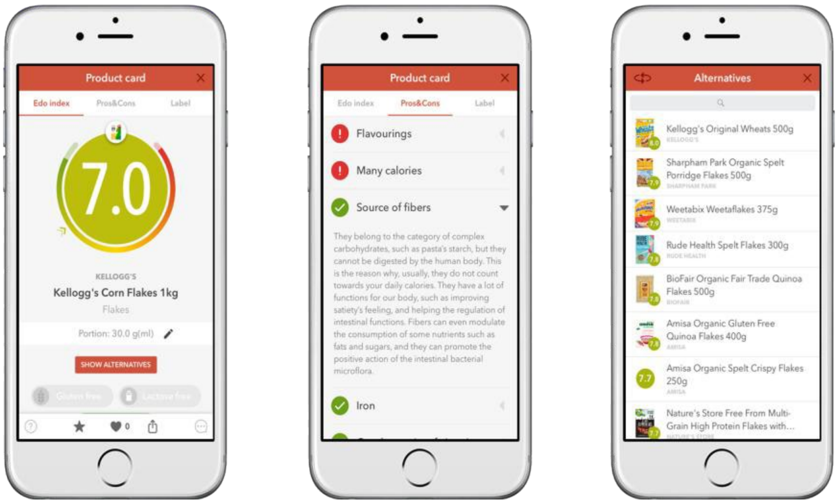
WHO (2018). Non-communicable diseases – Key Facts. https://www.who.int/en/news-room/fact-sheets/detail/noncommunicable-diseases Accessed 08 July 2019

Zhao, J., Freeman, B., & Li, M. (2016). Can mobile phone apps influence people's health behavior change? An evidence review. *Journal of Medical Internet Research*, *18*(11), 1-12. https://doi.org/10.2196/jmir.5692.

Appendix 1 - EDO APP

Edo mobile phone app is aimed at profiling food products from a nutritional point of view and supporting app users in increasing knowledge in the nutritional profile of food products. It helps to read product labels and assess the quality of ingredients and nutritional values. Edo gathers all data that can be found on food labels (e.g.: nutrition facts, ingredients, certifications). Then it processes and summarizes these data turning them into easily understandable information for the app user. Edo can be used at the supermarket or at home.

Once the barcode is framed on the product packaging, the algorithm of the program analyses all the information on the label, combined with user's personal data (such as age and physical activity level), and returns a score from 0 to 10, indicating how healthy that product is for the single user. In addition, the app indicates the pros and cons of each product, based on personal parameters, and the possible presence of ingredients to which the user is intolerant or allergic. Finally, Edo summarizes the main positive and negative characteristics of the product, recommending healthier alternatives. To use the app, the user frames the barcode with the smartphone or search for a product manually. The user can also visualize suggested healthier alternatives to the scanned product.



USERS (ITALY)	
Registered users	459,000
Active users/month	39,430
Active users/day	2,560
Visualised products/month	139,110
PRODUCTS (ITALY)	
Products	70,020
Total barcode scanned products (since opening)	8,987,180
Total visualised products (since opening)	13,029,040

Note: Updated on 26th October 2018

Appendix 2 – Factor analysis of HBM constructs

CONSTRUCTS/ITEMS/FACTOR LOADING	Crombach's alpha	BARRIERS	SUSCEPTIBILITY	SEVERITY	CUE TO ACTION	FAMILY INFLUENCE	SELF-EFFICACY	BENEFITS_APPEARANCE	Mean value (t0)	Crombach's alpha	BARRIERS	SUSCEPTIBILITY	SEVERITY	CUE TO ACTION	FAMILY INFLUENCE	SELF-EFFICACY AND BENEFITS_APPEARANCE	Mean value (t1)	Difference in mean value (t1-t0)
My feelings about myself would change if I ate unhealthy food	*.653*			.797					3.6	*.775*			.681				3.6	0.0
I am afraid to even think about eating unhealthy food				.720									.866					
If I eat unhealthy food, my entire life would change				.747									.879					
My chances of eating healthy food are great	*.742*		.786						2.8	*.722*		.821					2.8	0.0
It is likely that I eat healthy			.811									.775						
My family habits makes it likely to eat unhealthy food	*.630*					.779			2.1	*.625*					.622		2.0	-0.1
My friends or family discourage me from eating healthy food						.802									.821			
I feel like I am not strong enough to eating healthy food	*.664*	.745							3.7	*.639*	.738						2.9	-0.8
Eating healthy food requires adopting a new habit, which is difficult		.752									.828							
Doctor or nurse recommendations prompted me to eat healthy food	*.635*				.792				3.4	*.620*				.784			3.4	0.0
Campaigns (e.g., media: press, TV, and radio) prompted me to eat healthy food					.692									.582				
Family members or friends with illnesses prompted me to eat healthy food					.711									.691				
I care to look attractive	*.712*							.743	4.3									
I care to have right weight								.764										
I believe that eating healthy food improves the way my body looks								.644		*.807*						.798	4.3	0.1
I believe that eating healthy food prevents diseases								.402								.770		
I feel better when eating healthy food	*.776*						.525		4.2							.854		
I usually eat the healthy food I choose for myself							.775									.400		
I am able to often eat healthy food							.640									.476		
I do eat the healthy food that I planned							.701									.535		

*difference between t1 mean of "Self-efficacy and Benefits_Appearance" and t0 mean of means "Self-Efficacy" and "Benefits_Appearance" factor

Table 1. Integration of the TTM stage of readiness and HBM constructs

Stage of readiness to change	Characteristics	Time frame	HBM Beliefs by TTM Stage
Precontemplation	Unaware of the problem, no interest in change my food behavior	Within the next six months	Very low susceptibility: 1 Very low severity: 1 Very low benefits: 1 Very high barriers: 5 Very low self-efficacy: 1 Very low cues to action: 1
Contemplation	Aware of problem, beginning to think of changing my food behavior	Within the next six months	Low susceptibility: 2 Low severity: 2 Low benefits: 2 High barriers: 4 Low self-efficacy: 2 Low cues to action: 2
Preparation	Realizes benefits of making changes, eating healthier food, and thinking about how to change	In the next month	Average susceptibility: 3 Average severity: 3 Average benefits: 3 Average barriers: 3 Average self-efficacy: 3 Average cues to action: 3
Action	Actively taking steps toward change and eating healthier food	Now	High susceptibility: 4 High severity: 4 High benefits: 4 Low barriers: 2 High self-efficacy: 4 High cues to action: 4
Maintenance	Initial healthy food eating behavior goals reached	For at least six months	Very High susceptibility: 5 Very High severity: 5 Very High benefits: 5 Very Low barriers: 1 Very High self-efficacy: 5 Very High cues to action: 5

Note: 1: very low; 2 low; 3: Average; 4: high; 5: very high

Table 2 – Data gathering and sample

Baseline (t0) Period: Start October 2017 - End November 2017		
Users:	N	%
Elicited for Baseline	6981	
Responded and filled in the questionnaire	489	7.0 (a)
Follow up (t1) Period: Start December 2017 - End March 2018		
Users:	N	%
Elicited for Follow-up	470 (b)	
Responded	143	30.4 (c)
Total emails of elicitations	6	
Respondents after 1 email	72	50.3
Respondents after 2 emails	24	16.8
Respondents after 3 emails	14	9.8
Respondents after 4 emails	8	5.6
Respondents after 5 emails	13	9.1
Respondents after 6 emails	12	8.4
Total number of respondents	143	100.0
Sample	% (d)	
Gender		
Women	55.9	
Men	44.1	
Total	100.0	
Level of education		
With academic degree	56.7	
Without academic degree	43.3	
Total	100.0	
Working status		
Employed	60.3	
Non-employed (student, retired, job seeking, etc.)	39.7	
Total	100.0	
Level of income		
No or low income (max 1000 euro/month)	44.3	
Medium or high income (above 1000 euro/month)	55.7	
Total	100.0	
Geographical location		
North Italy	62.1	
South Italy	37.9	
Total	100.0	

Note: (a) Percentage of respondents on total elicited users for Baseline questionnaire; (b) These were the valid email addresses; (c) Percentage of respondents on total elicited users for Follow-up questionnaire; (d) Percentages calculated on Respondents of Baseline and Follow-up questionnaires, that is 143 users.

Table 3. Number of users that varied the perception level of HBM constructs in TTM stages of readiness

Stages of readiness	Variations within stages of readiness (a)				Level of HBM constructs in TTM stages of readiness	Differences in the number of users between T1 and T0 (b)
	Positive changes	No changes	Negative changes	Total changes		
Precontemplation	8.4	76.9	14.7	100.0	Susceptibility: 1	-0.7
					Severity: 1	0.7
					Benefits: 1	0.0
					Barriers: 5	0.0
					Self-efficacy: 1	0.7
					Family influence: 1	0.0
Contemplation	30.8	49.0	20.3	100.0	Susceptibility: 2	-0.7
					Severity: 2	0.7
					Benefits: 2	1.4
					Barriers: 4	-9.1
					Self-efficacy: 2	0.7
					Family influence: 2	0.1
Preparation	28.0	49.7	22.4	100.0	Susceptibility: 3	-0.7
					Severity: 3	-1.4
					Benefits: 3	-1.4
					Barriers: 3	-2.8
					Self-efficacy: 3	-3.5
					Family influence: 3	0.0
Action	25.2	51.0	23.8	100.0	Susceptibility: 4	2.8
					Severity: 4	-1.4
					Benefits: 4	0.7
					Barriers: 2	7.7
					Self-efficacy: 4	0.7
					Family influence: 4	-0.1
Maintenance	25.2	52.4	22.4	100.0	Susceptibility: 5	-0.7
					Severity: 5	1.4
					Benefits: 5	-0.7
					Barriers: 1	-1.4
					Self-efficacy: 5	1.4
					Family influence: 5	0.0

Table 4. Regression analysis on level change in barriers perception, technology propensity and purchasing habits

	Unstandardized Coefficients		Standardized Coefficients	t	Sig. p-value
	B	Std. Error	Beta		
(Constant)	-1.053	.561		-1.878	.063
Food purchasing involvement	.231	.083	.246	2.776	.006
Food purchasing outlet	.115	.207	.046	.554	.580
Perceived diet healthiness	-.082	.104	-.076	-.785	.434
PIMs	-.041	.075	-.047	-.546	.586
App satisfaction	.106	.058	.160	1.835	.069

Note. Anova: F: 2.573; Sign.: .029

a. Dependent Variable: Change in level of Barriers perception

b. Indipendent Variables: All from 1 to 5, but Food Purchasing Outlet (1: Supermarket/Hypermarket; 2: Farmers/Small shops/Online)

Table

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*Graphical Abstract