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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

TITLE:

Assessment of nutrition-information mobile phone apps' influence on consumers' healthy food behavior and nutrition knowledge

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.

Keywords: Behavior change; Healthy Food; Consumer Behavior; Healthy Nutrition; Mobile app; Smartphone; Trans-theoretical model; Health Belief Model

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).

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

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

61 There has been an exponential rise in the availability of health and fitness apps
62 (Schoeppe et al., 2016, 2017; Lowe, Fraser, & Souza-Monteiro, 2015; Allman-Farinelli
63 & Gemming, 2017). Surveys have shown that nutrition-information and weight-loss
64 apps are the most popular among the health apps (Accenture, 2016; Krebs & Duncan,
65 2015; Franco, Fallaize, Lovegrove, & Hwang, 2016; Statista 2012). Apps offer
66 opportunities for consumers to monitor and manage their food purchasing and
67 consumption (Lupton, 2018).

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

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

97 food, whether the influence differs among various socio-demographic users, and
98 whether app users improve their healthy food and nutrition knowledge.

99 *1.1. Background*

100 There is some evidence of the effectiveness of mobile phone app interventions on
101 nutritional habits and medical care. Apps can be a useful and low-cost intervention
102 strategy to improve diet and nutrition (Schoeppe et al., 2016; Coughlin et al., 2015;
103 Covolo et al., 2017; Mummah et al., 2016; Rabbi, Pfammatter, Zhang, Spring, &
104 Choudhury, 2014). The effectiveness of the mobile phone apps was positively assessed in
105 intervention strategies that track diet and physical activity, like web-based, paper-
106 based, and website and paper food diary (Gasser et al., 2006; Carter, Burley, Nykjaer, &
107 Cade, 2013; Hutchesson, Roll, Callister, & Collins, 2015; Wharton et al., 2014),
108 counseling (Allen, Stephens, Dennison Himmelfarb, Stewart, & Hauck, 2013), health
109 education with health tips (Mendiola, Kalnicki, & Lindenauer, 2015), and Podcasts and
110 interaction on Twitter (Turner-McGrievy & Tate, 2011). The app interventions
111 measured changes in eating behaviors (e.g. self-reported dietary intake, calories,
112 calories from fat, fruit and vegetable intake) and related health outcomes (e.g. body
113 weight, fitness, blood pressure, glucose, cholesterol, quality of life) (Schoeppe et al.
114 2016; Covolo et al., 2017). Some interventions reported weight loss or reduction in
115 BMI or body fat (Payne, Lister, West, & Bernhardt, 2015); however, only three studies
116 reported significant results (Mattila et al., 2013; Turner-McGrievy et al., 2013; Thomas
117 & Wing, 2013).

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

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

134 Furthermore, numerous research papers and reviews evaluated the theoretical
135 foundations incorporated into diet and nutrition apps' design. Most of the reviewers
136 selected nutrition-information apps from Google Play and iTunes App Store (Franco et
137 al., 2016; Chen et al., 2015; West et al., 2013; Direito et al., 2014). These papers show
138 that there is a need to include more theoretical behavior change constructs into mobile
139 phone apps for promotion of healthy dietary behavior (West et al., 2013; Chen et al.,
140 2015; Allman-Farinelli & Gemming, 2017; Coughlin et al., 2015; Davis et al., 2016).
141 Thus far the minimal integration of health behavior theory into the app design is
142 considered an indicator for the low potential of apps to influence long-term behavior
143 change (Davis et al., 2016). The studies that reviewed apps support that the theories
144 adopted more frequently are the Health Belief Model and Theory of Planned Behavior.

145 Finally, past studies demonstrated that the behavior change techniques used in the app
146 design influences the app effectiveness. The most effective techniques were self-
147 monitoring, goal setting, and feedback (Schoeppe et al., 2016; Payne et al., 2015; Zhao
148 et al., 2016; Schumer, Amadi, & Joshi, 2018). Additional common techniques were
149 motivational messages, health education, reinforcement, gamification, exergames¹,
150 award and rewards, and social support (Coughlin et al. 2015).

151 2. Theoretical and methodological framework

152 2.1 Theoretical and methodological background of past studies

153 Past studies on the effectiveness of mobile phone apps on healthy food consumption
154 are grounded in health behavior change theories (Gilliland et al., 2015; Coughlin et al.,
155 2015; Schoeppe et al., 2016; Zhao et al., 2016; Michie & Johnston, 2012). The most
156 common behavior change theories applied in app-based interventions were Self-
157 determination Theory, Trans-theoretical Model, Social Cognitive Theory, Theory of
158 Planned Behavior, Control Systems Theory of self-regulation, and the Behavior
159 Change Wheel (Schoeppe et al., 2016; Payne et al., 2015). Michie and Johnston (2016)
160 emphasize the importance of setting a consumer health behavior change perspective as
161 the end-point of a behavioral intervention, in addition to evaluating the effectiveness of
162 an intervention in terms of physical performance (e.g. weight, blood glucose level).

163 The methodological approach of past studies on app-based healthy food consumption
164 interventions varied. Most studies using a mobile phone app in interventions on healthy
165 diet, nutrition and physical activity were randomized- controlled trials (Coughlin et al.,
166 2015; Schoeppe et al., 2016; Payne et al., 2015), targeted to adults (Coughlin et al. 2015;
167 Schoeppe et al., 2016) and with higher rates of female participants (on average 64%)
168 (Schoeppe et al., 2016). The majority of reviewed studies had a sample of less than 100
169 participants (Payne et al., 2015). The duration of interventions ranged from 1 to 24
170 weeks. The most common duration for follow-up assessments was at 12 weeks (Gilliland
171 et al., 2015; Schoeppe et al., 2016; Mummah et al., 2016). For the app interventions
172 researchers used commercially available apps or apps specifically developed for the
173 purpose of the intervention (Gilliland et al., 2015; Mummah et al., 2016; Elbert et al.,
174 2016; Rabbi et al., 2015; Hebden et al., 2012, 2014).

176 2.2 Theoretical and methodological background of the current study

177 The theoretical framework of the current research is based on the HBM and TTM
178 theories. These theories are widely applied for studies on food consumer behavior and
179 healthy food eating, and for the development and evaluation of diet and nutrition apps,
180 as supported by the literature review carried out (Lee-Lin & Menon, 2005; Lee-Lin et al.,
181 2013; Juniper, Oman, Hamm, & Kerby, 2004; Schoeppe et al., 2016; Mummah et al.,
182 2016; Coughlin et al., 2015; Payne et al., 2015). Therefore, they are useful
183 theoretical instruments to achieve the set research objectives. Table 1 presents the
184 details of the two health consumer behavior models adopted and the relationship
185 between them.

186 Under the HBM, an app user is more likely to adopt a healthy food consumption
187 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.

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

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

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

202 The two theories were extended with more constructs as suggested by previous studies
203 (Orji, Vassileva & Mandryk, 2012; Glanz et al., 2008). Past research findings have
204 shown that healthy food consumption behavior is driven by consumers' concern for
205 appearance, attractiveness, and popularity (Nejad et al., 2004; Runfola et al., 2013).
206 The society attaches a lot of importance on an individual's physical appearance. This is
207 evident in the wide public, and even more so among younger generation, often
208 attracted by the use of technologies to monitor and control their performance in healthy
209 eating. Thus concern with appearance may be a motivating factor in preventive healthy
210 eating behaviors. The other construct added to the model was the degree to which an
211 individual is willing to try out any new mobile technology service (PIMs) (Rai et al.,
212 2013). PIMs can be a predictor of consumer mobile technology usage intentions to try
213 out mobile technology for health information searches. The propensity towards this
214 technology may favor the effectiveness of a nutrition-information app in increasing
215 healthy food behavior and food knowledge.

216 *2.2.1 Data gathering*

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

226 App users were provided with a presentation letter describing the research aims. The
227 app users that accepted to fill the questionnaire were re-contacted for follow-up after
228 twelve weeks of app use. Both questionnaires were filled in on line with the support of
229 Google-forms. Respondents consulted the app at least once a week, with a time
230 average session of three minutes and twelve seconds, in line with average use of the
231 app by common users. Data collection was carried out from October 2017 until March
232 2018. The participation was incentivized by sending two nutritional guidelines to
233 respondents, one for each questionnaire filled in. The study was conducted in
234 accordance with the privacy policy of the app company, that asked app users to fill the

235 data privacy declaration and the study informed consent on line before proceeding with
 236 the first questionnaire.

237 The sample includes a good balance of respondents in terms of level of education,
 238 gender, income, working status, and geographical distribution. The age range is from
 239 18 to 71 year-old, with an average age of 38-year-old (std. dev.: 14.49). Furthermore,
 240 around 30% have declared allergies, 25% have chronic diseases, and 55% use more
 241 than one health and fitness apps.

242 **Table 2 – Data gathering and sample**

243 *2.2.2 Questionnaires*

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

252 **Figure 1. Questionnaire constructs**

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

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

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

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

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

258 ***** Rai et al., 2013

259 *2.2.3 Data elaboration*

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

270 Bartlett's test of sphericity was highly significant in both elaborations (0.000). These
271 values supported the appropriateness of the data for the analysis. The factors had an
272 eigenvalue criterion higher than 1, with a cumulated variance explained by the factors
273 taken together. Cronbach alphas for each factor-construct ranged from 0.63 (family
274 influence) to 0.77 (self-efficacy) in baseline factors, and from 0.62 (cues to action) to
275 0.81 (self-efficacy) in follow-up factors.

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

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

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

294 Finally, the research explored whether there was a relation between the effectiveness
295 of the app, that is the most significant variations in constructs' values, and the app
296 users' purchasing habits, perceived personal diet healthiness, app satisfaction and PIMs.
297 The elaboration was based on a multivariate linear regression with the enter method.
298 Correlation matrix of independent variables showed that VIF values are all in between
299 1 and 1.3 and Tolerance between .6 and .8. The low level of correlation supports that
300 all independent variables are acceptable. Data elaboration was carried out with the
301 support of SPSS (vers. 21.0 Chicago: SPSS Inc.).

302 3.Results

303 *3.1 App users' evolution in stages of readiness towards healthy food* 304 *behavior*

306 Questionnaire items' loading in the factors identified in data elaboration is consistent.
307 This confirms the validity of the theoretical models adopted. The factors identified in
308 both t0 and t1 factor analyses are Barriers, Susceptibility, Severity, and Cue-to-Action.
309 These factors confirm the HBM constructs. There are two further factors identified by
310 the present research. These complete the framework of how to approach healthy food
311 consumption behavior. They are Self-Efficacy-Benefit-Appearance, and Family
312 Influence. App users merge construct items of self-determination with the perception
313 of the benefits coming from disease prevention and body appearance. Consumers
314 approach similarly these constructs, supporting that there is a conceptual overlap
315 among physical health, appearance, and attractiveness. Moreover, app users consider

316 the family influence as a specific construct. Family members and friends play a role in
317 healthy food behavior inclination, which does not mix with other influencing elements.

318 Average values of app users' level of agreement on the constructs support that the most
319 important impact of using a nutrition-information app is on the perceived barriers (-
320 0,8) (see Appendix 2). After around twelve weeks of app usage, eating healthy food
321 and adopting healthier food habits are less difficult, and the perceived personal
322 strength in approaching healthy food is higher. All other constructs' relevance remains
323 constant between t0 and t1. The use of an app does not contribute in varying the Self-
324 Efficacy-Benefits-Appearance, that remains high (4.2-4.3), and the Severity and Cue to
325 action that remain quite important (respectively 3.6 and 3.4). Moreover, app users keep
326 on perceiving of having a medium susceptibility on unhealthy eating (2.8) and a low-
327 medium influence coming from the social environment (2.1).

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

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

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

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

355

356 *3.2 App effectiveness and app users' characteristics*

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

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

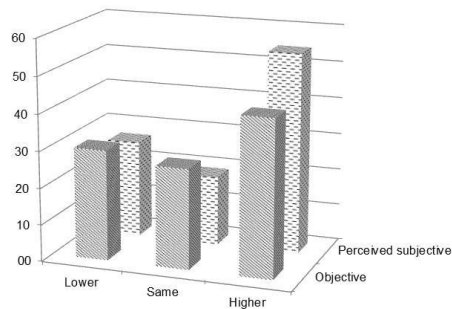
369 Finally, the research explored if the most significant identified effectiveness of the app,
370 that is the change in the relevance of the barriers, has a relation with app users'
371 purchasing habits, technology inclination, and satisfaction of their dietary lifestyle and
372 technology (Table 4). The aim was to better understand the nutrition-information app
373 impact in relation to the app users' characteristics. In particular, the research explored
374 if the app has been more effective for the user highly involved in the food purchasing
375 phase; for the user thinking to have a healthy diet; for the user that buys in a
376 supermarket or discount; and for the user with a good level of PIMs. Results support
377 that there is a relation with the high involvement in food purchasing (Sig. p-value:
378 0.006) and the app satisfaction (Sig. p-value: 0.069). If the app user is in charge of
379 food purchasing, then the user will have benefits from the nutrition-information app
380 use and will decrease the perceptions of the barriers to a healthy nutrition. Moreover, if
381 the app user was satisfied by the app, then the barriers to healthy nutrition will
382 decrease. The extent to which the user is technology driven or personally healthy food-
383 oriented does not have a relation with the impact of using a nutrition-information app.

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

386 *3.3 App users' nutrition knowledge*

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

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



403

404 4. Discussion

405 4.1 Effectiveness of nutrition-information apps

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

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

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

436 services may include alerts on new products or promotional offers of food products
437 similar to the ones scanned, but with better balanced nutritional profiles.

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

455 The present findings show positive changes in the consumers' objective and subjective
456 level of knowledge on healthy food when using an app. This supports previous
457 literature, suggesting that apps usage may increase nutrition knowledge and awareness
458 of consumption practices (Lowe et al., 2015). On the other hand, the results show that
459 consumers may become complacent with their knowledge and overestimate their
460 familiarity of healthy food. Consumers' level of familiarity and capability to
461 understand nutrition information varies, as well as their ability to define correctly the
462 nutritional content of the combination of more than one food products. The promotion
463 of the use of a nutrition-information app can provide a more comprehensive healthy
464 food purchasing and consumption experience. The higher impact of multi-component
465 interventions is widely supported by the literature (Schoeppe et al., 2016; Covolo et al.,
466 2017; Allman-Farinelli & Gemming, 2017).

467 *4.2 Theoretical and methodological considerations*

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

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

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

493 5.Limitations

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

517 6.Conclusion and recommendations

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

527 Furthermore, the study leads to the definition of a number of conclusive
528 recommendations. First, there is a need for cooperation in app development between
529 consumer behavior scientists, nutritionists, marketing experts, and app developers to
530 incorporate behavior change theories and techniques into the app development. This
531 will improve the scientific quality and effectiveness of the apps. Second, nutrition apps

532 should provide information and advice not only for the single app user, but for all
533 family household components. The members of the family may have specific needs
534 that the person responsible for food purchase or preparation may satisfy with the
535 support of the app. Third, the background of different socio-economic groups, due to
536 various religions, cultures, and countries, should be taken into account in the app
537 development. Dietary habits may differ significantly among the various social groups'
538 lifestyles. Fourth, nutrition-information apps may become an effective instrument
539 within a public health perspective. App developers may cooperate with public health
540 administrations, public canteens in schools, universities, and catering services. The
541 consumer may receive useful information to correctly estimate the nutritional content
542 of food, to know how many calories and what nutrients were consumed in a
543 determined meal. It may include suggestions on what to consume in the other meals to
544 obtain a nutritionally-balanced daily diet. This implies the promotion of a public-
545 private cooperative environment, where app companies support the public institutions'
546 aims of prevention of diseases and promotion of citizens' health.
547

548
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552

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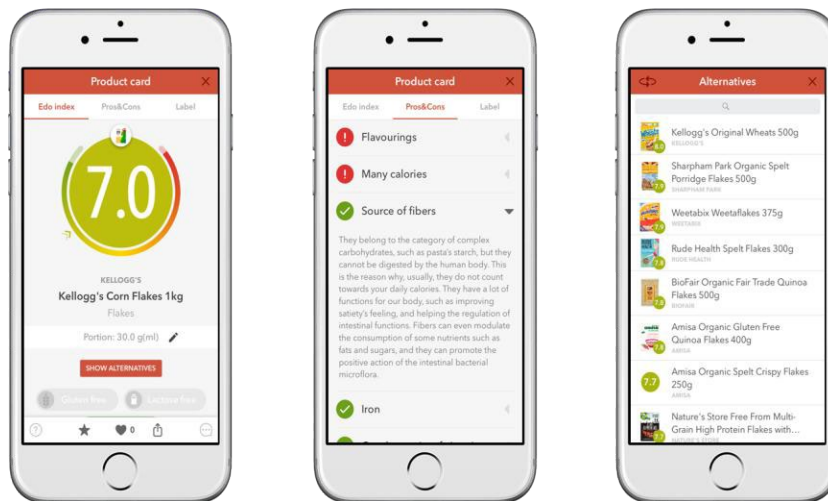
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Appendix 1 - EDO APP

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

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

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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

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Appendix 2 – Factor analysis of HBM constructs

CONSTRUCTS/ITEMS/FACTOR LOADING	Cronbach's alpha	BARRIERS	SUSCEPTIBILITY	SEVERITY	CUE TO ACTION	FAMILY INFLUENCE	SELF-EFFICACY	BENEFITS_APPEARANCE	Mean value (t0)	Cronbach'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
<i>Precontemplation</i>	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
<i>Contemplation</i>	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
<i>Preparation</i>	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
<i>Action</i>	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
<i>Maintenance</i>	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

<i>Baseline (t0) Period: Start October 2017 - End November 2017</i>		
Users:	N	%
Elicited for Baseline	6981	
Responded and filled in the questionnaire	489	7.0 (a)
<i>Follow up (t1) Period: Start December 2017 - End March 2018</i>		
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
<i>Sample</i>		
<i>Gender</i>		
Women	55.9	-
Men	44.1	
Total	100.0	
<i>Level of education</i>		
With academic degree	56.7	-
Without academic degree	43.3	
Total	100.0	
<i>Working status</i>		
Employed	60.3	-
Non-employed (student, retired, job seeking, etc.)	39.7	
Total	100.0	
<i>Level of income</i>		
No or low income (max 1000 euro/month)	44.3	
Medium or high income (above 1000 euro/month)	55.7	
Total	100.0	
<i>Geographical location</i>		
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. Independent Variables: All from 1 to 5, but Food Purchasing Outlet (1: Supermarket/Hypermarket; 2: Farmers/Small shops/Online)

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<i>Contemplation</i>	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
<i>Preparation</i>	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
<i>Action</i>	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
<i>Maintenance</i>	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

Effectiveness of nutrition-focused apps on consumers' food behavior and knowledge

