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Effects of Expert- and User-Generated Evaluations on Food Product Choices via a Food Literacy App

Short Paper

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Abstract

With the proliferation of mobile apps to promote healthy diets, it is important to understand the influence of evaluation information presented through these apps on users' decisions. Deriving from information processing concepts, we examine the influence of information cues (authority and social proof cues) obtained via food literacy apps on users' food product choices. We employ clickstream data from such an app that provides labeling information, expert grades, and user ratings/reviews of food products. We use a regression discontinuity design to uncover the effects of authority cue (expert grade) and Poisson regression to analyze the effects of social proof (user rating, review) on food product choices. The initial results add to our knowledge of the influence of these two key cues (authority and social proof) on food product choice. There are also salient implications for the app providers, for experts evaluating food products, for users, and for public health.

Keywords: Food Literacy Mobile App, Food Product Choices, Information Evaluation, Authority Cue, Social Proof Cue, Regression Discontinuity Design

Introduction

Mobile apps have become a popular delivery mode to promote healthy food choices, with more convenient information access as compared to even web-based applications (DiFilippo et al. 2015). With the increasing amounts of nutrition information provided through mobile apps, the influence of such information on users' behavior is drawing attention (Lu et al. 2018). Specifically, *food literacy apps* (e.g., Fooducate) typically provide nutrition information about food products, recommendations on healthy foods, as well as social functions aiming to improve users' food knowledge and skills (Wickham and Carbone 2018).

The availability of vast amounts of online food information in recent times has altered the way people process and are influenced by such information (Lim and Van Der Heide 2014; Metzger and Flanagin 2013). Particularly, these environments allow users access to the views of other users on a variety of food products i.e., *user-generated evaluations*, which may serve as social proof cues to influence their decisions (Fu and Sim 2011). In general, *evaluation from an expert* is considered an important authority cue for users e.g., nutrition evaluation from a licensed dietitian. Specifically, food products typically have labels that provide nutrition information in the form of calories, fat, cholesterol, sodium, carbohydrate, protein, vitamin, and mineral information per serving[1]. While such information is usually difficult for the lay consumer to comprehend and assess (Viola et al. 2016), an expert evaluation on a food product in the form of a grade (e.g., A, B, C, and D) could be easy for a general consumer to comprehend and utilize in their choice, and is a typical feature of food literacy apps that we are studying. However, with the presence of social proof cues, arguments have been offered for and against the diminished influence of authority cues (Metzger and

[1] https://www.fda.gov/media/97153/download

Flanagin 2013). Thus, there is a need to understand the effects of these two key information cues on users. Additionally, food products differ from other products whose choice has been researched previously, as described next.

To some extent, food products are similar to *search* goods (Nelson 1970) such as cameras, where the quality of the product can be inferred prior to purchase from the product specifications (e.g., the objective camera specs in an e-commerce site). However, for food products the specifications i.e., food nutrition labels, are typically complex (e.g., information about many ingredients and the composition), and thereby often difficult to be understood and assessed by lay consumers (Viola et al. 2016). Thus, expert or authority cues could matter more for consumers assessing food products as compared to these other search products.

At the same time, food products have some similarity with *experience* goods (Nelson 1970) such as movies, books, and music, where the quality can be evaluated only after purchase, and there are few objective criteria for their evaluation. For example, information about its taste and cooking properties are largely obtained after purchase of the food product. Thus, social proof cues such as peer reviews could be important to inform consumers in their choices of such products (Cialdini and Cialdini 2007).

Specifically, food products have unique attributes that distinguish them from all other products. Food products are purchased on a regular basis by all and have important consequences for consumers' lives i.e., their health and well-being (Booth, 2001). This differs from most other products (whether experience or search), such as cameras or books. This comparison indicates that food product choice should be examined in its own right.

Further, we found several gaps in prior research in this area. First, most prior empirical studies have focused on examining the effects of either social proof cues (Lee and Sundar 2013; Rieh and Hilligoss 2008), or authority cues (Karakostas and Zizzo 2016; Thon and Jucks 2017), with limited studies investigating the effect of both cues on users' judgement (Kim and Gambino 2016; Venkataramani et al. 2016). Specifically, Kim and Gambino (2016) compared the effects of user-generated and expert information on credibility perceptions of users about movie reviews. Their results indicated that social proof cues had a greater effect with high information volume, but authority cues dominated otherwise. Venkataramani et al. (2016) compared the effects of authority cues vs peer or stranger tweets on risk health information. They found that authority cues dominated users' credibility perceptions. However, these prior studies were conducted in other, simpler contexts – as we described earlier food product choice is more complex and important than most other product choices.

Second, the effect of food product category has rarely been considered in previous research on food product choices. Yet, Liu et al. (2018) found that when consumers are asked to judge the healthiness of consumed food, their judgments are highly sensitive to food category, e.g., chocolate (unhealthy) versus almond (healthy), but not to food quantity. Considering the effect of food category on the perception of consumers, we chose a specific food category to focus on i.e., organic food. Specifically, organic food is considered important for a healthy diet due to beneficial nutrients, such as antioxidants, being more present in organic foods than in their conventionally-grown counterparts (Hofmann et al. 2014).

Motivated thus, this study investigates how two information sources, i.e., expert and user-generated evaluations, affect users' food product choices on a food literacy app. Specifically, we examine the following research questions: (1) *Does expert evaluation (authority cue) affect food product choice?* If so, *(2) Does user-generated evaluation (social proof cue) affect food product choice under the conditions of a given authority cue?*

To explore our research questions, we obtained clickstream data of 30 million logs[2] from the food literacy app[3] that indicates what a user has viewed, wrote, and clicked. It shows the full set of events allowing us to understand the behaviors of users on the app across time. On the app, users can view the *label information of each product, expert's grade, user's ratings and comments on the product*. They can include food products in or remove them from their online basket (as an indicator of choice). Thus, the app is suitable to estimate the effect of authority and social proof cues on users' food product choices. As an identification strategy, we use a regression discontinuity design (RDD) that documents the effects of authority cue (i.e., expert grade as a treatment) near the cut-off of a running variable of food score. Under the conditions of

[2] Due to the lack of space we did not include the details of clickstream data in the paper. The details can be provided on request.
[3] This is a major food literacy app, with 15,108 food products which cover most of the packaged foods in supermarkets in South Korea.

given expert evaluation, we analyze the effects of social proof (volume and valence of ratings and comments) on users' food choice using a Generalized Estimating Equation (GEE) for Poisson regression.

Our preliminary results confirm the significance of authority cues in the organic food category i.e., organic food with higher expert grade is more likely to be placed in users' baskets as compared to a lower graded food. Under the conditions of a given authority cue, we saw a partial effect of social proof i.e., the valence of ratings affects users' food product choice.

Our study contributes to the literature by investigating the effect of both authority and social proof cues jointly on food product choices. It also adds to prior research by using longitudinally collected clickstream data from a major food literacy app to gain a better understanding of users' responses to both forms of cues. Further, the RDD design we employed is empirically much more rigorous than prior correlational studies. The findings are important for providers of food literacy apps, who would like to understand how the cues on their apps influence users. The results are also valuable for nutrition experts, app users, and public health officials to understand what influences users' food product choices.

Theoretical Background

Information processing theories (Chaiken et al. 1996) suggest that information processing is an important determinant of whether a given piece of information actually changes people's attitudes, beliefs, and behavior. The cues in online information can trigger heuristics that aid behavior changes (Fu and Sim 2011; Metzger and Flanagin 2013). Yet, there is a limited understanding of how online information cues influence people's food choice, which is a critical part of our lives and is unique in terms of its complex psychological, economic, and sensory aspects (Shepherd and Raats 2006). Further, empirical support is required by testing the suggested relationships between such cues and individuals' health-related behavior changes. To understand these relationships, we draw on the concepts of information cues and their influence.

Information Cues and Influence

Sundar et al. (2009) defined a *cue* as "a piece of information provided by a medium that allows for evaluation of that information, possibly by triggering heuristics" (p. 4233). As there is information overload on most digital (including mobile) platforms, users are likely to evaluate information based on cues. The cues can stem from external advice given by experts and the general public (Axsom et al. 1987). Accordingly, these two endorsement-based cues, authority and social proof**,** have been widely discussed in the literature (Metzger et al. 2010).

Authority cue presents when people's information processing assigns credibility after judging whether the source is from an official authority or not (Metzger et al. 2010). For instance, health professionals can trigger the heuristic process with a certificate or license, which makes users believe that the information provided by them is credible. Authority cues are useful for quality control considering the abundance of information online. Authority cues for food product information are crucial because there is limited easy-to-read information on food labels. While governments require food manufacturers to list information about food nutrition on their products, many consumers find it challenging to interpret nutritional information on the labels (Viola et al. 2016). Often information, such as a "low fat" label, is mainly for marketing purposes, which can promote over-consumption of unhealthy foods (Monteiro et al. 2018). Thus, evaluation information provided by reliable official sources (e.g., government agencies) or by credentials (e.g., nutrition experts) may make food product information more credible.

Social proof is another key cue wherein people copy the actions of others when undertaking behavior in a given situation (Cialdini and Cialdini 2007). For instance, the probability of individual adoption of a product or service increases according to the accumulated and crowdsourced opinions of many others who have already done so, because users refer to predecessors' behaviors, which strengthens collective approval (Fu and Sim 2011). Especially, investigation of the effects of social proof cues, which have accumulated by a longitudinal aggregation of users' evaluation of specific products, is vital to a holistic understanding of user responses to it (Fu and Sim 2011).

The effect of social proof has been seen through the impacts of consumer reviews on product sales. This was investigated by assessing *the volume* (Ghose and Ipeirotis 2011; Zhu and Zhang 2010), and *valence of the reviews* (Chevalier and Mayzlin 2006; Hu et al. 2012; Zhu and Zhang 2010). The prior studies noted that review volume has a positive impact on sales growth because it can be perceived as the products' popularity by consumers (Ghose and Ipeirotis 2011; Zhu and Zhang 2010). On the other hand, the effect of the valence of reviews on products' sale is not as consistent. Negative reviews were found to harm product sales (Chevalier and Mayzlin 2006), but were also found to cause sales growth if the consumer could clearly understand the merits and demerits of the product through the reviews (Ghose and Ipeirotis 2011). More predictably, positive reviews were observed to increase product sales because such products were perceived as more trustable than products with negative reviews (Chevalier and Mayzlin 2006). In this study, we estimate the effects of both volume and valence of user-generated evaluations on users' food product choice.

Data Description

To empirically examine our research questions, we obtained clickstream data of 30 million logs of 100,368 users from a food literacy app over 80 weeks from July 2017 to January 2019. It includes label and nutrition information, expert evaluation (grades), and user-generated evaluation (likes/dislikes and reviews) for 15,108 food products available in supermarkets in South Korea. Users can view the products' information and can include food products in or remove them from their online baskets (as an indicator of food product choice). Thus, this app is suitable to empirically investigate how the focal cues of interest can influence users' food product choices. We chose the organic food category because of its importance in modern diets, with beneficial nutrients such as antioxidants being more present in organic foods than in their conventionally-grown counterparts (Hofmann et al. 2014). Furthermore, choosing organic foods is perceived as part of a healthy lifestyle especially among young adults (Von Essen and Englander 2013). Specifically, such health conscious users may utilize more food product information as compared to others. The organic food category in this app includes a wide variety of products such as noodles or snacks made by organic flour or bean, sausages or hams made by organic meat, and organic fruit drinks.

This app is ideal for our study of *authority cues* as experts grade each food product (i.e., A, B, C, and D), which can be used as a treatment to identify their causal effect on food product choice. We also collected users' reviews of food products in our sample over 80 weeks as *social proof cue*, which was measured through the *volume and valence* of user reviews and ratings. Our dataset contains 45,391 user-generated comments, 11,407 likes and 5,122 dislikes. Our product-week level panel dataset contains the following variables (ranges in brackets): 1) Volume of comments - the aggregated number of users' comments (0~164) on each product until week t, 2) Valence of comments - the average score of the sentiment (-1 to 1) of users' comments on each product until week t, 3) Volume of the rating (i.e., likes/dislikes) - the aggregated number of users' rating (0~175) on each product until week t, and 4) Valence of the rating - the average proportion of the likes (0~1) to total number of likes and dislikes on each product until week t. As a complementary to the review sentiment measures extracted using sentiment analysis (Cui et al. 2006), we also include the bifurcated rating i.e., likes/dislikes. This simple rating is useful to measure the impact of others' negative or positive evaluation on users' product choices. The dependent variable, Food Choice $\text{Ratio}_j = \sum Choice_j \,/\, \sum View_j$ for food product j is calculated as a ratio, as the number of times users choose to put a particular food product in their basket depends on the number of views of the product. Please note, this is the aggregated choice of all users for a particular food product.

Empirical Analysis

We first investigate the causal effect of authority cue (expert evaluation) using an RDD approach, and then examine the effect of social proof (user-generated evaluation) under a given condition of authority cue, to understand the interaction of the cues. RDD is a quasi-experimental, pretest-posttest design that elicits the causal effects of interventions (Hahn et al, 2001) i.e., experts' grade (evaluation) in this study.

RDD for Effect of Expert Evaluation on Food Product Choice

On this app, experts' grades of food products are basically calculated by using a weighted average of five different scores[4] on the ingredients: 1) Balance score of carbohydrate, protein, and fat, 2) Fat score, 3) Sugar score, 4) Sodium score, and 5) Calories score, as per a formula provided by the Korean Nutrition Standard[5] (Ministry of Health and Welfare) and Food Safety Display Guideline[6] (Ministry of Food and Drug Safety). Interestingly, the app assigns experts' grades (i.e., A, B, C, and D) based on the adjusted weighted-average

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[4] Due to the lack of space we did not include the equations for grade computation in the paper. The details can be provided on request.

[5] http://www.mohw.go.kr/react/jb/sjb030301vw.jsp?PAR_MENU_ID=03&MENU_ID=032901&CONT_SEQ=337356&page=1

[6] https://www.foodsafetykorea.go.kr/portal/board/boardDetail.do#

of five scores determined by the firm's licensed dietitians. Therefore, two food products with similar or identical ingredients could be given different grades (e.g., B or C) if their average scores are placed just above or below the cutoff point. Because the grade is non-parametrically identified for products near the cutoff, it is suitable for an RDD. As per RDD, we compare observations (food products) that are close to each other on either side of the threshold (grade boundary) which have similar endogenous component of the error, thus are able to account for this issue.

As the assignment rule in this app is not fully complied because of their adjustment (not all of the food products assigned to treatment or control groups near the cutoff comply with their assignment), the fuzzy RDD is preferable in our case. In contrast to the sharp RDD, a fuzzy RDD does not require a sharp discontinuity in the probability of assignment but is applicable as long as the probability of assignment is different. Hahn et al. (2001) show that when fuzziness occurs, the local average treatment effect (LATE) may be inferred for the subset of observations which are induced into treatment at the cutoff. For our RDD, Figure 1 presents the kernel density plots for the normalized average score in each expert grade group: A-B, B-C, and C-D. For every grade transition, there is a range of scores (80 to 90 for A-B, 70 to 80 for B-C, and 60 to 70 for C-D) where there is considerable overlap between treated and untreated groups, which represents a lot of non-compliers.

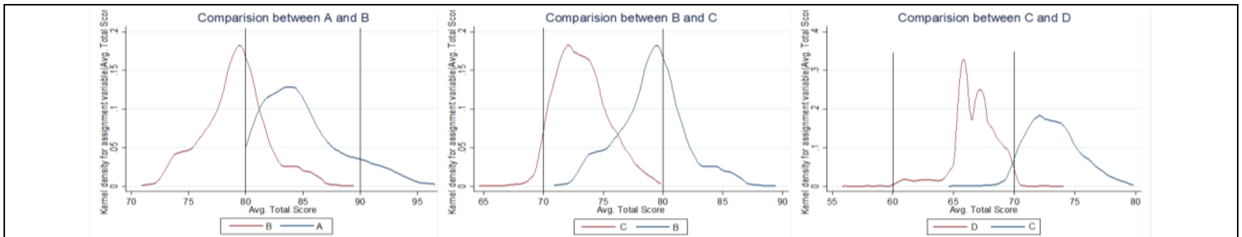

Figure 1. Kernel Density for Assignment Variable for Treatment and Comparison Groups

Assumptions of RDD approach

Following Angrist and Lavy (1999)'s and Hahn et al. (2001)'s fuzzy RDD approach, we employ the 2SLS IV approach for our analysis. In our context, instrumental variables (IV) estimate uses discontinuities in the relationship between food choice ratio and experts' grade, while the other relationship between average score and grade is controlled by including smooth functions (Angrist and Lavy 1999). As a result, the three assumptions of RDD outlined by Angrist and Lavy (1999) are applied in our context as follows: 1) The running variable Z (i.e., Average food score) is continuously distributed around the threshold (no sorting), 2) The probability of being treated (i.e., Highly graded) changes discontinuously, and there is a jump in the outcome variable at the threshold, and 3) In the absence of treatment, the expected outcome changes continuously around the threshold. We test the continuities of running variables and discontinuities in the relationship between choice ratio and grade, then we estimate the causal effects of experts' grade by adapting the LATE framework, as the subset of compliers was affected by the treatment T.

RDD Model Specification

In our study, for the treatment decision on product j, T_j (graded high or low) is a probabilistic function of the running variable Z_j (Average food scores). T_j is binary, where $T_j = 0$ if a food product is graded low and $T_j = 1$ if it graded high. Whether a food product receives treatment or not depends partially on the running variable Z. The observed outcome, which is the Food Choice Ratio is denoted as Y_j. Our 2SLS model is specified as follows:

$$\text{First-Stage: } T_j = \alpha_1 + \gamma_0 D_j + f_1(S_j) + \varepsilon_j \quad (1)$$

$$\text{Second-Stage: } Y_j = \alpha + \beta_0 \widehat{T_j} + f_2(S_j) + \mu_j \quad (2)$$

Where Y_j = Outcome (food choice ratio) for product j, $T_j = 1$ if product j receives the treatment, and 0 otherwise; $D_j = 1$ if product j is assigned to treatment based on the cut-point rule, and 0 otherwise; S_j = Average scores for product j; $f_1(S_j)$ = the relationship between the average score and treatment receipt for product j; $f_2(S_j)$ = the relationship between the average score and outcome (food choice ratio) for product j; ε_j = random error in the first stage regression assumed to be identically and independently distributed; and μ_j = random error in the second stage regression assumed to be identically and independently distributed. The first-stage equation in this model is estimated using ordinary least squares (OLS) regression. Then the predicted value of the mediator, $\widehat{T}_j$ in the second-stage, which replaces cut-point rule from the first-stage, produces an estimate of β_0. In this 2SLS method, in both stages $f_1(S_j), f_2(S_j)$ the same functional form is often used for both regressions in practice (Jacob et al. 2012).

Initial Results for the Effect of Expert Evaluation on Food Product Choice

First, we graphically and parametrically test for the continuity assumption using the McCrary (2008) tests. Due to the page limit of a short paper, we do not report the test results in full. The result shows there is no sorting or manipulation of the running variable around the threshold at standard statistical confidence level (A-B Discounuity: 0.227, s.e.: 0.108, B-C: 0.063, s.e.: 0.086, and C-D: 0.166, s.e.: 0.063). This evidence shows that the RDD assumption is satisfied. Second, Figure 2 reports graphical evidence around the threshold of expert grade changes which are normalized to zero. Our graphical evidence shows that 1) the experts' grade affects the food choice ratio for organic foods, and 2) the food choice ratio increases when the food is graded as B rather than C.

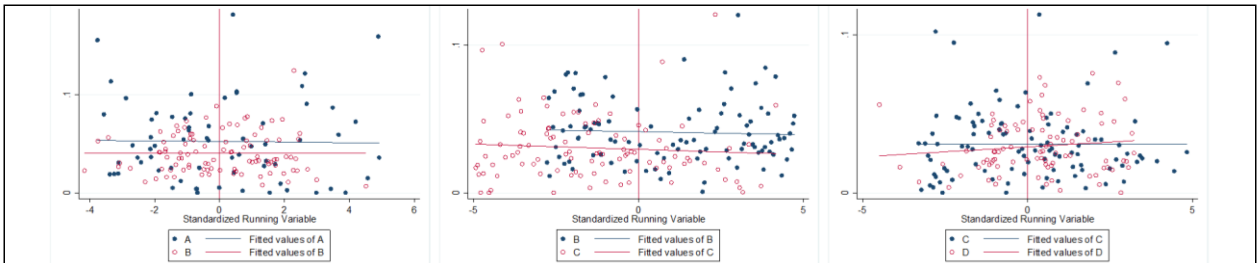

Figure 2. Graphical Analysis of Discontinuity Test of the Average Scores in Organic Foods

In Table 1, the first row reports the second-stage treatment estimates T_j for experts' grade, while the second row reports the estimates of assignment variable D_j in the first stage. The bottom two rows show the average in the sample sizes of treated and untreated groups. Consistent with the results shown in Figure 2, the coefficient of T_j in the B-C range ($\beta = 0.041$, $p < 0.01$) shows a strong positive relationship between the experts' grade and the outcome. The reason why the coefficients of treatment T_j in the A-B and C-D ranges are not significant maybe because of the small sample sizes and many non-compliers in these ranges.

Table 1. Fuzzy RD estimates of LATE (effects of experts' grade on food choice ratio)

	A-B range, coef (s.e.)	**B-C range, coef (s.e.)**[7]	C-D range, coef (s.e.)
Treatment T_j	0.009 (0.032)	**0.041** (0.014)**	-0.000 (0.030)
Assignment D_j	-0.001 (0.002)	0.000 (0.000)	-0.000 (0.001)
N untreated	104	211	225
N treated	67	150	7

Note: * p<0.05; ** p<0.01; *** p<0.001

While the coefficient of the treatment T_j is significant, the strength of the correlation between T_j and D_j should be tested. To check the coefficient γ_0 of instrument D_j in the first stage, we checked the F statistics for each range. The F-test value in the B-C range is over 10, a diagnostic rule of thumb, suggesting that the instrument D_j is not weak (Stock et al. 2002). As expected, the F statistic values in A-B and C-D ranges are below 10, indicating that the instruments in these ranges have no significant explanatory power. As a robustness check, we analyzed how the parameter changes when we added *control variables* such as numbers of views, price, brand, and social proof variables (i.e., volume and valence of rating and comments) which can be regarded as omitted variables. The result shows that the estimate for T_j is a little smaller (0.036**), but still significant at p<0.01 which implies that the finding is robust.

[7] Please note that the coefficient of the instrumental variable (D_j), reported in Table 1, is not statistically significant due to small sample size. Subsequently, we have increased the number of observations by adding more products in the other categories. For the B-C range, the numbers of untreated and treated products are 914 and 1,168, respectively. We re-estimated the fuzzy RDD model, and the coefficient of the instrumental variable (D_j) is statistically significant (γ = 0.001, p<0.001) along with the qualitatively similar treatment effect (T_j)(β = 0.013, p<0.01).

Effect of User-Generated Evaluation on Food Product Choice

We further investigate the effect of user-generated evaluation on users' food product choice under the given condition of authority cue, using the same dependent variable as used in the RDD model. Since the dependent variable is a proportion, which is bounded between 0 and 1, standard linear models may not provide an accurate picture of the effects of social proof cues on the choice ratio throughout the entire distribution. Following Wooldridge (2012), we use Generalized Estimating Equations (GEE) with a fixed-effects model specification to estimate the parameters of a generalized linear model with a possible unknown correlation between outcomes. Furthermore, as the distribution of the count-dependent variable is not continuous, OLS regression with a discrete dependent variable may perform poorly because the Gaussian probability distribution function results in inconsistent, biased results (Wooldridge 2012). For that reason, either Poisson regression or negative binomial regression is a better choice over OLS to estimate Equation (3). To determine whether Poisson panel regression is valid for use with our data and satisfies the requirements necessary for a panel count data, we performed the Pearson test for checking over-dispersion. We conclude that the model fits reasonably well because the goodness-of-fit chi-squared test is not statistically significant.

We operationalized social proof by using the volume (Ghose and Ipeirotis 2011; Zhu and Zhang 2010) and valence (Chevalier and Mayzlin 2006; Hu et al. 2012) of user-generated reviews. Due to the skewness of ratings and comments, we took a log-transformation. To study the impact of user-generated evaluation on food product choice, we specify our model as follows:

$$\begin{aligned}\textstyle\sum_t Food\ Choice\ Ratio_{jt} = {} & \beta_0 + \beta_1 \log\textstyle\sum_t Rating\ Volume_{jt} + \beta_2\, Average\ Rating\ Valence_{jt} \\ & + \beta_3 \log\textstyle\sum_t Comment\ Volume_{jt} + \beta_4\, Average\ Comment\ Valence_{jt} \\ & + \beta_5 \log\textstyle\sum_t \text{Views}_{jt} + \beta_6\, \text{Price}_j + \beta_7\, \text{Food Brand}_j + \delta_j + \tau_t + \nu_{jt} \quad \sim \text{N}(0, \sigma_v^2) \qquad \textbf{(3)}\end{aligned}$$

For the conditions of the treated group and untreated group, we run the separate regressions with the product and week fixed effects model specification as shown in Table 2. As each range of the scores, which determines treatment and control, have a different number of observation, we report only the B-C range case because it has the most number of observations.

Initial Results for the Effect of User-Generated Evaluations on Food Product Choice

As presented in Table 2, the coefficients of the average rating valence are positive and statistically significant in both treated and untreated subsamples. The results suggest that an increase in the accumulated average valence of rating (i.e., more number of likes compared to dislikes) leads to an increase in the choice of the food product. It is noteworthy that the magnitude of the rating valence when it has been treated (i.e., Graded high, B) is greater than the magnitude of the rating valence when it has been untreated (i.e., Grade low, C). In other words, the effect of rating becomes more effective when the product has a higher grade compared to a lower grade. The finding indicates that users who view organic food products with high experts' grade (Authority cue) and high rating valence (A social proof cue) will be likely to choose the product. This suggests that users who are interested in the organic food category may use the authority cue and a partial social proof cue in their information processing.

Table 2. Generalized Estimating Equation for Poisson Regression Results for User-Generated Evaluation Variables (Organic foods Category)

Treatment (Expert's Evaluation)	**Treated (Grade B)**	**Untreated (Grade C)**
$\boldsymbol{\log\sum_t Rating\ Volume_{jt}}$	0.304 (0.177)	0.186 (0.153)
$\boldsymbol{Average\ Rating\ Valence_{jt}}$	**2.026*** (0.526)**	**1.110* (0.099)**
$\boldsymbol{\log\sum_t Comment\ Volume_{jt}}$	0.201 (0.155)	0.090 (0.114)
$\boldsymbol{Average\ Comment\ Valence_{jt}}$	0.391 (0.393)	0.527 (0.278)
Contant	1.294 (1.163)	1.592 (1.662)
No. of OBS	1,846	3,577
No. of Products	46	89
Week Fixed Effect	YES	YES
Product Fixed Effect	YES	YES
Controls (Views, price, and brand)	YES	YES

Wald χ^2	63.36	89.33
Despersion	0.009	0.012
R^2	0.480	0.417
VIF (Mean/ Max)	(1.89/3.47)	(1.46/1.95)

Note: * p<0.05; ** p<0.01; *** p<0.001

Discussion

Despite the growing importance of food information provided through food literacy apps, there is a lack of understanding of the effects of the information cues via these apps on users' choice decisions. In this regard, our study is among the first to assess the effects of two information cues (i.e., authority and social proof cues) on users' food product choice. While the effect of food product category has rarely been considered in previous research on food product choices, we chose a specific food category to focus on i.e., organic food. Our results suggest that an organic food product that is graded higher is more likely to be chosen than a lower graded food product, where other observable characteristics remain the same. Further, our results suggest that among social proof cues i.e., the volume and valence of user comments and ratings, only the valence of rating (i.e., likes/dislikes) influences users in their food choice. In short, users prefer to choose organic food products with more number of likes than dislikes. The valence of ratings affects users' food choice while the valence of comments does not. The differential results may occur because the valence of rating contains simple information compared to the valence of comments, which consist of a lot of subjective descriptions. Thus, these easy-to-read and comprehend, numerical information of rating valence may provide shortcuts to users' information processing for the social proof cue. Our findings contribute to the literature by providing theoretical explanations and empirical evidence on the consequences of information cues through a food literacy app. In practice, aside from helping users, understanding such effects is important for key stakeholders i.e., app providers, food experts, and government authorities in the food industry who decide and provide guidelines to users.

Limitations and Future Research Plan

Following this initial study, there are several avenues for our future research. First, we will further investigate the use of cues in the other food categories. Here, we focused on the organic food category due to its importance in modern diets. By comparing the effect of cues on users' food choices in other food categories, such as snacks and drinks, we may find interesting patterns of the influence of cues. Second, our social proof cue effect estimation may be endogenous because of omitted variable problems. Therefore, we plan to collect additional data that contain any promotional activities of food products because they may affect users' product choice. Third, we mainly examined the direct effects of expert and user-generated evaluations on food product choice. We will explore the effect of the interplay in our future research. Finally, we plan to conduct focus-group interviews to better understand users app use and food choice motivations. Nevertheless, our initial results provide interesting implications for research and practice.

References

Angrist, J.D., and Lavy, V. 1999. "Using Maimonides' Rule to Estimate the Effect of Class Size on Scholastic Achievement," *The Quarterly Journal of Economics* (114:2), pp. 533-575.

Axsom, D., Yates, S., and Chaiken, S. 1987. "Audience Response as a Heuristic Cue in Persuasion," *Journal of Personality and Social Psychology* (53:1), p. 30.

Booth, S.L., Sallis, J.F., Ritenbaugh, C., Hill, J.O., Birch, L.L., Frank, L.D., Glanz, K., Himmelgreen, D.A., Mudd, M., Popkin, B.M. and Rickard, K.A., 2001. "Environmental and Societal Factors Affect Food Choice and Physical Activity: Rationale, Influences, and Leverage Points," *Nutrition Reviews* 59(3), pp. 21-36.

Chaiken, S., Giner-Sorolla, R., and Chen, S. 1996. "Beyond Accuracy: Defense and Impression Motives in Heuristic and Systematic Information Processing," In P.M. Gollwitzer & J.A. Bargh (Eds.), *The Psychology of Action: Linking Cognition and Motivation to Behavior*, pp. 553-578. NY: Guilford.

Chevalier, J.A., and Mayzlin, D. 2006. "The Effect of Word of Mouth on Sales: Online Book Reviews," *Journal of Marketing Research* (43:3), pp. 345-354.

Cialdini, R.B., and Cialdini, R.B. 2007. "Influence: The Psychology of Persuasion," Collins, New York.

Cui, H., Mittal, V., and Datar, M. 2006. "Comparative Experiments on Sentiment Classification for Online Product Reviews," *AAAI*, p. 30.

DiFilippo, K.N., Huang, W.-H., Andrade, J.E., and Chapman-Novakofski, K.M. 2015. "The Use of Mobile Apps to Improve Nutrition Outcomes: A Systematic Literature Review," *Journal of Telemedicine and Telecare* (21:5), pp. 243-253.

Flanagin, A.J., and Metzger, M.J. 2013. "Trusting Expert-versus User-generated Ratings Online: The Role of Information Volume, Valence, and Consumer Characteristics," *Computers in Human Behavior* (29:4), pp. 1626-1634.

Fu, W.W., and Sim, C.C. 2011. "Aggregate Bandwagon Effect on Online Videos' Viewership: Value Uncertainty, Popularity Cues, and Heuristics," *Journal of the American Society for Information Science and Technology* (62:12), pp. 2382-2395.

Ghose, A., and Ipeirotis, P. G. 2011. "Estimating the Helpfulness and Economic Impact of Product Reviews: Mining Text and Reviewer Characteristics," *IEEE Transactions on Knowledge and Data Engineering* (23:10), pp. 1498-1512.

Hahn, J., Todd, P., and Van der Klaauw, W. 2001. "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design," *Econometrica* (69:1), pp. 201-209.

Hofmann, W., Adriaanse, M., Vohs, K.D., and Baumeister, R.F. 2014. "Dieting and the Self-Control of Eating in Everyday Environments: An Experience Sampling Study," *British Journal of Health Psychology* (19:3), pp. 523-539.

Hu, N., Bose, I., Koh, N.S., and Liu, L. 2012. "Manipulation of Online Reviews: An Analysis of Ratings, Readability, and Sentiments," *Decision Support Systems* (52:3), pp. 674-684.

Jacob, R., Zhu, P., Somers, M.-A., and Bloom, H. 2012. "A Practical Guide to Regression Discontinuity," *MDRC*. dev.mdrc.org/sites/default/files/regression_discontinuity_full.pdf

Kim, J., & Gambino, A. (2016). “Do we trust the crowd or information system? Effects of personalization and bandwagon cues on users' attitudes and behavioral intentions toward a restaurant recommendation website,” *Computers in Human Behavior* (65), pp. 369-379.

Lee, J.Y., and Sundar, S.S. 2013. "To Tweet or to Retweet? That is the Question for Health Professionals on Twitter," *Health Communication* (28:5), pp. 509-524.

Lim, Y.-S., and Van Der Heide, B. 2014. "Evaluating the Wisdom of Strangers: The Perceived Credibility of Online Consumer Reviews on Yelp," *Journal of Computer-Mediated Communication* (20:1), pp. 67-82.

Liu, P. J., Haws, K. L., Scherr, K., Redden, J. P., Bettman, J. R., and Fitzsimons, G. J. 2018. "The Primacy of “What” over “How Much”: How Type and Quantity Shape Healthiness Perceptions of Food Portions," *Management Science* (65:7), pp. 3353-3381.

McCrary, J. 2008. "Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test," *Journal of Econometrics* (142:2), pp. 698-714.

Metzger, M.J., and Flanagin, A.J. 2013. "Credibility and Trust of Information in Online Environments: The Use of Cognitive Heuristics," *Journal of Pragmatics* (59), pp. 210-220.

Metzger, M.J., Flanagin, A.J., and Medders, R.B. 2010. "Social and Heuristic Approaches to Credibility Evaluation Online," *Journal of Communication* (60:3), pp. 413-439.

Monteiro, C.A., Cannon, G., Moubarac, J.-C., Levy, R.B., Louzada, M.L.C., and Jaime, P.C. 2018. "The Un Decade of Nutrition, the Nova Food Classification and the Trouble with Ultra-Processing," *Public Health Nutrition* (21:1), pp. 5-17.

Nelson, P., 1970. "Information and consumer behavior," *Journal of Political Economy* (78:2), pp. 311-329.

Rieh, S.Y., and Hilligoss, B. 2008. "College Students’ Credibility Judgments in the Information-Seeking Process," *Digital Media, Youth, and Credibility*, pp. 49-72.

Shepherd, R. and Raats, M. eds., 2006. "The Psychology of Food Choice," (3), CABI.

Stock, J.H., Wright, J.H., and Yogo, M. 2002. "A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments," *Journal of Business & Economic Statistics* (20:4), pp. 518-529.

Sundar, S.S., Xu, Q., and Oeldorf-Hirsch, A. 2009. "Authority vs. Peer: How Interface Cues Influence Users," *CHI'09 Extended Abstracts on Human Factors in Computing Systems: ACM*, pp. 4231-4236.

Thon, F.M., and Jucks, R. 2017. "Believing in Expertise: How Authors’ Credentials and Language Use Influence the Credibility of Online Health Information," *Health Communication* (32:7), pp. 828-836.

Venkataramani, Vijaya, et al. (2016). "Social networks and employee voice: The influence of team members’ and team leaders’ social network positions on employee voice," *Organizational Behavior and Human Decision Processes* (132), pp. 37-48.

Viola, G.C.V., Bianchi, F., Croce, E., and Ceretti, E. 2016. "Are Food Labels Effective as a Means of Health Prevention?," *Journal of Public Health Research* (5:3).

Von Essen, E., and Englander, M. 2013. "Organic Food as a Healthy Lifestyle: A Phenomenological Psychological Analysis," *International Journal of Qualitative Studies on Health and Well-being* (8:1), p. 20559.

Wickham, C.A., and Carbone, E.T. 2018. "What's Technology Cooking Up? A Systematic Review of the Use of Technology in Adolescent Food Literacy Programs," *Appetite* (125), pp. 333-344

Wooldridge, J. 2012. "Panel Data Models with Heterogeneity and Endogeneity," *Institute for Fiscal Studies*.

Zhu, F., and Zhang, X. 2010. "Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics," *Journal of Marketing* (74:2), pp. 133-148.