



# Who doesn't read online consumer reviews, and why?

Adrian R. Camilleri

UTS Business School, University of Technology Sydney (UTS), Sydney, Australia

## ARTICLE INFO

### Keywords:

Survey  
Information avoidance  
Word-of-mouth  
Online reviews  
Personality  
Decision-style

## ABSTRACT

Consumers increasingly rely on online consumer review (OCRs) to help them make purchase decisions. However, in a nationally representative sample of 1400 Australians, our survey revealed that 17.6% of consumers had never looked at an OCR in the past 12 months. We investigated the demographic, psychographic, and attitudinal variables that predicted being a non-user of OCRs. Non-users tended to be male, older, less educated, less digitally literate, less extraverted, open, and neurotic, and find OCRs relatively untrustworthy and unhelpful. Additionally, we investigated the reasons for why these non-users avoided OCRs. The two most common reasons were a lack of trust in OCRs and a preference to rely on other sources, particularly personal experience. We discuss the implications of these findings for businesses, review platforms, and consumer advocates.

## 1. Introduction

Online consumer reviews (OCRs) are an important source of information for many consumers. According to one recent survey, 82% of consumers read OCRs and 91% of them agree that positive reviews make them more likely to use a business (Brightlocal, 2019). Moreover, empirical research confirms the relationship between OCRs and sales (Zhu & Zhang, 2010). This article is concerned with those *not* part of the 82%; the often-forgotten group of consumers who do *not* read OCRs.

Although we have a good understanding of why consumers read OCRs (Goldsmith & Horowitz, 2006; Hennig-Thurau & Walsh, 2003; see Supplementary Materials for a summary table of all relevant literature) there exists a research gap describing which consumers categorically do *not* read OCRs and the reasons for their avoidance. We note that it is problematic to assume that research from more than a decade ago investigating the early adopters *most* likely to read OCRs and their motives reveals insights today about the laggards *least* likely to read OCRs and their motives. Even among today's population one particular group, for example males, could be both the most and least likely to read OCRs, and for different reasons.

Understanding who these non-users of OCRs are as well as their motivations is important for several reasons. First, given that OCRs are often considered an excellent source of information, non-users may be a vulnerable consumer group in need of additional support from consumer advocates. Second, for businesses that are increasingly focused on online brand management, non-users represent a consumer group that must be reached by other means. Third, for review platforms, non-users represent an untapped market and the reasons for their non-use can inform

these platforms' strategy.

According to Kim et al. (2011), there are three categories of reasons for why consumers use OCRs: reduce the risk of making a poor purchase, quickly gather useful information, and obtain social reassurance that a good purchase decision is being made. Our overarching hypothesis was that non-users of OCRs did not obtain these benefits or obtained them from elsewhere. In the next sections, we expand on this general hypothesis by describing the demographic, psychographic, and attitudinal variables that are potentially relevant in understanding non-users of OCRs. A conceptual overview is presented in Fig. 1.

### 1.1. Demographics

Demographics refers to demographic variables that describe a person such as age and gender. With respect to the question of who does not use OCRs, our analysis permitted directional hypotheses for age, gender, and education. Additionally, we measured other demographic variables for exploratory purposes.

Those who are older are often regarded as "laggards" in the diffusion process of innovations (Rogers, 1995) and are less trusting of the internet (Blank & Dutton, 2012). Other research indicates that older consumers tend to have lower digital literacy (The Office of the eSafety Commissioner, 2018). Consistent with these findings, a recent poll found that 75% of 18–55-year-olds search for businesses online each week compared to just 35% of those aged 55+ (Brightlocal, 2019). Therefore, we hypothesized that non-users (vs. users) of OCRs would be older.

Males are often considered to be more heuristic and self-orientated in their consumption behavior (Meyers-Levy & Loken, 2015). Consistent

E-mail address: [adrian.camilleri@uts.edu.au](mailto:adrian.camilleri@uts.edu.au).

<https://doi.org/10.1016/j.paid.2021.110954>

Received 15 November 2020; Received in revised form 10 March 2021; Accepted 19 April 2021

0191-8869/© 2021 Elsevier Ltd. All rights reserved.

with this belief, females tend to rely more heavily on word-of-mouth (Bae & Lee, 2011) and are more influenced by it during online shopping (Zhang et al., 2014). Females also put more weight on trust in the context of shopping online (Awad & Ragowsky, 2008) and are more likely to read OCRs for convenience and quality reasons (Kim et al., 2011). Therefore, we hypothesized that non-users (vs. users) of OCRs would be more likely male.

Education is one indicator of social class. Those who are more educated tend to more often own computers, have internet access, spend time online, find the internet easier to use, and possess the capability to keep up with technological advancements (Buente & Robbin, 2008; Porter & Donthu, 2006). Consistent with these findings, digital literacy has been shown to be positively associated with education (Scheerder et al., 2017). Therefore, we hypothesized that non-users (vs. users) of OCRs would be less educated.

1.2. Psychographics

Psychographics refers to psychological variables that describe a person such as their activities, interests, and opinions. One of the most important psychographic variables is personality (Baumgartner, 2002); that is, the combination of qualities that form a person’s distinctive character. The most well-accepted model of personality is the five-factor model (McCrae & Costa, 1987) according to which an individual’s personality can be described in terms of openness (the tendency to appreciate new ideas and behaviors), conscientiousness (the tendency to be self-disciplined, rule-abiding, and goal-driven), extraversion (the tendency to be sociable, active, and assertive), agreeableness (the tendency to be cooperative and good-natured), and neuroticism (the tendency to frequently feel anxious, insecure, and hopeless). Several papers have linked these factors to online consumer behavior. Internet usage is positively associated with extraversion, neuroticism, and

conscientiousness (Mark & Ganzach, 2014). Intention to shop online is positively associated with openness and negatively associated with neuroticism and agreeableness (Bosnjak et al., 2007). Intention to provide OCRs is positively associated with neuroticism and conscientiousness (Picazo-Vela et al., 2010). Conceptually, searching online and using OCRs to inform purchase decisions should involve mobilizing self-discipline to carry out a plan in pursuit of a goal (associated with conscientiousness), being active on the internet (associated with extraversion), being curious and interested in learning about other people’s opinions (associated with openness), being motivated to seek out and engage with information that could alleviate anxiety (associated with neuroticism), and being trusting and deferring to others (associated with agreeableness). Therefore, we hypothesized that non-users (vs. users) of OCRs would tend to be less conscientious, extraverted, open, neurotic, and agreeable.

Another important psychographic is the consumer’s decision style; that is, the type of approach used when evaluating options and making a choice between them (Scott & Bruce, 1995). A “rational” decision style is characterized by the thorough search for information and a systematic evaluation of all options whereas an “intuitive” decision style is characterized by the use of quick decision-making based on hunches and feelings (Hamilton et al. 2016). Conceptually, being systematic in gathering information online via OCRs is consistent with a rational decision style. Therefore, we hypothesized that non-users (vs. users) of OCRs would tend to have a less rational, more intuitive decision style.

One important aspect of decision-making style is maximization tendency. When making decisions, “maximizers” tend to search extensively through many alternatives with the goal of making the best choice whereas “satisficers” tend to search only until they identify an option that meets their standards (Schwartz et al., 2002). Thus, maximization is associated both with the goal of choosing the best option as well as the strategy of searching extensively (Cheek & Schwartz, 2016).

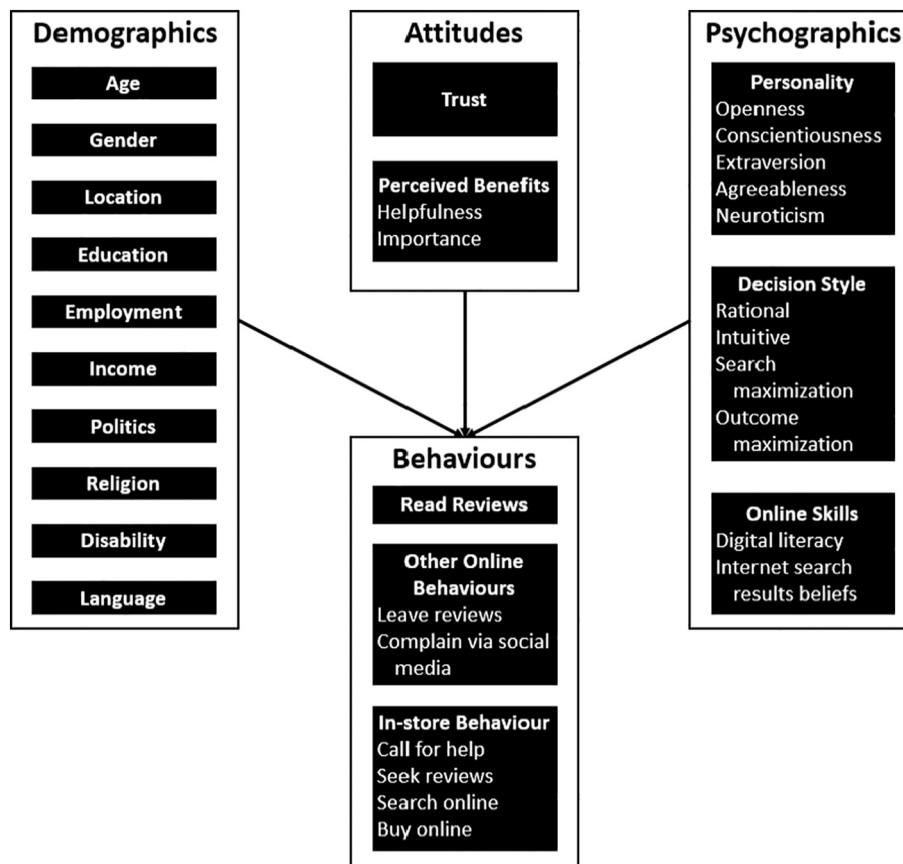


Fig. 1. A conceptual overview of the demographic, psychographic, and attitudinal variables predicting behaviors such as being a non-user of OCRs.

Correspondingly, maximizers have been shown to consider more options and spend more time and effort making decisions (Polman, 2010). Conceptually, searching extensively should include using OCRs. Therefore, we hypothesized that non-users (vs. users) of OCRs would tend to be less maximizing.

A final variable of interest is digital literacy; that is, an individual's internet-related skills and knowledge (Janssen et al., 2013). Digital literacy includes the technical skills of how to use the internet as well as problem-solving skills and content creation skills (Van Deursen et al., 2016). Research has shown that those with better digital literacy also tend to have better online information search competencies (Çoklar et al., 2017). Conceptually, those who are more skilled at navigating the internet should be more likely to seek out and find OCRs. Therefore, we hypothesized that non-users (vs. users) of OCRs would have lower digital literacy.

### 1.3. Attitudes

Attitudes refer to the relatively enduring set of beliefs, feelings, and behavioral tendencies towards something. One factor that drives attitudes towards OCRs is trust (Mumuni et al., 2019). Indeed, one of the most important factors determining the influence of OCRs on behavior is the degree of trust users have in OCRs (Cheung & Thadani, 2012). According to one report, 76% of consumers trust OCRs as much as recommendations from family and friends (Brightlocal, 2019). However, nearly half believe that it is hard to tell if OCRs are truthful and unbiased (Pew Research Center, 2016). Conceptually, consumers should be more likely to rely on information that they believe is credible and accurate (Dabholkar, 2006; Ha, 2004; Wang & Emurian, 2005). Ultimately, OCRs cannot serve to reduce risk if they are not trusted. Therefore, we hypothesized that non-users (vs. users) of OCRs would have a lower degree of trust in OCRs.

Another factor that drives attitudes towards OCRs is the perceived benefit (Mumuni et al., 2019). Indeed, one of the most important factors determining the influence of OCRs on consumer behavior is the degree of perceived benefit users have in OCRs (Park & Lee, 2009). Correspondingly, OCRs that are rated as more "helpful" tend to have a stronger influence on consumers' purchase decisions (Dhanasobhon et al., 2007). Conceptually, consumers should be more likely to rely on information that they believe is useful and beneficial (Sussman & Siegal, 2003). Ultimately, OCRs cannot serve to quickly gather useful information if they are not perceived as helpful. Therefore, we hypothesized that non-users (vs. users) of OCRs would perceive less benefit in OCRs as measured by perceived helpfulness and importance of OCRs.

### 1.4. Behaviors

The primary behavior of interest in this study was whether the consumer reported using OCRs. In addition, our survey measured related behaviors that we believed would be related to reading OCRs (e. g., shopping online, leaving OCRs, complaining to companies via social media) and thus similarly impacted by the demographic, psychographic, and attitudinal variables discussed above. In addition, we presented participants with a hypothetical scenario question in which they had the opportunity to use OCRs in a shopping context. Given their lack of preference for and familiarity with OCRs, in the scenario we hypothesized that non-users (vs. users) of OCRs would trust the presented OCRs less, be less likely to purchase the item, and have less confidence in their decision.

## 2. Methods

### 2.1. Participants

A marketing research firm sent 2294 Australians participants to the survey. Based on responses to quota questions, 1400 participants

ultimately completely the survey to be representative of the adult population in terms of age, gender, and location. Among the sample, 49% were males and the average age was 46.7 years. The full set of demographic characteristics is provided in the Supplementary Materials.

### 2.2. Procedure

The research was conducted with approval from the university IRB. Participants first answered three quota questions related to age, gender, and location. The participants who met the quota criteria were then presented with an ethics information page. For those who agreed to participate, there were a series of questionnaires that were presented in the order listed in Section 2.3. For non-users of OCRs, the survey took a median of 9.3 min to complete. The complete survey instrument for those classified as non-users of online reviews can be found online.<sup>1</sup> Note that participants who did use OCRs were presented with additional questions not discussed here.

### 2.3. Measures

#### 2.3.1. Demographics

Questions asked about age, gender, state location, living area (i.e., urban, suburban, rural), level of education, employment status, household income, political orientation on economic and social issues, political party affiliation, religion affiliation, god importance, degree of disability (with regards to seeing, hearing, walking, remembering, self-care, and communication on a 4-point scale ranging from "no difficulty" to "cannot do at all"), languages spoken, and English language proficiency

For the purposes of simplifying the analysis, we (1) converted the location question into a binary variable, *Rural*, which was coded "1" if the participant had indicated that they lived in a rural area otherwise "0"; (2) converted the employment status question into a binary variable, *Unemployed*, which was coded "0" if the participant had indicated that they were engaged in full-time or part-time work otherwise "1"; (3) converted the political affiliation question into a binary variable, *Politically Conservative*, which was coded "1" if the participant had selected "Liberal Part of Australia" or "Australian National Party" otherwise "0"; (4) converted the religion affiliation question into a binary variable, *Religious*, which was coded "0" if the participant had selected "No religion" otherwise "1"; (5) averaged the six questions measuring degree of disability into a new variable, *Disability*; (6) converted the languages spoken question into a binary variable, *Multilingual*, which was coded "0" if the participant had selected "English only" otherwise "1".

#### 2.3.2. Naïve internet search beliefs

One question adapted from the Ofcom (2019) media use and attitudes report coded "0" if the participant selected "I think that some websites will be accurate or unbiased and some won't be" or "1" otherwise.

#### 2.3.3. Digital literacy

Five questions answered on a 6-point scale taken from the Internet Skills Scale (Van Deursen et al., 2016). Example item: "I find it easy to find a website I visited before". The five items were averaged to form a single score (Cronbach's  $\alpha = 0.75$ ).

#### 2.3.4. Personality

Ten questions answered on a 5-point scale taken from the Ten-Item Personality Inventory (Gosling et al., 2003) measured extraversion (Cronbach's  $\alpha = 0.51$ ), agreeableness (Cronbach's  $\alpha = 0.24$ ), conscientiousness (Cronbach's  $\alpha = 0.45$ ), emotional stability (Cronbach's  $\alpha = 0.53$ ), and openness to experience (Cronbach's  $\alpha = 0.29$ ). Example item:

<sup>1</sup> <https://osf.io/8pb9u/>

“Extraverted, enthusiastic”.

### 2.3.5. Decision-making style

Four questions answered on a five-point scale were adapted from Hamilton et al. (2016), the Maximization Inventory (Turner et al., 2012), and the Maximizing Tendency Scale (Diab et al., 2008) to measure rational, intuitive, search maximizing, and outcome maximizing decision-making style. Example item: “When making decisions, I rely mainly on my gut feelings”.

### 2.3.6. Online shopping frequency

One question answered on a 5-point scale measured how often purchases were made online in fifteen different categories (e.g., home, groceries).

### 2.3.7. Source importance

One question answered on a 5-point scale measured how important nine different sources of information were when learning about new products and services (e.g., family/friends, OCRs).

### 2.3.8. In-store behavior

Four questions answered with either “yes” or “no” were taken from the Pew Research Center (2016) online shopping and e-commerce report to measure the extent to which mobile phones were used to help with in-store purchasing decisions. Example item: “Tried to find a better price online”.

### 2.3.9. Provided online consumer reviews

Two questions answered on a 5-point scale asked how often the participant had, in the last 12 months, provided a star rating or written a review. The two items were averaged to form a single score (Cronbach's  $\alpha = 0.85$ ).

### 2.3.10. Looked at online consumer reviews

One question answered on a 5-point scale asked how often the respondent had, in the last 12 months, looked at OCRs before buying a new product, visiting a restaurant or hotel, or using a service. Those who indicated “Never” were classified as a non-user of OCRs whereas everyone else was classified as a user of OCRs.

### 2.3.11. Trust

One question answered on a 5-point scale asked the degree of trust in five different sources of information (e.g., OCRs, experts).

### 2.3.12. Helpfulness

One question answered on a 5-point scale asked for an evaluation of the helpfulness of OCRs and government regulations at encouraging consumer confidence, making companies accountable, and ensuring product safety.

### 2.3.13. Reasons

One question asked the participant to indicate the reasons why they do not look at OCRs. Eight reasons were presented based on informal qualitative interviews with non-users. Example item: “I do not trust online reviews or ratings”. The participant could also articulate additional reasons by checking “Other” and typing a response.

### 2.3.14. Complained online

One question answered with either “yes” or “no” asked whether the respondent had ever made a complaint to a company directly via social media.

### 2.3.15. Scenario

Participants were asked to imagine they were searching for car insurance and had come across an unfamiliar insurer with cheap prices. An OCR was presented for the insurer. Based on publicly available statistics,

we estimated that approximately 85% of our sample were drivers, suggesting that the scenario was relevant to most participants. Participants were asked how likely they were to buy the car insurance, their degree of confidence in their decision, and the degree to which they trusted the OCR.

## 3. Results

### 3.1. Who Doesn't read OCRs?

The survey revealed that 247 of the 1400 respondents (17.6%) were non-users of OCRs. To examine the data, we conducted five logistical regressions where the dependent variable was whether the participant was a non-user (vs. user) of OCRs and the independent variables were the set of demographics, psychographic, attitudinal, behavioral, or all variables, respectively. The results of these analyses are presented in the different panels of Table 1. A parallel analysis using linear regression and the original 5-point dependent variable is presented in the Supplementary Materials. We acknowledge that both analyses may be threatened by endogeneity problems that can muddy inferences of causality.

In terms of demographics, non-users of OCRs were, as predicted, more likely male, older, and less educated on average. In addition, non-users had less household income, supported more conservative political parties, and had more disabilities on average.

In terms of psychographics, non-users of OCRs were, as predicted, less digitally literate, less extroverted, less neurotic, less open, and less often possessed a maximizer decision style on average. The other variables of interest – namely, agreeableness, conscientiousness, and decision styles – provided only directional support for the hypotheses.

In terms of attitudes, non-users of OCRs tended to, as predicted, trust OCRs less and consider OCRs to be less beneficial (in terms of being a less important source of information and less helpful at increasing consumer confidence). Additionally, non-users of OCRs also found salespersons to be a significantly more important source of information.

In terms of behaviors, non-users of OCRs tended to be, as predicted, less likely to engage in related activities, such as leaving OCRs and searching for product-related information online while shopping in-store. In the hypothetical shopping scenario, non-users of OCRs had less trust in OCRs, were less likely to purchase, and overall had less confidence in their decision.

The analysis that included all variables in a logistic regression revealed that the six strongest predictors were whether the consumer themselves left OCRs, their degree of trust in OCRs, their perceived helpfulness of OCRs, whether they sought OCRs while shopping in-store, their degree of digital literacy, and whether they found salespeople an important information source.

We conducted a series of exploratory mediation analyses using Hayes' PROCESS tool (v3.5) for SPSS. The most insightful model is presented in Fig. 2, which used PROCESS' model 8 with 5000 bootstrap samples. Age, gender, and their interaction were entered as predictors, trust in OCRs (*Trust - Online Reviews*) and perceived helpfulness of OCRs (*Helpfulness of Consumer Reviews - Confidence*) were added as mediators, and non-use of OCRs was entered as the predicted variable. The analysis revealed that those who were older were more likely to be non-users of OCRs and this was driven by the fact that older participants trusted OCRs less and found OCRs less helpful. This result was true for both males and females.

### 3.2. Why Don't some people read OCRs?

The reasons why non-users did not read OCRs are presented in Fig. 3. The most common reason (32.4%) was a lack of trust in OCRs. Exploratory post-hoc analyses revealed that this reason was particularly common among those who were older and those who did not have a maximizing decision style. The second most common reason (29.1%) was a strong reliance on personal experience when making purchase



**Table 1**

The output of five logistical regressions predicting non-users of OCRs from the set of demographics, psychographic, attitudinal, behavioral, and all variables.

| Predictor                               | Estimate (SE) <sup>a,b</sup>             |                              |
|---|--|------------------------------|
|   | Analysis with only demographic variables | Analysis with all variables  |
| Intercept                               | -0.12 (1.34)                             | +10.62 (2.50) <sup>***</sup> |
| Age                                     | +0.02 (0.00) <sup>***</sup>              | -0.02 (0.01) <sup>#</sup>    |
| Gender [woman]                          | -0.56 (0.15) <sup>***</sup>              | -0.38 (0.24)                 |
| Rural [false]                           | -0.28 (0.19)                             | -0.49 (0.30)                 |
| Education                               | -0.08 (0.04) <sup>*</sup>                | -0.06 (0.07)                 |
| Unemployed [false]                      | -0.05 (0.18)                             | -0.05 (0.27)                 |
| Household income                        | -0.07 (0.03) <sup>**</sup>               | +0.03 (0.04)                 |
| Political orientation - economic issues | +0.01 (0.08)                             | -0.06 (0.12)                 |
| Political orientation - social issues   | -0.00 (0.07)                             | -0.06 (0.11)                 |
| Politically conservative [false]        | -0.30 (0.15) <sup>#</sup>                | -0.14 (0.24)                 |
| Religious [false]                       | +0.18 (0.19)                             | -0.13 (0.29)                 |
| God importance                          | -0.07 (0.06)                             | +0.02 (0.10)                 |
| Disability                              | +0.37 (0.17) <sup>*</sup>                | +0.49 (0.28) <sup>#</sup>    |
| Multilingual [false]                    | +0.18 (0.31)                             | -0.11 (0.45)                 |
| English language proficiency            | -0.30 (0.27)                             | -0.76 (0.40) <sup>#</sup>    |
| Observations                            | 1395 <sup>c</sup>                        |                              |
| Adjusted R <sup>2</sup>                 | 0.06                                     |                              |

| Predictor                                   | Estimate (SE) <sup>a,b</sup>               |                             |
|---|--|-----------------------------|
|   | Analysis with only psychographic variables | Analysis with all variables |
| Intercept                                   | +3.41 (0.77) <sup>***</sup>                |                             |
| Naive internet search beliefs [false]       | -0.29 (0.16) <sup>#</sup>                  | -0.29 (0.25)                |
| Digital literacy                            | -0.56 (0.09) <sup>***</sup>                | -0.49 (0.14) <sup>***</sup> |
| Personality: extraversion                   | -0.11 (0.04) <sup>*</sup>                  | -0.04 (0.07)                |
| Personality: agreeableness                  | +0.10 (0.06) <sup>#</sup>                  | +0.11 (0.09)                |
| Personality: conscientiousness              | +0.10 (0.06) <sup>#</sup>                  | +0.05 (0.09)                |
| Personality: neuroticism                    | -0.15 (0.05) <sup>**</sup>                 | -0.1 (0.07)                 |
| Personality: openness                       | -0.12 (0.05) <sup>*</sup>                  | +0.1 (0.09)                 |
| Decision-making style: rational             | -0.09 (0.12)                               | +0.04 (0.18)                |
| Decision-making style: intuitive            | -0.01 (0.08)                               | +0.04 (0.12)                |
| Decision-making style: search maximization  | -0.22 (0.11) <sup>*</sup>                  | +0.07 (0.17)                |
| Decision-making style: outcome maximization | -0.11 (0.11)                               | -0.14 (0.18)                |
| Observations                                | 1400                                       |                             |
| Adjusted R <sup>2</sup>                     | 0.07                                       |                             |

| Predictor  | Estimate (SE) <sup>a,b</sup>             |                             |
|--|--|-----------------------------|
|  | Analysis with only attitudinal variables | Analysis with all variables |
| Intercept  | +4.13 (0.45) <sup>***</sup>              |                             |
| Source importance - family/friends                   | -0.04 (0.11)                             | -0.03 (0.13)                |
| Source importance - critics/experts                  | -0.08 (0.12)                             | +0.00 (0.14)                |
| Source importance - bloggers/influencers/celebrities | -0.08 (0.13)                             | +0.02 (0.16)                |
| Source importance - online reviews                   | -0.26 (0.11) <sup>*</sup>                | -0.10 (0.13)                |
| Source importance - offline advertising              | -0.01 (0.14)                             | -0.01 (0.17)                |
| Source importance - online advertising               | +0.26 (0.14) <sup>#</sup>                | +0.32 (0.17) <sup>**</sup>  |
| Source importance - store browsing                   | -0.06 (0.10)                             | +0.02 (0.12)                |
| Source importance - salesperson                      | +0.30 (0.12) <sup>*</sup>                | +0.38 (0.14) <sup>**</sup>  |
| Source importance - government sources               | -0.05 (0.12)                             | -0.02 (0.15)                |
| Trust - online reviews                               | -0.96 (0.13) <sup>***</sup>              | -0.75 (0.15) <sup>***</sup> |
| Trust - experts                                      | -0.23 (0.13) <sup>#</sup>                | -0.12 (0.16)                |

**Table 1 (continued)**

| Predictor  | Estimate (SE) <sup>a,b</sup>             |                             |
|--|--|-----------------------------|
|  | Analysis with only attitudinal variables | Analysis with all variables |
| Trust - government                                 | -0.03 (0.12)                             | +0.00 (0.16)                |
| Trust - businesses                                 | +0.06 (0.12)                             | +0.02 (0.14)                |
| Trust - comparator websites                        | -0.08 (0.12)                             | -0.13 (0.14)                |
| Helpfulness of consumer reviews - confidence       | -0.67 (0.13) <sup>***</sup>              | -0.7 (0.16)                 |
| Helpfulness of consumer reviews - accountable      | -0.08 (0.12)                             | -0.04 (0.15)                |
| Helpfulness of consumer reviews - safety           | +0.08 (0.11)                             | +0.14 (0.14)                |
| Helpfulness of government regulation - confidence  | +0.10 (0.12)                             | -0.07 (0.16)                |
| Helpfulness of government regulation - accountable | -0.13 (0.13)                             | -0.07 (0.16)                |
| Helpfulness of government regulation - safety      | -0.05 (0.12)                             | -0.13 (0.16)                |
| Observations                                       | 1388 <sup>c</sup>                        |                             |
| Adjusted R <sup>2</sup>                            | 0.28                                     |                             |

| Predictor                                | Estimate (SE) <sup>a,b</sup>            |                             |
|--|---|-----------------------------|
|  | Analysis with only behavioral variables | Analysis with all variables |
| Intercept                                | -0.03 (0.50)                            |                             |
| Online shopping frequency                | -0.05 (0.12)                            | +0.03 (0.17)                |
| In-store behavior - called [no]          | +0.37 (0.21) <sup>#</sup>               | +0.33 (0.26)                |
| In-store behavior - sought reviews [no]  | +1.51 (0.20) <sup>***</sup>             | +1.00 (0.25) <sup>***</sup> |
| In-store behavior - searched online [no] | +0.67 (0.21) <sup>**</sup>              | +0.62 (0.26) <sup>**</sup>  |
| In-store behavior - bought online [no]   | +0.28 (0.21)                            | +0.24 (0.26)                |
| Provided online reviews                  | -1.90 (0.21) <sup>***</sup>             | -2.08 (0.26) <sup>***</sup> |
| Complained online [no]                   | +0.29 (0.27)                            | +0.17 (0.32)                |
| Observations                             | 1388 <sup>c</sup>                       |                             |
| Adjusted R <sup>2</sup>                  | 0.28                                    |                             |

<sup>a</sup> The dependent variable was coded as 0 = *Does read OCRs* and 1 = *Does not read OCRs*.

<sup>b</sup> Note that \*\*\* indicates  $p < .001$ , \*\* indicates  $p < .01$ , \* indicates  $p < .05$ , and # indicates  $p < .1$ .

<sup>c</sup> A small number of observations were missing for one question and so these respondents were removed from the analysis.

decisions. The third most common reason (23.9%) was a reliance on other sources of information. Those who selected (vs. did not select) this reason tended to rate friends/family and critics/experts as significantly more important sources of information. “Other” reasons (6.8%) were frequently ones that fell under the existing categories (e.g., a lack of trust) or the lack of relevance OCRs have to the products that are typically purchased by the respondent (e.g., groceries and fuel).

**4. Discussion**

Previous research has found that usage of OCRs is ubiquitous. Consumers use them for three main reasons: to reduce risk, gather useful information, and obtain social reassurance (Kim et al., 2011). However, not all consumers use OCRs. We set out to discover who these non-users were and their reasons for avoiding OCRs using a large, representative sample. Our main finding was that certain types of consumers did not obtain any of these benefits or obtained them elsewhere.

With respect to reducing risk, non-users did not trust OCRs. Rather, the free response comments suggested a perception that OCRs were biased or fake. For example, one participant wrote, “Companies can write their own glowing reviews under false names”. This distrust is likely driven by the anonymity of reviews and inability of consumers to verify that OCRs derive from legitimate other consumers. Users of OCRs were asked a follow-up question regarding their ideal OCR platform

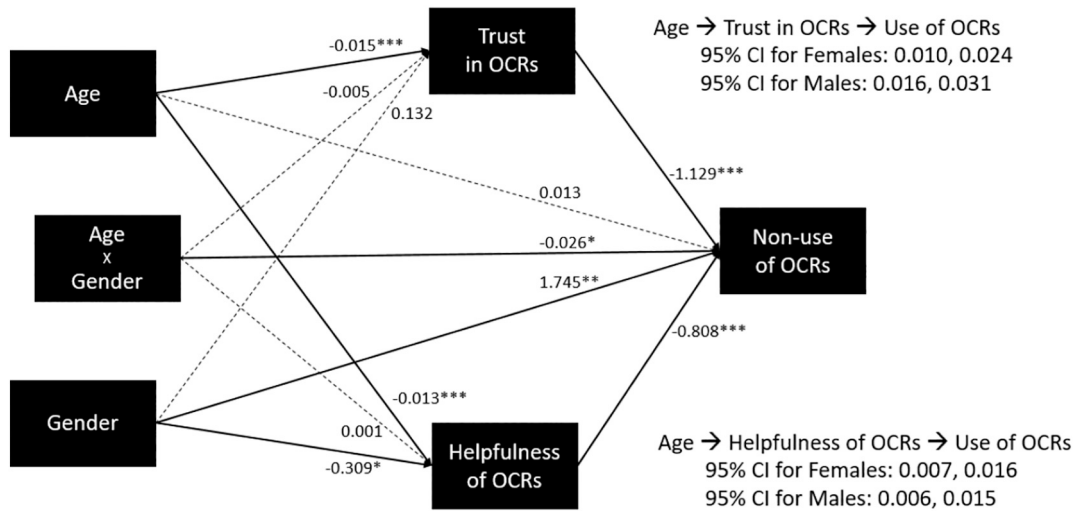


Fig. 2. Moderated mediation model predicting non-use of OCRs from age and gender via trust in and perceived helpfulness of OCRs. Note that the dashed lines indicate non-significant paths, and the solid lines indicate significant paths where \*\*\* indicates  $p < .001$ , \*\* indicates  $p < .01$ , and \* indicates  $p < .05$ .



Fig. 3. The proportion of non-users of OCRs selecting each reason for why they do not read OCRs.

features. The features most strongly endorsed were those that increased reviewer transparency, including a profile page for each reviewer displaying their average review score (82% agreement), total number of reviews (81% agreement), distribution of reviews (69%), membership duration (64% agreement), geographic location (62% agreement). OCR platforms could help alleviate trust concerns by providing such features and giving priority to reviews from verified purchasers.

With respect to gathering useful information, non-users did not find OCRs helpful in a way that could increase their confidence of making an informed decision. This finding relates to the Technology Acceptance Model (TAM; Davis, 1989), which explains the adoption of new information technology, including OCRs. According to TAM, a major determinant of engaging with technology is perceived usefulness. Rather than finding OCRs useful, non-users believed they were able to obtain information from other sources, often relying on their own personal experience. For non-users of OCRs (or those who fit the profile), platforms could prominently display OCRs from friends of the consumer and highlight the correspondence between OCRs and (the more trusted) experts' opinions.

With respect to obtaining social reassurance, non-users were able to find this support from alternative offline sources. These sources included friends and family but also the salespeople in-store. This latter result may be particularly concerning for consumer advocates because

salespeople are biased sources of information. From a theoretical perspective, previous research and models such as TAM do not account for the perceived benefits of alternatives to the adoption of the new technology, which our results suggests is important.

Demographically, non-users were more likely male, older, and less educated. We are the first to document that being older is associated with less trust of OCRs and perceiving them as less helpful, which are both associated with a decreased likelihood of using OCRs. In terms of psychographics, we are the first to show that non-users tended to have lower digital literacy, a decision style less concerned with maximizing the search for information, and a personality that was less extraverted, open, and neurotic.

**Funding**

This research was largely funded by the Consumer Policy Research Centre. Any views expressed in this article are those of the author and do not represent the views of the Consumer Policy Research Centre.

**CRedit authorship contribution statement**

Adrian Camilleri: Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing, Visualization.

**Appendix A. Supplementary materials**

Supplementary materials related to this article can be found online at <https://doi.org/10.1016/j.paid.2021.110954>.

**References**

Awad, N. F., & Ragowsky, A. (2008). Establishing trust in electronic commerce through online word of mouth: An examination across genders. *Journal of Management Information Systems*, 24, 101–121.

Bae, S., & Lee, T. (2011). Gender differences in consumers' perception of online consumer reviews. *Electronic Commerce Research*, 11, 201–214.

Baumgartner, H. (2002). Toward a personology of the consumer. *Journal of Consumer Research*, 29, 286–292.

Blank, G., & Dutton, W. H. (2012). Age and trust in the internet: The centrality of experience and attitudes toward technology in Britain. *Social Science Computer Review*, 30, 135–151.

Bosnjak, M., Galesic, M., & Tuten, T. (2007). Personality determinants of online shopping: Explaining online purchase intentions using a hierarchical approach. *Journal of Business Research*, 60, 597–605.

Brightlocal. (2019). Local Consumer Review Survey 2019. In.

- Buente, W., & Robbin, A. (2008). Trends in internet information behavior, 2000–2004. *Journal of the American Society for Information Science and Technology*, 59, 1743–1760.
- Cheek, N. N., & Schwartz, B. (2016). On the meaning and measurement of maximization. *Judgment and Decision making*, 11, 126–146.
- Cheung, C. M., & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. *Decision Support Systems*, 54, 461–470.
- Çoklar, A. N., Yaman, N. D., & Yurdakul, I. K. (2017). Information literacy and digital nativity as determinants of online information search strategies. *Computers in Human Behavior*, 70, 1–9.
- Dabholkar, P. A. (2006). Factors influencing consumer choice of a "rating web site": An experimental investigation of an online interactive decision aid. *Journal of Marketing Theory and Practice*, 14, 259–273.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319–340.
- Dhanasobhon, S., Chen, P.-Y., Smith, M., & Chen, P.-y. (2007). An analysis of the differential impact of reviews and reviewers at Amazon.com. *ICIS 2007 Proceedings*, 94.
- Diab, D. L., Gillespie, M. A., & Highhouse, S. E. (2008). Are maximizers really unhappy? The measurement of maximizing tendency. *Judgment and Decision Making Journal*, 3, 364–370.
- Goldsmith, R. E., & Horowitz, D. (2006). Measuring motivations for online opinion seeking. *Journal of Interactive Advertising*, 6, 2–14.
- Gosling, S. D., Rentfrow, P. J., & Swann, W. B., Jr. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in Personality*, 37, 504–528.
- Ha, H. Y. (2004). Factors influencing consumer perceptions of brand trust online. *Journal of Product & Brand Management*, 13, 329–342.
- Hamilton, K., Shih, S.-I., & Mohammed, S. (2016). The development and validation of the rational and intuitive decision styles scale. *Journal of Personality Assessment*, 98, 523–535.
- Hennig-Thurau, T., & Walsh, G. (2003). Electronic word-of-mouth: Motives for and consequences of reading customer articulations on the internet. *International Journal of Electronic Commerce*, 8, 51–74.
- Janssen, J., Stoyanov, S., Ferrari, A., Punie, Y., Pannekeet, K., & Sloep, P. (2013). Experts' views on digital competence: Commonalities and differences. *Computers & Education*, 68, 473–481.
- Kim, E. E. K., Mattila, A. S., & Baloglu, S. (2011). Effects of gender and expertise on consumers' motivation to read online hotel reviews. *Cornell Hospitality Quarterly*, 52, 399–406.
- Mark, G., & Ganzach, Y. (2014). Personality and internet usage: A large-scale representative study of young adults. *Computers in Human Behavior*, 36, 274–281.
- McCrae, R. R., & Costa, P. T. (1987). Validation of the five-factor model of personality across instruments and observers. *Journal of Personality and Social Psychology*, 52, 81–90.
- Meyers-Levy, J., & Loken, B. (2015). Revisiting gender differences: What we know and what lies ahead. *Journal of Consumer Psychology*, 25, 129–149.
- Mumuni, A. G., Lancendorfer, K. M., O'Reilly, K. A., & MacMillan, A. (2019). Antecedents of consumers' reliance on online product reviews. *Journal of Research in Interactive Marketing*, 13, 26–46.
- Ofcom. (2019). **Adults: Media Use and Attitudes Report 2019**. In.
- Park, C., & Lee, T. M. (2009). Antecedents of online reviews' usage and purchase influence: An empirical comparison of US and Korean consumers. *Journal of Interactive Marketing*, 23, 332–340.
- Pew Research Center. (2016). **Online Shopping and E-Commerce**. In.
- Picazo-Vela, S., Chou, S. Y., Melcher, A. J., & Pearson, J. M. (2010). Why provide an online review? An extended theory of planned behavior and the role of Big-Five personality traits. *Computers in Human Behavior*, 26, 685–696.
- Polman, E. (2010). Why are maximizers less happy than satisficers? Because they maximize positive and negative outcomes. *Journal of Behavioral Decision Making*, 23, 179–190.
- Porter, C. E., & Donthu, N. (2006). Using the technology acceptance model to explain how attitudes determine internet usage: The role of perceived access barriers and demographics. *Journal of Business Research*, 59, 999–1007.
- Rogers, E. (1995). *Diffusion of innovations*. New York: Free Press.
- Scheerder, A., van Deursen, A., & van Dijk, J. (2017). Determinants of internet skills, uses and outcomes. A systematic review of the second- and third-level digital divide. *Telematics and Informatics*, 34, 1607–1624.
- Schwartz, B., Ward, A., Monterosso, J., Lyubomirsky, S., White, K., & Lehman, D. R. (2002). Maximizing versus satisficing: Happiness is a matter of choice. *Journal of Personality and Social Psychology*, 83, 1178–1197.
- Scott, S. G., & Bruce, R. A. (1995). Decision-making style: The development and assessment of a new measure. *Educational and Psychological Measurement*, 55, 818–831.
- Sussman, S. W., & Siegal, W. S. (2003). Informational influence in organizations: An integrated approach to knowledge adoption. *Information Systems Research*, 14, 47–65.
- The Office of the eSafety Commissioner. (2018). *Understanding digital behaviours of older Australians - full report*. In.
- Turner, B. M., Rim, H. B., Betz, N. E., & Nygren, T. E. (2012). The maximization inventory. *Judgment and Decision making*, 7, 48–60.
- Van Deursen, A., Helsper, E. J., & Eynon, R. (2016). Development and validation of the internet skills scale (ISS). *Information, Communication & Society*, 19, 804–823.
- Wang, Y. D., & Emurian, H. H. (2005). An overview of online trust: Concepts, elements, and implications. *Computers in Human Behavior*, 21, 105–125.
- Zhang, K. Z., Cheung, C. M., & Lee, M. K. (2014). Examining the moderating effect of inconsistent reviews and its gender differences on consumers' online shopping decision. *International Journal of Information Management*, 34, 89–98.
- Zhu, F., & Zhang, X. (2010). Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of Marketing*, 74, 133–148.