Decision Support Systems 133 (2020) 113307

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

# The importance of online reviews depends on when they are presented

Adrian R. Camilleri

*UTS Business School, University of Technology Sydney, Australia*

ARTICLE INFO

*Keywords:*
Consumer choice
Online review
Online word-of-mouth
Order effects
Anchoring-and-adjustment

ABSTRACT

Imagine that you are a marketer with a good product but mediocre online reviews. When would be the best time to present the review score information to consumers: before the product description, with the product description, or after the product description? In order to answer this question, we carried out three online experiments in which we manipulated the order of information (reviews presented first or last), and timing of information (reviews presented simultaneously with or sequential to the product description). Overall, consumers put more weight on information that was seen most recently, particularly when the product description and review information was presented sequentially and the average review score was relatively low. That is, consumers put more weight on review score information after they had first formed an independent opinion based on the product description. Theoretically, these findings are best explained by an adjustment-based anchoring account. Practically, these findings arm managers with effective tactics regarding the placement of review score information.

## 1. Introduction

Imagine that you are a marketer with a good product but mediocre online reviews. What should you do? More specifically, when should you show consumers the review score information: before the product description, with the product description, or after the product description? This decision depends critically on which condition will make the product appear most appealing. Despite a wealth of research on electronic word-of-mouth (henceforth, eWOM) and online reviews (e.g., [1,8,11,54]), there is little pertinent research available to help a marketer answer this question. Yet the answer is important for marketers' decision of whether to present product and review score information jointly or separately and, if the former, the most appropriate order.

Is there any reason to imagine that consumers will form different product evaluations depending on when they are presented with review score information? A reasonable response would be *no*; after all, when the time comes to make a final evaluation the consumer has exactly the same information. On the other hand, evidence from the persuasion and advice taking literatures suggests that the answer may be *yes*; judgments can and often do vary as a function of information order and when evaluations take place. However, these literatures are far from unequivocal and rely on paradigms that neglect unique aspects of eWOM.

In this paper, we attempt to answer the marketer's dilemma by conducting three online experiments. To preview our results, we find that intentions to buy a product do vary as a function of when review score information is presented. Specifically, reviews appear to have the most impact after a consumer has first formed an impression based on the product description. To explain this observation, we rely on an adjustment-based anchoring account.

The rest of this paper is structured as follows. In Section 2, we review order effects in online reviews, persuasion, and advice-taking literatures before describing an anchoring-and-adjustment theoretical account. In Sections 3, 4, and 5 we describe three experiments designed to test the anchoring-and-adjustment account. Finally, in Section 6 we discuss the findings, implications, limitations, and avenues for future research.

## 2. Literature review and hypotheses development

### 2.1. Order effects in consumer review contexts

Consumer leave online reviews for various reasons including building a sense of belonging and enjoyment from helping other consumers [7,31]. In turn, most consumers self-report that they use review score information to help them make purchase decisions [33]. Correspondingly, there has been a large body of research investigating the relationship between online reviews and sales that has culminated in recent meta-analyses [1,20,54]. These analyses have focused on understanding how review score metrics (e.g., volume, valence), platform characteristics (e.g., platform maturity, presence of helpfulness

*E-mail address:* adrian.camilleri@uts.edu.au.

https://doi.org/10.1016/j.dss.2020.113307
Received 21 June 2019; Received in revised form 17 April 2020; Accepted 19 April 2020
Available online 23 April 2020
0167-9236/ 

ratings), and product characteristics (e.g., tangibility, maturity, risk level) relate to purchase intention and sales. A more descriptive literature analysis has produced an integrative model of the impact of eWOM communication comprising five factors: stimuli (e.g., valance, quality), receiver (e.g., involvement, prior knowledge), communicator (e.g., expertise, trustworthiness), context (e.g. platform characteristics), and responses (e.g., perceived usefulness and credibility) [8]. Unsurprisingly, the conclusion from these analyses is that online reviews influence consumer behavior. More surprisingly, these analyses are silent with respect to our central question: does it matter *when* a consumer is exposed to a product's review scores? The answer is important because this is a variable well within the control of marketers as well as potential decision support tools.

An evaluation of the consumer review literature does reveal some investigation of order effects with respect to the sequence of reviews (e.g., [24,35,40]). For example, the order in which different products (including information about their average review score) is presented can influence choice [49], often with the first presented product having an advantage [28]. Other research has revealed that the perceived usefulness of reviews is enhanced when there is a match between the overall review set valance and the valance of the first and last reviews in a sequence of mixed reviews [34]. Related research has shown that ordering reviews by their type – attribute-based reviews or experience-based reviews – influenced perceived helpfulness contingent on the type of product [23]. More recent research suggests that reordering reviews based on content could actually boost conversions [27]. Another strand of research focuses on how the order of posted reviews influences review helpfulness [56]. However, insight from these studies with regard to the current question is limited. This is because the previous investigations have focused on the order of individual reviews rather than the timing of review information relative to product information. Therefore, we turned our attention to order effects in other contexts.

### 2.2. Order effects in persuasion and advice taking contexts

In typical persuasion studies, participants are presented with two opposing arguments - one supporting an outcome and one opposing the same outcome - in different orders. Although unique in several ways, this paradigm is conceptually similar to our opening scenario: a good product with a persuasive product description coupled with mediocre reviews. Two basic order effects are possible: primacy and recency. A primacy effect occurs when judgment is more consistent with the *first* presented argument whereas a recency effect occurs when judgment is more consistent with the *last* presented argument.

The literature associated with order effects in persuasion is quite mixed with some studies finding primacy effects and some finding recency effects (see [15,19] for reviews). It is likely that these inconsistencies stem partly from the diverse procedures that have been used including different presentation form, message length, complexity of arguments, and number of communicators. For example, Buda and Zhang [4] conducted a study in which participants evaluated a new product. The order in which product information and the results of a successful test market were manipulated. Attitude towards the new product was higher when the test market results were presented last (i.e., recency). However, this main effect interacted with message framing and source credibility.

In typical advice-taking studies, an advisee is asked to provide an independent opinion on a simple judgment task (e.g., the year of a historical event), then presents the advisee with the opinion of an advisor, and then gives the advisee a chance to revise their initial opinion in light of the advisor's opinion (see [2], for a review). Again, although unique in several ways, this paradigm is conceptually similar to the opening scenario in that reviews are a form of advice from other people about the relative value of a product or service.

The literature associated with order effects in advice-taking indicates that advisees do not use advice particularly well, often overweighting their own opinion [52], or ignoring the advice that they receive altogether [39]. A rough estimate is that, on average, advisees tend to weight their own opinion 70%, which is consistent with a primacy effect. There have been a limited number of studies in the advice taking literature that have examined situations in which the advice was presented *before* having the opportunity to first form an opinion ([36,51], Study 3). The general finding from these studies is again primacy: advisees place more weight on advice when that advice comes before their own evaluation.

Several theories – for example, various consistency theories (e.g., [9]) and pure anchoring accounts (e.g., [12]) can explain these primacy observations. However, one important way in which the current context differs from typical advice-taking paradigms is the information complexity: eWoM is relatively more complex. In the following section, we describe a theory that takes into account information complexity and thus makes different predictions in our novel eWOM context.

### 2.3. An anchoring-and-adjustment account

Anchoring refers to the tendency to rely too heavily on the first piece of information encountered when making judgments or decisions, even when that information is clearly irrelevant [12]. Recent accounts of anchoring suggest that it occurs primarily at the retrieval stage through biased accessibility of anchor-consistent information: the "anchor" either primes anchor-consistent information in memory [30], or more generally primes people to focus first on anchor-consistent features of the target. Anchoring has been argued to be one of the main reasons to explain observations of primacy in the advice-taking literature [51].

Anchoring is often described in terms of anchoring-and-adjustment [12,45]. According to one prominent adjustment-based anchoring model, an individual's current opinion is adjusted by the impact of subsequent pieces of evidence [19]. The theory makes different predictions based on certain sub-processes, two of which are pertinent here. First, whether evidence is encoded as positive or negative relative to a constant hypothesis (an "evaluation" task), or whether evidence is encoded relative to a variable reference point (an "estimation" task). Within the framework of this model, a consumer integrating product information and review score information is completing a short series estimation task.

Second, whether evidence is processed and the associated belief is revised after each new piece of information (a "step-by-step" strategy), or only after all of the information has been acquired (an "end-of-sequence" strategy). According to the theory, a step-by-step strategy always produces recency effects. In contrast, an end-of-sequence strategy produces primacy effects when the information is *simple* (e.g., minimal and familiar) but recency effects when the information is *complex* (e.g., maximal and unfamiliar). Correspondingly, in the persuasion literature, research has revealed that the degree to which information is grouped partly determines whether primacy or recency is observed [32].

In the context of eWOM, when a product description and product reviews are presented on different pages, a step-by-step strategy is likely invoked. Note that a step-by-step strategy can be compelled if an explicit evaluation is requested after each new piece of information is presented. According to the theory, such a step-by-step strategy should produce recency effects.

When a product description and product reviews are presented on the same page, a step-by-step strategy or end-of-sequence strategy are both possible. According to Hogarth and Einhorn [19], "people try to match cognitive strategy with response mode but shift strategies if this proves too demanding" (p. 13). In other words, consumers should default to an end-of-sequence strategy but if information-processing demands are too high, they will move to a step-by-step strategy in order to cope with the cognitive demands. We began by assuming that most people would find the level of information processing required in the task to be moderate (relative to that in typical persuasion and advice taking studies), thus invoking an end-of-sequence strategy. According to the theory, such an end-of-sequence strategy should produce primacy effects.

In summary, our main hypothesis was that when evaluating a product, those presented with product information and product reviews separately would show a stronger recency effect (i.e., put more weight on the information presented last) than those presented with product information and product reviews together.

## 3. Experiment 1

The purpose of Experiment 1 was to examine whether product evaluation varied depending on when review score information was presented. Our key hypothesis related to whether review scores were presented separately from, or together with, product description. Therefore, we began our investigation by presenting participants with product information on one page followed by reviews on a second page (encouraging a step-by-step strategy), or both at the same time (encouraging an end-of-sequence strategy). In order to strengthen the manipulation, and similar to what is done in the advice-taking literature, we asked participants in the former group to provide an evaluation after each new piece of information, thereby forcing a step-by-step strategy. Our design produced two groups:

Group 1: Product Description ➔ Evaluation ➔ Reviews ➔ Evaluation;
Group 2: Product Description + Reviews ➔ Evaluation.

Based on pilot work, we discerned that most people tended to have a moderately positive disposition towards our product description. In order to provide a strong test of our prediction, we decided to manipulate the valance of the average review score. The rationale was to show an interaction: placing more weight on reviews after using a step-by-step strategy should increase (decrease) product evaluation when the reviews were positively (negatively) valenced. Pilot work revealed that many people tended to view 4.0 (out of 5) as a salient threshold delineating a “bad” and “good” average review score. Therefore, we presented participants with review score information either below or above this expectation.

Our main hypothesis – that processing information step-by-step produces recency – translated into an expected interaction between information ordering and valance: relatively more negative product evaluations when provided with a below-expectations review score and relatively more positive product evaluations when provided with an above-expectations review score for those in Group 1 (vs Group 2).

Given that previous research has shown that product type moderates consumers' judgment of review helpfulness [20], we also explored the generalizability of the hypothesized effect across product types. In particular, we compared an “experience good” – a product dominated by attributes that can only be evaluated *after* consumption – with a “search good” – a product dominated by attributes that can be evaluated *prior* to purchase [26,42].

### 3.1. Methods

#### 3.1.1. Participants

The participants were 409 American adults (222 female; $M_{\text{age}} = 31.50$, $SD_{\text{age}} = 10.70$) recruited from Amazon's Mechanical Turk (AMT) [13].

#### 3.1.2. Design

The experiment used a 2 (Order: Product-then-Reviews vs. Product-and-Reviews) × 2 (Review Score Mean: 3.4 vs. 4.6) × 2 (Product Type: Search vs. Experience) between-subjects design. Participants in the Product-then-Reviews group were exposed to a product description before providing an initial evaluation of the product. Participants were then exposed to review score information before making a second evaluation. In contrast, those in the Product-and-Reviews group were exposed to both the product description and the review score information simultaneously before providing a single evaluation of the product.

For the review score mean manipulation, we presented review score distributions with averages of either 3.4 out of 5 stars (designed to be below expectations) or 4.6 out of 5 stars (designed to be above expectations). For the product type manipulation, following Ullah, Amblee, Kima and Lee [47], we presented participants with either an experience good (a rice cooker) or a search good (a printer).

There were two dependent variables. First, a variable measuring stated intention to purchase the product, which was measured along a 10-point scale ranging from 1 = *Not likely at all* to 10 = *Very likely*. Second, a variable measuring expected satisfaction, which was measured as a constant sum item asking participants to predict the likelihood that they expected to “love”, “like”, “think it was ok”, “dislike”, or “hate” the product one year after having purchased it. Participants rated the likelihood that they would feel each of these five ways about the product from 0 to 100 with the total percentage required to equal 100%. The layout of this question was designed to mimic the layout of the review score distribution chart that was associated with 5-star rating levels. We combined these stated likelihoods into a single expected satisfaction score by assigning a score of 5 to “love”, 4 to “like”, 3 to “ok”, 2 to “dislike”, and 1 to “hate”, summing these scores weighted by their expected likelihood, and then dividing by 100. In practice, we found a strong positive association between the two dependent variables ($r = 0.59$, $p < .0001$) and similar patterns of results during analysis. In order to conserve space and eliminate redundancy, in this manuscript we only report on the intention measure.

#### 3.1.3. Materials

Each product was associated with two types of information: product description and review score information (see Supplementary material). The product description included a summary of the product's main features (i.e., a small image of the product, a one-sentence description of the product, the model number, top features, and price) together with much more detailed product-related information (e.g., the printer product description included print speed, print resolution, wireless functionality, and card slot access).

The review score information showed a summary score out of 5, five white stars that were partially colored yellow to match the score, the number of customer reviews, and a frequency distribution chart showing the percentage of 5-, 4-, 3-, 2-, and 1-star reviews. The number of customer reviews was set at 250. The distribution of reviews was manipulated to show the desired average review score.

#### 3.1.4. Procedure

The study was conducted online. On the first page, all participants were presented with a short paragraph asking them to imagine that they were browsing an online website for a product and had come across a product that met the minimum criteria. Participants in the Product-then-Reviews group were then presented with the product description. On the next page, these participants were asked for their initial product evaluation. On the next page, these participants were presented with the review score information associated with the product. On the next page, these participants were asked for their overall product evaluation. In contrast, participants in the Product-and-Reviews group were presented with the product description and review score information on the same page. On the next page, these participants were asked for their overall product evaluation.

After the choice stage, participants completed a series of exploratory follow-up questions. Given that these questions were for exploratory purposes, we do not discuss them any further. After the exploratory questions, participants completed some attention check and manipulation check items. The manipulation check question measured the participants' perceived ability to judge the performance of six products at different times: three "experience" products (rice cooker, movie, novel) and three "search" products (printer, television, digital camera). Similar to [29], participants rated their ability to judge the performance of each product *before* purchasing the product as well as *after* (hypothetically) purchasing and consuming the product. These questions were answered on a scale ranging from 1 = "Not at all" to 10 = "Very well". Finally, all participants completed a series of basic demographic questions (e.g., gender, age, education level, etc.).

### 3.2. Results

Given that all reported analyses in this paper produced qualitatively similar results regardless of whether those who failed the attention check items were removed or retained, we elected to retain all participants in all analyses.

#### 3.2.1. Manipulation check

In order to confirm that the manipulation was successful, we subtracted each participant's judged ability to evaluate the performance of a product *after* versus *before* consumption for the two products of interest: the rice cooker and the printer. The perceived ability to judge both products was seen as easier after consumption compared to before (both $p$'s $< .0001$). However, as expected, the judged ability difference between *after* and *before* consumption was significantly larger for the rice cooker ($M = 3.1$, $SD = 2.9$) than the printer ($M = 2.6$, $SD = 2.6$), $t(408) = 4.60$, $p < .0001$. These results support the belief that the rice cooker was more strongly perceived as an experience good and the printer was more strongly perceived as a search good.

#### 3.2.2. Intention

The average intention to buy the product is presented in Fig. 1. The first thing to note in this figure is the dotted line, which presents the average intention to buy the products based only on the product descriptions. Recall that this information was only measured for participants in the Product-then-Reviews group. As can be seen, intention to buy without yet having seen the reviews was significantly higher than the scale midpoint, $t(204) = 13.42$, $p < .0001$. This observation confirms our pilot work indicating a positive disposition towards the product based on its description alone.

In order to analyze the data, we carried out an ANOVA with Order, Average Review Score, and Product Type entered as independent variables, and intention to buy entered as the dependent variable. Consistent with our main prediction, there was a significant interaction between Order and Average Review Score, $F(1, 401) = 9.36$, $p = .002$. This interaction appears consistent with a stronger recency effect – in this case, more weight on reviews, which were presented second – for those in the Product-then-Reviews group. Indeed, planned follow-up contrasts revealed that, when the average review score was 3.4, intention was significantly lower for those in the Product-then-Reviews group compared to those in the Product-and-Reviews group, $F(1, 401) = 8.22$, $p = .004$. However, when the average review score was 4.6, intention was not significantly different between different Order groups $F(1, 401) = 2.14$, $p = .14$. The analysis also revealed a significant main effect for Average Review Score, $F(1, 401) = 97.60$, $p < .0001$, and a significant a main effect for Product Type, $F(1, 401) = 12.37$, $p = .0005$. No other contrasts were significant ($ps > .05$).

### 3.3. Discussion

The results of Experiment 1 revealed that in some contexts people put more weight on review score information in a Product-then-Reviews scenario than a Product-and-Reviews scenario. Specifically, we observed that a negatively-valanced average review was more likely to reduce product evaluation when that review score information was learned about separately and after the description. This observation, which is consistent with a recency effect, was observed with both an experience good and a search good. Interestingly, recency occurred only when the rating valance was negative and not when it was positive. This observation is consistent with a negativity bias where the psychological effects of negative information outweigh those of positive information [37]. Such a negativity bias has been observed in the context of consumer reviews ([38], but see [50]). In short, it may simply be that 3.4 out of 5 stars is more negative than 4.6 out of 5 stars is positive.

In order to confirm our initial observations, we carried out a replication study with 1294 American adults (672 female; $M_{\text{age}} = 32.98$, $SD_{\text{age}} = 10.79$) recruited from AMT. This time, the participant was asked to evaluate a television and we focused on situations where the average review score was below expectations for all participants. As a result, rather than an interaction, the predicted recency effect would be indicated by a main effect of order. We also explored whether a number of other eWoM factors might moderate the order effect. Therefore, the experiment was a 2 (Order: Product-then-Reviews vs. Product-and-Reviews) × 2 (Average Review Score: 2.6 vs. 3.4) × 2 (Number of Reviewers: 25 vs. 250) × 4 (Distribution Shape: U-shaped vs. Inverted-U-shaped vs. Negatively Skewed vs. Positively Skewed) between-subjects design. Supporting our expectations, this replication study revealed a main effect for Order, $F(1, 1262) = 25.47$, $p < .001$: people put more weight on review score information in the Product-then-Reviews group than the Product-and-Reviews group. This main effect did not interact with any of the other factors ($ps > 0.05$).

Theoretically, these observations are consistent with an anchoring-and-adjustment account. Those in the Product-then-Reviews group formed an initial evaluation based on the product description, which was positive, and then adjusted that evaluation downward (upward) given the negative (positive) reviews. By design, participants in the Product-then-Reviews group were obliged to use a step-by-step processing strategy, which produced recency. In contrast, those in the Product-and-Reviews group were free to use either a step-by-step strategy or an end-of-sequence strategy because all the available information was presented on a single page. We suggest that the nature of the task encouraged at least some of the participants in the Product-and-Reviews group to adopt an end-of-sequence strategy, which tended to produce primacy. The net result was relatively more weight on the last piece of information – review score information – by those in the Product-then-Reviews group.

There are two limitations of the first experiment and its replication that we addressed in the following experiments. First, based on the observations made in the first experiment, we could not rule out the explanation that consumers simply put more weight on review score information when it is presented separately from other information. For example, it could well be the case that consumers place more weight on review score information when it is separately presented before (as well as after) product information. Second, the design of the first experiment attempted to force a step-by-step strategy for those in the in the Product-then-Reviews group by requiring two product evaluations: one before and one after being presented with the reviews. As a result, this design produced a confound: those in the Product-then-Reviews group made two evaluations whereas those in the in the Product-and-Reviews group made only one evaluation. Such a confound could be the source of an alternative explanation for the observations made in experiment 1 and its replication: conversational norms.

Grice's [14] conversational norms describe the assumptions that people tend to hold when they engage in conversation to exchange information or to complete tasks. The ultimate consequence of these norms is that listeners can reasonably assume that speakers are trying to be informative, truthful, relevant, and clear [6,41]. For example, the maxim of relevance holds that speakers should make all communications relevant to the aims of the ongoing conversation and listeners

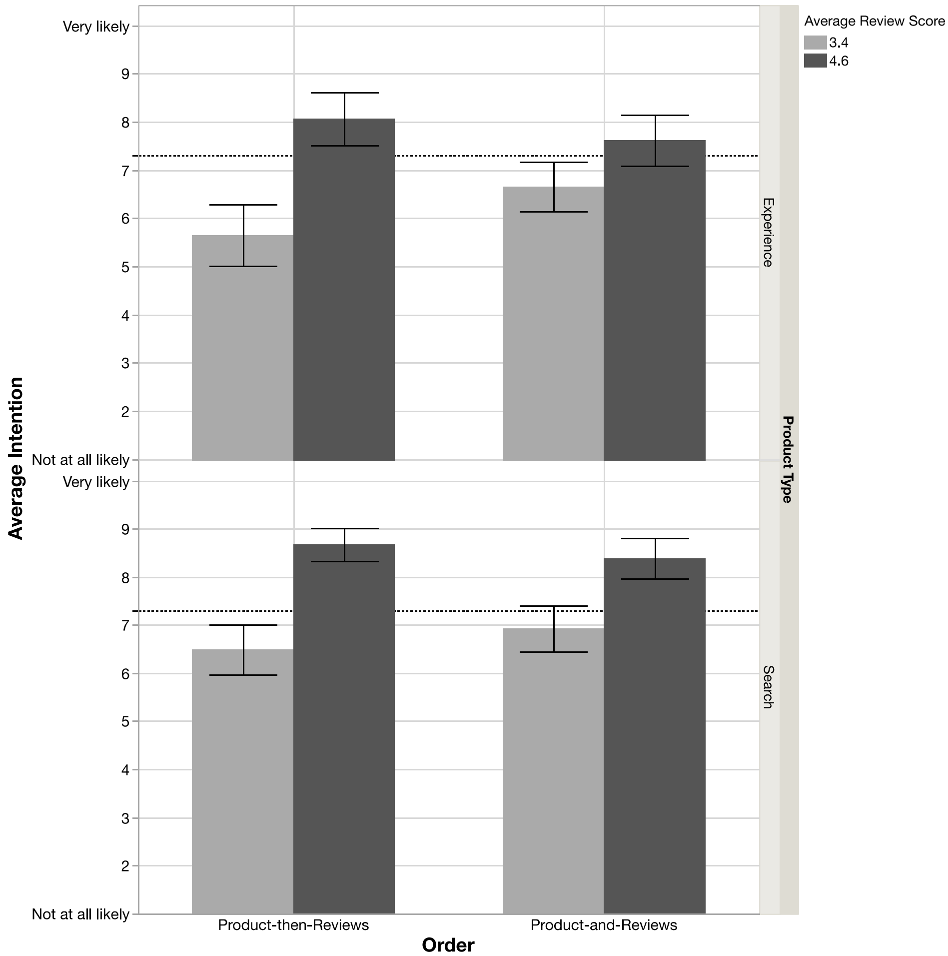


**Fig. 1.** Average intention to purchase in Experiment 1 split by Order, Average Review Score, and Product Type. The dotted line represents the average intention score prior to seeing the review scores for those in the Product-then-Reviews group. Error bars are 95% confidence intervals.

should try to determine the intended meaning of the speaker's communication. Therefore, asking a research participant the same question – for example, "how likely are you to buy this product?" – before versus after being presented with reviews may create a conversation "implicature", based on the maxim of relevance, that the reviews are important and that the original response was inadequate and should be modified. If participants in the Product-then-Reviews group formed final evaluations by attempting to follow the rules of Gricean conversational norms, then they might be relatively more influenced by reviews when asked to revise their evaluation compared to those in the Product-and-Reviews group who had not be asked to revise their opinion in light of new information. We designed Experiment 2 to rule out this alternative explanation.

## 4. Experiment 2

The observations made in Experiment 1 are consistent with both adjustment-based anchoring and Gricean conversational norms accounts. The purpose of Experiment 2 was to distinguish between them. To do so, in this experiment we always placed the product and reviews information on different pages, and manipulated the order. We also manipulated how many times a product evaluation was elicited. Similar to the Experiment 1 replication study and the opening scenario, we simplified the design by focusing only on situations with a low average review score. Our design produced four groups:

Group 1: Product Description ➔ Reviews ➔ Evaluation;
Group 2: Product Description ➔ Evaluation ➔ Reviews ➔ Evaluation;
Group 3: Reviews ➔ Product Description ➔ Evaluation;
Group 4: Reviews ➔ Evaluation ➔ Product Description ➔ Evaluation.

According to the Gricean conversational norms account, greater weight on review score information by those in the Product-then-Reviews group in Experiment 1 was the result of these participants believing that the researcher wanted them to revise their initial evaluation using the second piece of information (a demand effect). This account critically depends on participants being asked to make two evaluations. The main prediction from this account was an interaction effect with intention to buy higher for Group 1 than 2, and lower for Group 3 than 4.

According to the adjustment-based anchoring account, greater weight on review score information by those in the Product-then-Reviews group in Experiment 1 was the result of a step-by-step processing strategy. As discussed earlier, those in the Product-then-Reviews must use a step-by-step strategy, which produces recency. In contrast, at least some of those in the Product-and-Reviews group used an end-of-sequence strategy, which produces primacy. This difference between step-by-step processing (causing recency) and end-of-sequence processing (causing primacy) was responsible for the order effect. In the current experiment, all information was presented on sequential pages. Therefore, unlike the previous experiments, our design encouraged a step-by-step strategy for all groups, which should result in recency for all groups. The main prediction from the adjustment-based anchoring account was a main effect of order (i.e., average of Groups 1 and

2 < average of Groups 3 and 4) with no differences between Groups 1 and 2, and also no differences between Groups 3 and 4.

### 4.1. Methods

#### 4.1.1. Participants

The participants were 201 American adults (97 female; $M_{\text{age}} = 32.41$, $SD_{\text{age}} = 10.47$) recruited from AMT.

#### 4.1.2. Design

The experiment used a 2 (Order: Product-then-Reviews vs. Reviews-then-Product) × 2 (Number of Evaluations: 1 vs. 2) between-subjects design. The Order manipulation determined whether participants were presented with the product description first and review score information second, or the reverse order. The Number of Evaluations manipulation determined whether or not the participant was asked to make an evaluation after each new piece of information was presented or only after all information was presented. The dependent variables were the same as those used in Experiments 1.

#### 4.1.3. Materials

Given the absence of differences between search and experience goods in Experiment 1, in this experiment we presented all participants with a television stimulus (see Supplementary material). The review score information was the 2.6 out of 5 star negatively skewed distribution based on 25 reviews.

#### 4.1.4. Procedure

The study was conducted online. The overall procedure was similar to that undertaken in Experiment 1 with the addition of some new exploratory questions relating to perceived review score validity and confidence in the predicted satisfaction measure. Given that these questions were for exploratory purposes, we do not discuss them any further.

### 4.2. Results

The average intention to buy the product is presented in Fig. 2. The first thing to note in this figure is the dotted and dashed lines. The dotted line presents the average intention to buy the product based only on the product description by those in the Product-then-Reviews group. This group's initial intention to buy was significantly higher than the scale midpoint, $t(48) = 6.83$, $p < .0001$. The dashed line presents the average intention to buy the product based only on the reviews by those in the Reviews-then-Product group. This group's initial intention to buy was significantly lower than the scale midpoint, $t(49) = -6.89$, $p < .0001$.

In order to analyze the data, we carried out an ANOVA with Order and Number of Evaluations entered as independent variables, and intention entered as the dependent variable. Consistent with the anchoring-and-adjustment account, there was a significant effect for Order, $F(1, 197) = 11.82$, $p = .0007$, and no interaction, $F(1, 197) = 2.31$, $p = .13$. The main effect indicates recency: more weight on the information presented last. Planned follow-up contrasts revealed no support for the Gricean conversational norms account: for those in the Product-then-Reviews group, there was no intention difference between those making 1 or 2 evaluations, $F(1, 197) = 1.85$, $p = .18$. Similarly, for those in the Reviews-then-Product group, there was no intention difference between those making 1 or 2 evaluations, $F(1, 197) = 0.61$, $p = .43$.

### 4.3. Discussion

The observations made in Experiment 2 support an adjustment-based anchoring account over the Gricean conversational norms account. More specifically, the adjustment-based anchoring predicted a recency effect regardless of the number of evaluations whereby the information presented last would have a relatively stronger impact on final evaluations. Taking into account the independent evaluations of each piece of information (i.e., product description is a positive cue and reviews are a negative cue), this was exactly the pattern of results that were observed.

Importantly, this experiment also allowed us to rule out the alternative explanation for the observations made in Experiment 1: that consumers simply put more weight on review score information when it is presented separately from other information. Such an account would predict no differences between the groups in Experiment 2 given that all information was presented on separate pages. This is clearly not what happened. Rather, the order of the separately presented information influenced overall product evaluations.

One limitation of the second experiment is that it did not include a control condition in which both product description and product reviews were shown on the same screen. As a result, there was no way to compare the importance of sequential versus simultaneous presentation of product and review information. We carried out Experiment 3 to address this limitation.

## 5. Experiment 3

The observations made in Experiments 1 and 2 suggest that the order in which product information and review score information is presented influences purchase intention. The purpose of Experiment 3 was to examine the importance of information timing, specifically, simultaneous versus sequential presentation. Therefore, we carried out an experiment that crossed the order of information with its timing. Our design produced four groups:

Group 1: Product Description + Reviews ➔ Evaluation;
Group 2: Product Description ➔ Reviews ➔ Evaluation;
Group 3: Reviews + Product Description ➔ Evaluation;
Group 4: Reviews ➔ Product Description ➔ Evaluation.

As in previous experiments, we expected an overall recency effect that would be indicated by a main effect for order (i.e., higher intention to buy for those in Groups 3 and 4 averaged than those in Groups 1 and 2 averaged). In addition, we expected an interaction between order and timing. This is because, according to the anchoring-and-adjustment model, when information is sequentially presented, people tend to use a step-by-step strategy, which produces recency. In contrast, when information is simultaneously presented, people can use either a step-by-step or end of sequence strategy, which should produce a mix of recency and primacy among the participants in this group. Therefore, we expected to see a larger difference between Groups 2 and 4 than between Groups 1 and 3.

For generalizability, in this experiment, we changed the primary dependent variable from stated intention to buy (i.e., "*Would I consider buying this*?") to stated willingness to pay (i.e., "*If I did buy this*, *how much would I spend on it*?"). A secondary benefit of the willingness to pay measure was that it provided some indication of how much a seller could expect to financially benefit from harnessing the order effect investigated here.[1]

[1] In a separate study, we presented 51 Americans recruited from AMT with the television product description and reviews (on the same page) and then asked each participant their intention to buy and willingness to pay (on different pages). The correlation between stated intention and willingness to pay was strongly positive ($r = 0.54$, $p < .0001$).

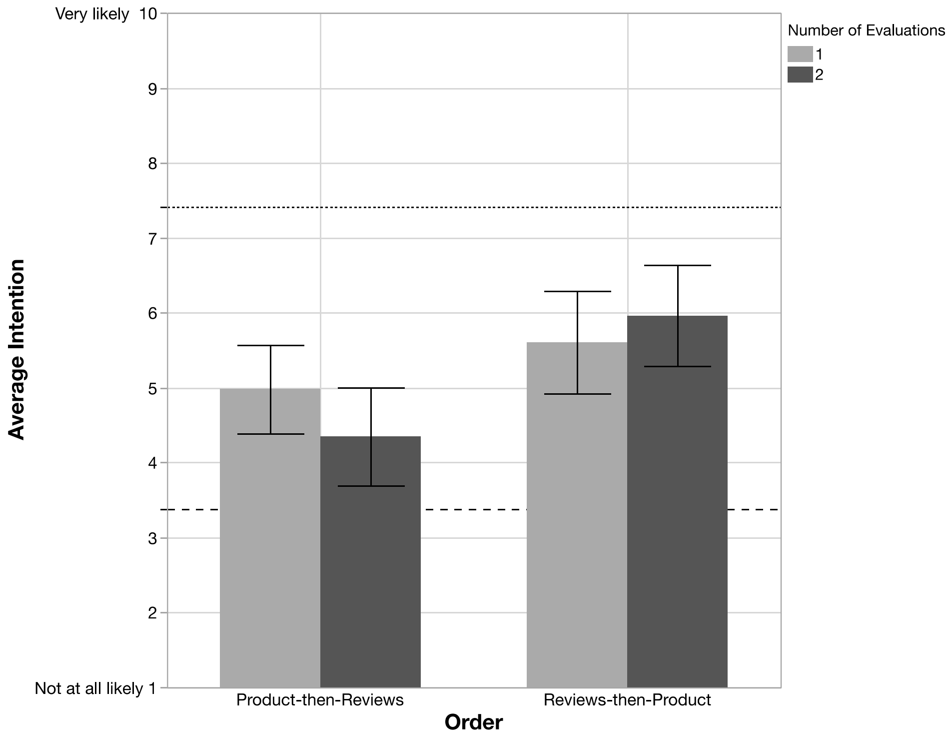


**Fig. 2.** Average intention to purchase in Experiment 2 split by Order and Number of Evaluations. The dotted line represents the average intention to buy prior to seeing the review for those in the Product-then-Reviews group. The dashed line represents the average intention to buy prior to seeing the product description for those in the Reviews-then-Product group. Error bars are 95% confidence intervals.

## 5.1. Methods

### 5.1.1. Participants

The participants were 505 American adults (280 female; $M_{age}$ = 33.8, $SD_{age}$ = 11.1) recruited from AMT.

### 5.1.2. Design

The experiment used a 2 (Order: Product-then-Reviews vs. Reviews-then-Product) × 2 (Timing: Simultaneous vs. Sequential) between-subjects design. We also included two control groups: one in which the participants were only presented with the product description (i.e., no reviews information at all) before making an evaluation, the other in which the participants were only presented with the reviews information (i.e., no product information at all) before making an evaluation. There were approximately 100 participants in each of the four treatment groups and approximately 51 participants in each of the two control groups.

The Order manipulation determined whether participants were presented with the product description first and review score information second, or the reverse order. The Timing manipulation determined whether the product description and review score information were presented on the same page or on different pages. Note that when Timing was simultaneous, then product description and review score information were presented on the same page just in a different order. The dependent variable was hypothetical willingness to pay, which was measured using a slide scale that was anchored at $0 with a maximum of $500.

### 5.1.3. Materials

The stimuli for this experiment were similar to those used for Experiment 2. In order to strengthen our manipulation, we removed price information from the product description and used a product with a more impressive product description and a set of reviews that were even more negative; namely, 2.3 out of 5 starts based on 134 reviews (see Supplementary materials).

In addition, we added a question that briefly explained the purpose of the study and then asked, "How ethical do you think it is for marketers to change the order in which product information is presented to consumers with the goal of influencing their judgements and decisions?". The question was answered on a 7-point scale ranging from 1 = "Extremely unethical" to 7 = "Extremely ethical".

### 5.1.4. Procedure

The study was conducted online. The overall procedure was similar to that used in Experiment 2.

## 5.2. Results

The average willingness to pay for the product is presented in Fig. 3. The first thing to note in this figure is the dotted and dashed lines. The

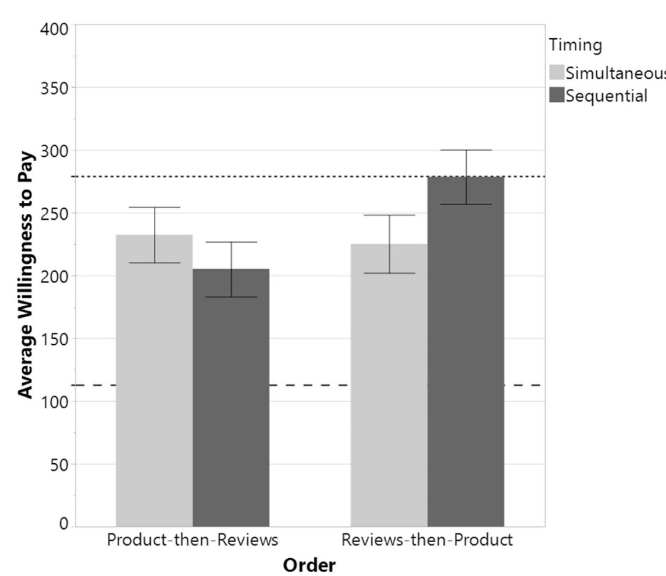


**Fig. 3.** Average willingness to pay in Experiment 3 split by Order and Timing. The dotted line represents the average willingness to pay based on the product description alone. The dashed line represents the average willingness to pay based on the reviews alone. Error bars are 95% confidence intervals.

dotted line presents the average willingness to pay for the product based only on the product description by those Product control group ($279). The dashed line presents the average willingness to pay for the product based only on the reviews by those in the Reviews control group ($113). The significant difference between these control groups ($p < .0001$) indicates that the manipulation was effective: the product description is a positive cue and the product review score information is a negative cue.

In order to analyze the data, we carried out an ANOVA with Order and Timing entered as independent variables, and willingness to pay entered as the dependent variable. The two control groups were not included in this analysis. The analysis revealed a significant main effect for Order, $F(1, 398) = 8.80$, $p = .003$. This main effect is consistent with the recency effect observed in the previous experiments: more weight on the information presented last. Consistent with expectations, the interaction between Order and Timing was also significant, $F(1, 398) = 13.11$, $p = .0003$. Planned follow-up contrasts supported our prediction: the average willingness to pay was significantly lower for those in the sequential Product-then-Reviews group than those in the sequential Reviews-then-Product group, $F(1, 398) = 21.70, p < .0001$. In contrast, the average willingness to pay was not significantly different between those in the simultaneous Product-then-Reviews group and the simultaneous Reviews-then-Product group, $F(1, 398) = 0.21$, $p = .64$.

With regards to the ethics question, the mean, median, and modal response was 4.0 ($SD = 1.45$) and thus not significantly different from the scale mid-point, $t(1, 504) = 0.12$, $p = .90$. An inspection of the descriptive statistics revealed that 40% of participants indicated that changing the order of the information was neither unethical nor ethical; only 15% indicated that it was moderately or extremely unethical.

### 5.3. Discussion

The observations made in Experiment 3 again indicate that consumers tend to display a recency effect whereby they put more weight on the information that is presented last. This behavior is consistent with a step-by-step anchoring and adjustment account. In this study, we were interested to learn how evaluation timing – simultaneous or sequential – would moderate this recency effect. In further support of the step-by-step anchoring account, we found a clear recency effect when product information and review score information were presented sequentially, which is an arrangement that encourages step-by-step processing.

The absence of a significant difference between Groups 1 and 2 is conceptually inconsistent with the observations made in Experiment 1. We suspect that this is due to procedural differences between experiments associated with the sequential group. Specifically, only in Experiment 1 was the product description and reviews information separated by an explicit evaluation. It is likely that this explicit evaluation in Experiment 1 reinforced the step-by-step processing adopted by those in this group and thus increased the difference compared to those in the simultaneous group who were able to apply either step-by-step or end-of-sequence processing.

## 6. General discussion

The main observation we made across three experiments is that the weight accorded to review score information when consumers are making a product evaluation critically depends on when that information is encountered. Returning to the opening scenario of a marketer with a good product but mediocre online reviews wondering when to show consumers the ratings: Based on our observations, the best time would be together with the product information and the worst time would be alone and after the product information is presented. This is because consumers weigh review score information more when that information is received after they have formed an initial product evaluation from the product description. More generally, consumers display a recency effect whereby the last piece of individually presented information carries the most weight in a single product's evaluation. Notably, this recency effect was consistent across different types of the review score information, whether there were many or few reviews, the distribution of the review scores, and different types of products.

### 6.1. Theoretical implications

Given such consistent observations, it is easy to think that no other result was possible. Such thinking is quickly dispelled in light of relevant theory and observations in other contexts. For example, various consistency theories (e.g., [9]) would suggest that consumers should be motivated to remain consistent with their initial opinion. Similarly, pure anchoring accounts, particularly recent accounts of automatic accessibility-based anchoring [12], would suggest that consumers should not move far from their initial opinion. Moreover, there is also a wealth of evidence in the advice-taking and persuasion literatures that support theories such as consistency and anchoring. In fact, in the advice-taking literature, primacy is the typical finding. For example, Yaniv and Choshen-Hillel [51] asked participants to estimate the caloric values of various foods with the benefit of five other people's estimates. They found that participants tended to give more weight to the first presented information - self-estimates in some cases, the five other people's estimates in other cases – in the final, revised estimate. In the persuasion literature, the observations are more mixed (e.g., [21,25]). For example, Brunel and Nelson [3] found primacy effects when two different advertisements were presented encouraging charity donation. Relatedly, Haugtvedt and Wegener [15] found primacy effects when presenting arguments to begin senior comprehensive exams as a graduation requirement. However, this effect reversed when the decision was of low personal relevance. Using a similar task, Petty, Tormala, Hawkins and Wegener [32] found that when arguments were not grouped together, people who were relatively highly motivated to think were more susceptible to recency effects. However, this effect reversed when the arguments were grouped together (i.e., “chunked”).

How do we unite these observations with our own? As discussed earlier, though conceptually similar, there are several differences between advice-taking tasks, persuasion tasks, and the product evaluation task used here. The difference that we believe is particularly relevant is the complexity of the information, which is relatively higher in our product evaluation task. This difference is critical when considered within Hogarth and Einhorn's [19] adjustment-based anchoring model. According to this model, consumers generate an initial evaluation based on the product description that they assume is close to the true value of the product but readily adjust away from given new information. The model describes how this adjustment process occurs: People use new pieces of information to update the existing estimate according to an averaging process as they try to appraise the true value. This averaging process can take place either after each new piece of information (a step-by-step processing strategy) or only after all pieces of information have been presented (an end-of-sequence processing strategy). Following Hogarth and Einhorn, we argue that, where possible, people try to match cognitive strategy with response mode. Therefore, when consumers first form their own evaluation from a product description and then learn about product reviews, a step-by-step processing strategy is adopted. In contrast, when consumers' form an evaluation based on both the product description and reviews presented together, then an end-of-sequence processing strategy or step-by-step processing strategy can be adopted. Importantly, the model predicts recency when adopting a step-by-step strategy and primacy when adopting an end-of-sequence strategy. These predictions are borne out by all our experiments.

A possible alternative explanation for our results comes from the opinion dynamics literature. The basic premise of this literature is that individuals' opinions evolve due to their interactions in a social network: when an individual is exposed to the opinions of others, they modify their own opinion [10]. Over time, the opinions of individuals form a stable structure of consensus, polarization, or fragmentation [16]. There are many models attempting to explain these dynamics. According to bounded models, individuals only interact with those who have relatively similar opinions [55]. Consequently, the final opinion of a "neighborhood" of individuals in a network is determined by both the similarity between those individuals as well as their initial opinions [48]. In the context of online reviews, a bounded model could manifest as an individual focusing on only those reviews that are consistent with their initial evaluation of the product. For example, in our studies, an individual with a positive attitude towards the product after reading its description and specifications might choose to exclusively read the reviews from those who left a relatively high product rating. However, we do not believe that such an explanation applies to our studies. This is because in our studies consumers were only presented with the average review score. As a result, there was no opportunity to narrow down the information to only the opinions of similar others. This mirrors most consumer online marketplace experiences in which only the average review score is presented on the product search results page and further search is required to see only specific types of reviews. Nevertheless, it is possible that the account of bounded models could apply for consumers who navigate to a product's "reviews section" and choose to narrow the available information to only certain opinions (e.g., only those reviews awarding 5 out of 5 stars). Moreover, a prediction from bounded models would be that an individual, after forming a positive opinion of a product based on its description, which was the case for our average participant, would be less likely to update their positive opinion in light of very dissimilar negative opinions from others compared to a situation in which that individual did not have a positive initial opinion. However, we observed the opposite: individuals were more likely to update their positive opinion in light of very dissimilar negative opinions from others.

### 6.2. Practical implications

Marketers have little control over what consumer's write in their reviews. In contrast, marketers have complete control over the product description, which can be designed to be appealing. Additionally, for retailer-hosted consumer review platforms, marketers have control over *when* product information and consumer review information is presented. In general, the adjustment-based anchoring model highlights that marketers will have more control over consumer's evaluation processing and evaluations whenever information is presented sequentially. For example, review score information on a product page could be defaulted to be automatically displayed or to require a button press to display depending on the favorability of the average review score.

Based on our findings, retailer-hosted consumer review platforms would do better to (1) display favorable average review score information after the appealing product description, (2) display unfavorable average review score information simultaneously with the appealing product description. Of course, marketers must be careful not to place unfavorable information at the top of a page because this may lead to the option being eliminated from search prior to reaching the appealing product description, particularly for those using a more heuristic choice strategy. For this reason, we endorse the approach used by Walmart.com: Currently, items listed on the Walmart.com search results page display as, from top-to-bottom, product image, price, product name, star rating, and shipping information. On each product description page, rating information (e.g., the distribution of stars) is placed at the bottom of the page. As a more extreme example, the Australian retailer Myer does not reveal any review score information at all until the consumer navigates to the product description page. There also exist differences between mobile and desktop platforms. For example, Myer places a products' star rating at the top of desktop-viewed product page but at the bottom of mobile-viewed product pages.

Another example in which the current findings could be applied is online product magazines. For example, Walmart's online weekly ad magazine presents for each product a short description, photo, and price. In some cases the average review score is also presented when the consumer hovers their cursor over the product. Managers could tactically provide review score information for only certain products. For example, a manager pushing a particular product that has a high average review score may consider revealing that information only after the consumer hovers their cursor over the product. Ultimately, platforms must be wary of reputational risk if they are perceived to be strategically manipulating the placement and timing of reviews based on whether those reviews are positive or not, particularly if the majority of products on the platform are poorly rated.

From the perspective of consumers, the presence of order effects can produce lower-quality decisions due to lack of consistency and evaluations dependent on the order of information. For example, many consumers use a search strategy that involves filtering options based on a minimum average review score, such as 4.0 out of 5 stars, and then largely ignoring review score information. By using this strategy, consumers essentially self-select into a sequential information presentation mode in which the last piece of information presented is the marketer-controlled, and likely very appealing, product description. This situation is likely to lead to inflated product evaluations. We would recommend first shortlisting appealing items based on their description followed by eliminating items based on their reviews.

Another basic consumer-level strategy to move to a less biased approach may be to implement a two-step process. First, following the suggestion of dialectical bootstrapping [18], the consumer could form an evaluation based on the product description alone, and also independently form an evaluation based on the reviews alone. Second, following the approach of support theory [46], consumers could average these two evaluations weighted by the support associated with each information source. For example, a consumer who is very informed about the product category should give more weight to their own evaluation. Similarly, an average review score based on a large number of reviewers should also be given relatively more weight. Software could be developed to facilitate such a strategy where, for example, a consumer pre-specifies for a product category of interest how much more appealing a product is with an additional 0.5 stars.

In Experiment 3, we also explored people's perception of the ethics associated with using information order effects for profit. For the vast majority, this was not an issue or was even considered an ethical practice. Presumably, one can defend the practice of a business using information order effects to increase sales with the argument that businesses are solely responsible for making a profit by all means within the law. On the other hand, there was a minority who found the practice unethical. Presumably, one can find the practice of a business using information order effects to increase sales manipulative and compromising personal autonomy. Such concerns link to a larger debate regarding the ethicality of nudging people's behavior by changing the "choice architecture" that surrounds their decisions [43]. We note that, on the one hand, there is no such thing as neutral choice architecture; information must be provided and the order of that information will always impact judgments and decisions. However, unlike, for example, advertising, which transparently aims to influence behavior, harnessing information order effects to influence behavior intentionally attempts to bypass conscious, rational decision-making. Under many definitions, this classifies as manipulative and, therefore, potentially unethical. Perhaps the most ethical approach for a business to take is to default consumers into the most profitable information order but give consumers the ability to customize the information order based on personal preferences.

### 6.3. Limitations and suggested future work

We examined only situations of separate evaluation where there was just one product being evaluated at any one time. In reality, there are often multiple items in the consideration set and the variable of interest is choice between products rather than intention to buy a single product. Order effects also exist with respect to the arrangement of different options [49]. Moreover, consumers may be making a purchase decision not only on the basis of the reviews of a particular product, but also by referring to the reviews of competing products. Indeed, some research shows that consumers can form different product evaluations depending on whether options are evaluated simultaneously or separately [22]. Therefore, it would be interesting to test if the current findings extend to situations of joint evaluation.

We presented multiple review scores in an aggregated format (i.e., a frequency distribution chart). An alternative way of presenting these scores is to show each individual review score, which is more similar to the method used in advice taking studies with multiple pieces of advice (e.g., [53]). There is also evidence that consumers form different opinions depending on whether information is presented in aggregated summary or disaggregated format [5,17]. Research has also shown the importance of review comments in determining choice [44]. Therefore, it would be useful for future research to test if the current findings extend to situations in which individual review scores are presented individually and together with qualitative comments.

### 6.4. Conclusions

With the growth of online-shopping, consumers are increasingly relying on customer review scores to guide their purchase decisions. In this paper, we sought to investigate order effects relating to how review score information influenced purchase intentions as a function of *when* those reviews were learned about. Our findings suggest that reviews are given considerably more weight when consumers have pre-existing product evaluations. As consumer reliance on customer reviews increases, which we expect with the rapid advancement and popularity of review platform technology, researchers will play an increasingly critical role both in outlining tactics for managers to make the most of customer reviews to sell their products, as well as designing tools to help consumers appropriately weight such reviews against their own evaluations in order to make informed purchases. This paper provides a step towards achieving these goals.

## Author contributions

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

## Declaration of competing interest

None.

## Acknowledgments

The author thanks Rick Larrick, Christina Rader, Leona Tam, Darren Dahl, Jerry Han, Eugene Chan, and James Bettman for helpful comments on this project. The author also thanks Mirra Seigerman for valuable research assistance.

## Appendix A. Supplementary materials

Supplementary materials to this article can be found online at https://doi.org/10.1016/j.dss.2020.113307.

## References

[1] A. Babić Rosario, F. Sotgiu, K. De Valck, T.H. Bijmolt, The effect of electronic word of mouth on sales: a meta-analytic review of platform, product, and metric factors, J. Mark. Res. 53 (3) (2016) 297–318.
[2] S. Bonaccio, R.S. Dalal, Advice taking and decision-making: an integrative literature review, and implications for the organizational sciences, Organ. Behav. Hum. Decis. Process. 101 (2) (2006) 127–151.
[3] F.F. Brunel, M.R. Nelson, Message order effects and gender differences in advertising persuasion, J. Advert. Res. 43 (3) (2003) 330–341.
[4] R. Buda, Y. Zhang, Consumer product evaluation: the interactive effect of message framing, presentation order, and source credibility, Journal of Product & Brand Management 9 (4) (2000) 229–242.
[5] A.R. Camilleri, The presentation format of review score information influences consumer preferences through the attribution of outlier reviews, J. Interact. Mark. 39 (2017) 1–14.
[6] N.N. Cheek, B. Schwartz, Judgment in a social context: biases, shortcomings, and the logic of conversation, Adv. Exp. Soc. Psychol. 26 (1994) 123–162.
[7] C.M. Cheung, M.K. Lee, What drives consumers to spread electronic word of mouth in online consumer-opinion platforms, Decis. Support. Syst. 53 (1) (2012) 218–225.
[8] C.M. Cheung, D.R. Thadani, The impact of electronic word-of-mouth communication: a literature analysis and integrative model, Decis. Support. Syst. 54 (1) (2012) 461–470.
[9] R.B. Cialdini, M.R. Trost, J.T. Newsom, Preference for consistency: the development of a valid measure and the discovery of surprising behavioral implications, J. Pers. Soc. Psychol. 69 (2) (1995) 318.
[10] Y. Dong, Q. Zha, H. Zhang, G. Kou, H. Fujita, F. Chiclana, E. Herrera-Viedma, Consensus reaching in social network group decision making: research paradigms and challenges, Knowl.-Based Syst. 162 (2018) 3–13.
[11] W. Duan, B. Gu, A.B. Whinston, Do online reviews matter?—an empirical investigation of panel data, Decis. Support. Syst. 45 (4) (2008) 1007–1016.
[12] N. Epley, A tale of tuned decks? Anchoring as accessibility and anchoring as adjustment, The Blackwell Handbook of Judgment and Decision Making, (2004), pp. 240–256.
[13] J.K. Goodman, G. Paolacci, Crowdsourcing consumer research, J. Consum. Res. 44 (1) (2017) 196–210.
[14] P.H. Grice, Logic and conversation, in: P. Cole, J.L. Morgan (Eds.), Syntax and Semantics III: Speech Acts, Academic Press, New York, 1975.
[15] C.P. Haugtvedt, D.T. Wegener, Message order effects in persuasion: an attitude strength perspective, J. Consum. Res. (1994) 205–218.
[16] R. Hegselmann, U. Krause, Opinion dynamics and bounded confidence models, analysis, and simulation, J. Artif. Soc. Soc. Simul. 5 (3) (2002).
[17] R. Hertwig, I. Erev, The description–experience gap in risky choice, Trends Cogn. Sci. 13 (12) (2009) 517–523.
[18] S.M. Herzog, R. Hertwig, The wisdom of many in one mind improving individual judgments with dialectical bootstrapping, Psychol. Sci. 20 (2) (2009) 231–237.
[19] R.M. Hogarth, H.J. Einhorn, Order effects in belief updating: the belief-adjustment model, Cogn. Psychol. 24 (1) (1992) 1–55.
[20] H. Hong, D. Xu, G.A. Wang, W. Fan, Understanding the determinants of online review helpfulness: a meta-analytic investigation, Decis. Support. Syst. 102 (2017) 1–11.
[21] C.I. Hovland, W. Mandell, Is there a "Law of Primacy" in Persuasion, the Order of Presentation in Persuasion, (1957), pp. 1–22.
[22] C.K. Hsee, The evaluability hypothesis: an explanation for preference reversals between joint and separate evaluations of alternatives, Organ. Behav. Hum. Decis. Process. 67 (3) (1996).
[23] L. Huang, C.-H. Tan, W. Ke, K.-K. Wei, Do we order product review information display? How? Inf. Manag. 51 (7) (2014) 883–894.
[24] K. Kaushik, R. Mishra, N.P. Rana, Y.K. Dwivedi, Exploring reviews and review sequences on e-commerce platform: a study of helpful reviews on Amazon. in, J. Retail. Consum. Serv. 45 (2018) 21–32.
[25] R.E. Lana, Familiarity and the order of presentation of persuasive communications, J. Abnorm. Soc. Psychol. 62 (3) (1961) 573.
[26] A. Lingreen, A. Dobele, J. Vanhamme, L. Zhang, B. Ma, D.K. Cartwright, The impact of online user reviews on cameras sales, Eur. J. Mark. 47 (7) (2013) 1115–1128.
[27] X. Liu, D. Lee, K. Srinivasan, Large scale cross category analysis of consumer review content on sales conversion leveraging deep learning, J. Mark. Res. 56 (6) (2019) 918–943.
[28] A. Mantonakis, P. Rodero, I. Lesschaeve, R. Hastie, Order in choice: effects of serial position on preferences, Psychol. Sci. 20 (11) (2009) 1309–1312.
[29] K. Mitra, M.C. Reiss, L.M. Capella, An examination of perceived risk, information search and behavioral intentions in search, experience and credence services, J. Serv. Mark. 13 (3) (1999) 208–228.
[30] T. Mussweiler, F. Strack, Hypothesis-consistent testing and semantic priming in the anchoring paradigm: a selective accessibility model, J. Exp. Soc. Psychol. 35 (2) (1999) 136–164.
[31] K. Nam, J. Baker, N. Ahmad, J. Goo, Determinants of writing positive and negative electronic word-of-mouth: empirical evidence for two types of expectation confirmation, Decis. Support. Syst. (2019) 113168.
[32] R.E. Petty, Z.L. Tormala, C. Hawkins, D.T. Wegener, Motivation to think and order effects in persuasion: the moderating role of chunking, Personal. Soc. Psychol. Bull. 27 (3) (2001) 332–344.
[33] G.N. Punj, Do consumers who conduct online research also post online reviews? A model of the relationship between online research and review posting behavior, Mark. Lett. 24 (1) (2013) 97–108.

[34] N. Purnawirawan, P. De Pelsmacker, N. Dens, Balance and sequence in online reviews: how perceived usefulness affects attitudes and intentions, J. Interact. Mark. 26 (4) (2012) 244–255.
[35] N. Purnawirawan, N. Dens, P. De Pelsmacker, Balance and sequence in online reviews: the wrap effect, Int. J. Electron. Commer. 17 (2) (2012) 71–98.
[36] C.A. Rader, J.B. Soll, R.P. Larrick, Pushing away from representative advice: advice taking, anchoring, and adjustment, Organ. Behav. Hum. Decis. Process. 130 (2015) 26–43.
[37] P. Rozin, E.B. Royzman, Negativity bias, negativity dominance, and contagion, Personal. Soc. Psychol. Rev. 5 (4) (2001) 296–320.
[38] S. Sen, D. Lerman, Why are you telling me this? An examination into negative consumer reviews on the web, J. Interact. Mark. 21 (4) (2007) 76–94.
[39] J.B. Soll, R.P. Larrick, Strategies for revising judgment: how (and how well) people use others' opinions, J. Exp. Psychol. Learn. Mem. Cogn. 35 (3) (2009) 780.
[40] B.A. Sparks, V. Browning, The impact of online reviews on hotel booking intentions and perception of trust, Tour. Manag. 32 (6) (2011) 1310–1323.
[41] S. Sudman, N.M. Bradburn, N. Schwarz, Thinking About Answers: The Application of Cognitive Processes to Survey Methodology, Jossey-Bass, 1996.
[42] X. Sun, M. Han, J. Feng, Helpfulness of online reviews: examining review informativeness and classification thresholds by search products and experience products, Decis. Support. Syst. 124 (2019) 113099.
[43] C.R. Sunstein, The ethics of nudging, Yale Journal on Regulation 32 (2015) 413–450.
[44] A.S. Tsang, G. Prendergast, Is a "star" worth a thousand words? The interplay between product-review texts and rating valences, Eur. J. Mark. 43 (11/12) (2009) 1269–1280.
[45] A. Tversky, D. Kahneman, Judgment under uncertainty: heuristics and biases, Science 185 (4157) (1974) 1124–1131.
[46] A. Tversky, D.J. Koehler, Support theory: a nonextensional representation of subjective probability, Psychol. Rev. 101 (4) (1994) 547.
[47] R. Ullah, N. Amblee, W. Kima, H. Lee, From valence to emotions: exploring the distribution of emotions in online product reviews, Decis. Support. Syst. 81 (January) (2016) 41–53.
[48] R. Urena, G. Kou, Y. Dong, F. Chiclana, E. Herrera-Viedma, A review on trust propagation and opinion dynamics in social networks and group decision making frameworks, Inf. Sci. 478 (2019) 461–475.
[49] B. von Helversen, K. Abramczuk, W. Kopeć, R. Nielek, Influence of consumer reviews on online purchasing decisions in older and younger adults, Decis. Support. Syst. 113 (2018) 1–10.
[50] P.F. Wu, In search of negativity bias: an empirical study of perceived helpfulness of online reviews, Psychol. Mark. 30 (11) (2013) 971–984.
[51] I. Yaniv, S. Choshen-Hillel, Exploiting the wisdom of others to make better decisions: suspending judgment reduces egocentrism and increases accuracy, J. Behav. Decis. Mak. 25 (5) (2012) 427–434.
[52] I. Yaniv, E. Kleinberger, Advice taking in decision making: egocentric discounting and reputation formation, Organ. Behav. Hum. Decis. Process. 83 (2) (2000) 260–281.
[53] I. Yaniv, M. Milyavsky, Using advice from multiple sources to revise and improve judgments, Organ. Behav. Hum. Decis. Process. 103 (1) (2007) 104–120.
[54] Y. You, G.G. Vadakkepatt, A.M. Joshi, A meta-analysis of electronic word-of-mouth elasticity, J. Mark. 79 (2) (2015) 19–39.
[55] Y. Zhao, L. Zhang, M. Tang, G. Kou, Bounded confidence opinion dynamics with opinion leaders and environmental noises, Comput. Oper. Res. 74 (2016) 205–213.
[56] S. Zhou, B. Guo, The order effect on online review helpfulness: a social influence perspective, Decis. Support. Syst. 93 (2017) 77–87.

Adrian Camilleri is a consumer psychologist currently working as a senior lecturer in marketing at the University of Technology Sydney Business School. He uses experimental methods to understand, explain, and predict the cognitive processes underlying judgment and decision making, and the application of this knowledge to environmental, financial, and consumption contexts. His multidisciplinary research has been published in top academic journals in the fields of psychology, management, marketing, and public policy including *Nature Climate Change*, *Management Science*, *Organizational Behavior and Human Decision Processes*, *Journal of Experimental Psychology*: *General*, and the *Journal of Interactive Marketing*.