Attention-driven imitation in consumer reviews

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Product reviews on e-commerce platforms can have a pronounced effect on consumers' decisions. Less is known, however, whether the reviews written by others can shape a person's own written opinion of a product. We hypothesized that people who compose reviews on digital storefronts will try to imitate successful reviews, such that their content will show similarity with other reviews displayed at the time of writing. More specifically, we predicted that reviews will be more semantically similar to the most successful, salient, and readily accessible reviews written by others. To investigate this hypothesis, we extracted over 3 million reviews from a major online distribution platform and traced the reviews that were displayed at the time when each review was being composed. Using word embeddings from a pre-trained language model, we quantified the semantic similarity between a given review and other reviews that were visible (or not) to a user. We found that reviewers imitate the most helpful reviews written by others, especially those that are visually salient. Their reviews, in turn, gather more helpfulness ratings in the future, leading to a cascade of similar reviews. Our findings suggest that the default sorting and display format of reviews on online platforms will have a pronounced effect on the style and content of new reviews.

Keywords: online reviews, similarity, salience, order effects, text mining

Over the past few decades, the growing accessibility and popularity of digital storefronts has significantly changed how consumers make their purchasing decisions. A core feature of many modern online marketplaces is that they enable their customers to express opinions about their purchases by writing consumer reviews. It is now well established that such an electronic word-of-mouth communication can have a considerable impact on consumers' decisions (Chevalier & Mayzlin, 2006). Much of the existing research on the topic of electronic word-of-mouth focuses primarily on how specific features of written reviews (e.g., their style or content) and the unique characteristics of the online platforms (e.g., product types offered, design of the user interface) influence consumers' decision-making processes and purchasing behaviour (e.g., as measured by sales, consumers' information search, or their purchase intention; see Babić Rosario et al., 2016; Liu et al., 2019, for recent comprehensive reviews). A comparatively smaller stream of research focuses on the reviewers themselves, investigating different motivations that drive people to contribute their opinion on e-commerce platforms. Research from this literature has shown that people may write reviews to punish a seller (Lafky, 2014) or to simply relive their consumption experience (Yoo & Gretzel, 2008). At the same time, reviewers may also contribute in order to help other buyers make better decisions (Yoo & Gretzel, 2008) or to enhance their own feelings of belonging by being an active member of a community (Cheung & Lee, 2012). These motivations are likely to influence reviewers' own decisions on the content and style of their own review (Schindler & Bickart, 2012). To be able to help other consumers make better decisions, reviewers need to decide what makes a useful review. How do they do this? Are the reviewers influenced by the opinions shared by other users? If so, do more salient reviews have more impact on people's own contributions? In the present paper, we investigate whether reviewers' own contributions might be shaped by the immediate context afforded by the design features of the online

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platform. The goal of the present work is to understand the role this review-writing context plays in influencing the reviews that are written.

For this purpose, we build on a simple conceptual framework for understanding the diverse sources of influence on how consumers compose their reviews (see, e.g., Berger et al., 2020). Our fundamental assumption is that reviewers follow two broad types of motivation: First, every review is an expression of a person's own experience, and so their reviews are evaluative statements about that individual's consumption experience. Second, reviewers are also motivated by the goal of making a valued contribution to the community of other consumers on the same platform. Accordingly, they will craft their reviews with the goal of maximizing their helpfulness to others. Irrespective of whether the motivation to contribute on electronic word-of-mouth platforms fulfills personal needs (e.g., a sense of belonging among people with similar preferences) or reflects people's concerns with others' well-being (e.g., a sense of obligation to help others avoid bad products), it is likely that consumers contribute reviews by considering what types of reviews are valued in a given setting (Cheung & Lee, 2012).

Abstracting from a person's idiosyncratic consumption experience, what features of a review make it successful or liked by the community? In other words, how do consumers determine what makes a review "good"? Here, we propose that the main cognitive mechanism behind composing a good review is imitation (Offerman & Sonnemans, 1998). Consumers learn from the broader context of other available reviews about the desirable features of a good review. This mechanism could be deliberate, such that consumers actively try to mirror reviews that are rated as helpful (Eberhard et al., 2018), effectively constructing hypotheses about potential features of a review that could lead to a positive evaluation by others. If reviewers' perceptions were accurate (or they had in-depth knowledge of the academic literature), they could determine that reviews rated as helpful are those that include emotional language (Ahmad & Laroche, 2015), are more fluently written (Fang et al., 2016; Kronrod & Danziger, 2013; Moore, 2015; van Laer et al., 2018), are written by people who share broader consensus about a product (Naylor et al., 2011), or appear to have been written with more effort (Grewal & Stephen, 2019). Equally, consumers could avoid features of reviews that are too polarizing (Schoenmueller et al., 2020), or give an impression that they have been written by someone who did not purchase a product (Anderson & Simester, 2014). On a more implicit level, however, reviewers could also be influenced by the less relevant factors (e.g., Brandes & Dover, 2022). Here, a range of bottom-up attentional mechanisms could determine which reviews are imitated (Ashby et al., 2015). First, we expect that the visual salience should play a significant role. There is a large literature in basic research showing that particularly salient elements capture decision makers' attention (Desimone & Duncan, 1995) and there is evidence that larger and more central displays are more salient (Buscher et al., 2009; Kosslyn & Alper, 1977; Roth et al., 2013; Yantis & Jonides, 1984). Based on this research, we expect that reviewers pay more attention to, and therefore imitate, the more prominently featured reviews written by others. Second, but relatedly, the order with which reviews are displayed may influence which reviews are imitated as well. In terms of purchasing decisions, past research has shown that reviews that are displayed first (i.e., on top) have a larger effect than those shown thereafter (Kapoor & Piramuthu, 2009; Vana & Lambrecht, 2021; Wang et al., 2015). Evidence from eye-tracking studies also shows that reviews are scanned sequentially and that reviews that are later in a sequence are processed more superficially (McCarthy, 2013; Nielsen, 2010). In line with the rationale behind the effect of salience, we expect reviewers to be most affected by those that are displayed at the top of a page where they are readily accessible.

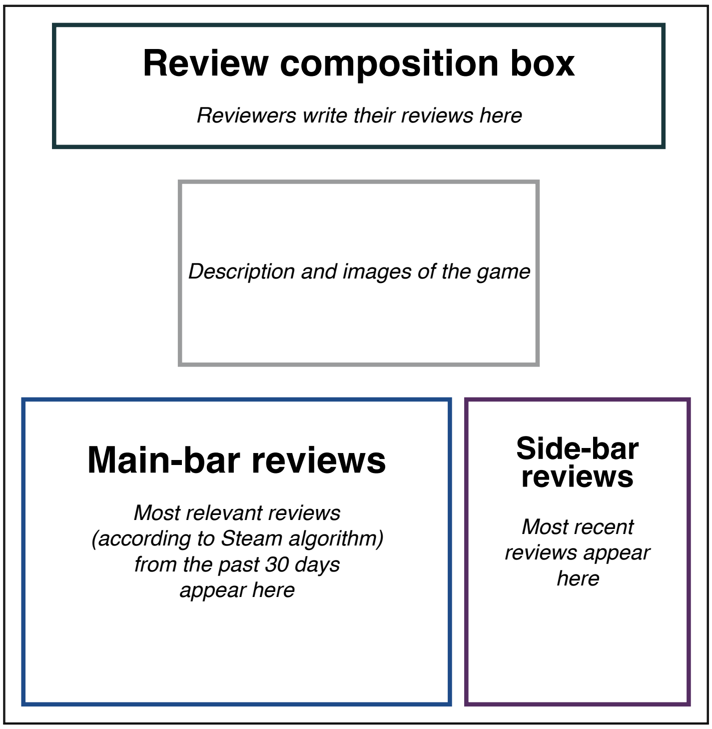
To investigate our hypothesis and assess to what extent reviewers imitate other people's reviews, we rely on the data from a large online video-game platform. We develop an algorithm to trace back and simulate all the reviews that were visible to each reviewer at the time at which the reviewers were composing their own reviews. We use natural language processing to represent user-generated reviews in a vector space and compute the similarity between them. Foreshadowing our main results, we find that user reviews are most similar to prominently displayed and salient reviews, appearing at the top of the center of the page, and the more similar a review is to the most salient review displayed on the page, the more helpfulness votes it receives. Reviewers seem to attempt to imitate successful reviews, which in turn increases the chances of their reviews to become successful themselves. Taken together, our results highlight the importance of display characteristics on user-generated content.

Method

The present study uses the 'Steam' online video-game distributional platform to investigate the cognitive processes underlying review writing. To do so, we computed the similarity between a large number of reviews on this platform with reviews that were accessible to the reviewers at the time of writing their review. The main advantage of Steam is that the user-generated reviews are presented in a rather unique manner that allows to disentangle the cognitive processes discussed above (see Figure 1). Here, two types of reviews are shown in the review section of each video-game page. The first is what we will refer to as the 'main-bar reviews'. These reviews make up a visually dominant proportion of the review section on a Steam web page. They are sorted by helpfulness and explicitly presented to users as "MOST HELPFUL REVIEWS" (in capital letters). We classify re-

Figure 1

A sketch of the web-page that a reviewer would observe while writing their own review on Steam. Figure is for illustration purposes and is not drawn to scale.



views appearing there as being 'salient'. The second type of review consists of recency-sorted reviews. These reviews are displayed in a smaller side bar of the review section and positioned next to the main bar on the right-most part of the page. Reviews appearing there are classified as being 'non-salient'. Additionally, we identified and extracted reviews that were written within the previous 30 days (from the time when the target review was written) but which were *not* visible on either the main or the side bar of the review page. These reviews are used to obtain a control condition. As the second independent variable, we coded the order of appearance of reviews (from top to bottom).

By calculating the similarity of a target review and reviews that were a) in the main-bar, b) in the side-bar, and c) *not* visible on the main page (control condition), we can control for idiosyncratic variations in review style across games and time. Importantly, because the control condition includes reviews that were written within the same time window as the reviews displayed in the main bar and the side bar (i.e., within the 30 days preceding the target review), it controls for a range of time- and game-sensitive features of the successful and recent reviews (e.g., releases of patches, bugs, marketing campaigns, etc.).

To obtain the necessary amount of reviews and compute the variables from those reviews, our study involved the three steps of data extraction and wrangling, text mining, and the statistical analyses, which are illustrated in Figure 2 and will be described in detail in the following sections.

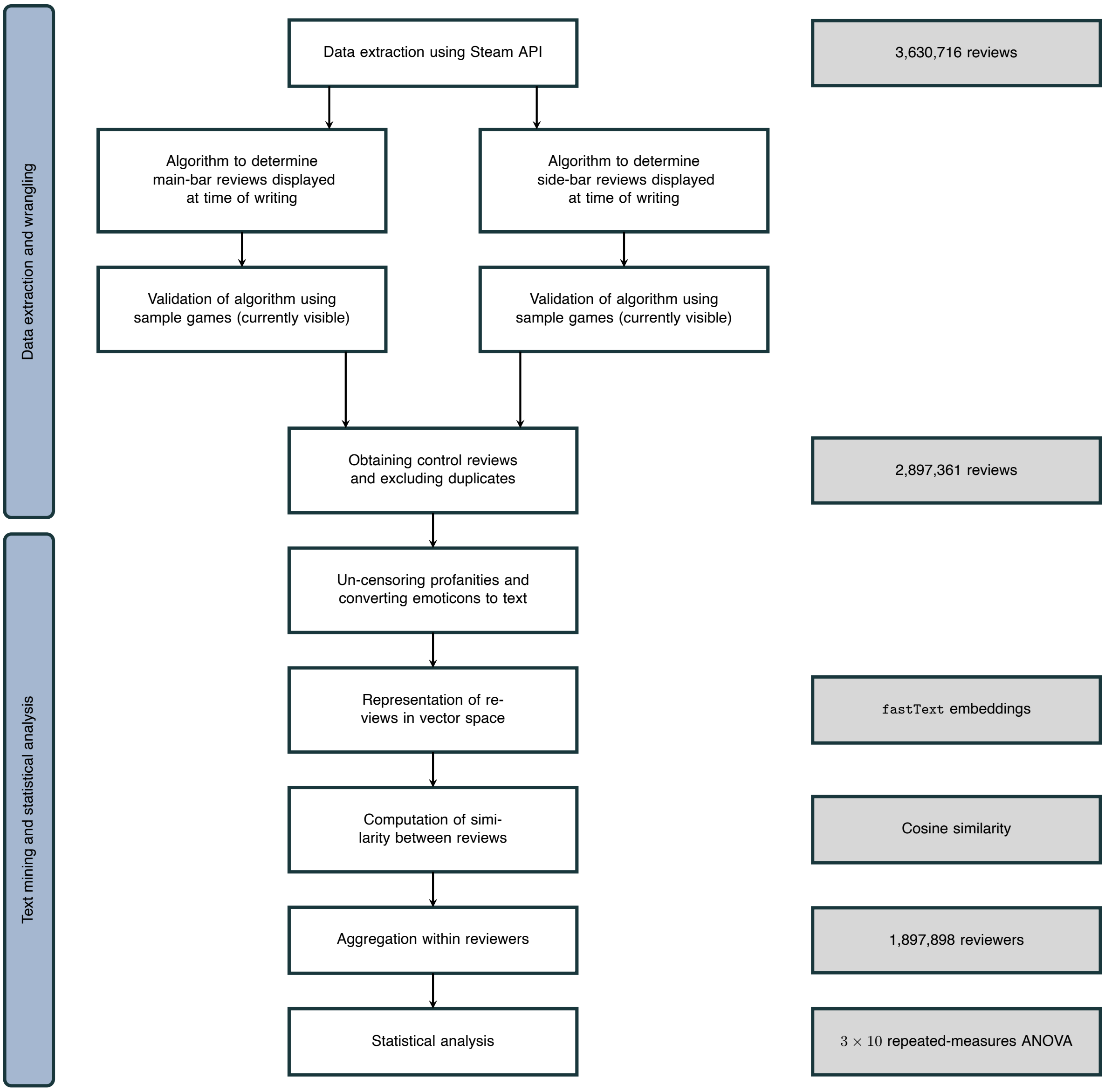
Data extraction and wrangling

For our study, we collected all reviews from all games on Steam that were tagged as both "singleplayer" and "FPS" (first-person shooter), as identified by the "1663%2C4182" tag in the official Steam API. The data were scraped on 26$^{\text{th}}$–27$^{\text{th}}$ of January 2024 and resulted in a total of 3,630,716 reviews across 2,304 games. While scraping, some web pages have changed, so that 7,117 of the reviews that were scraped were exact duplicates, which we removed. Additionally, the official Steam API did not return any reviews for 1,378 games. A vast majority of these games (944 or 68.5%) indeed had 0 reviews and only a very small proportion (67 or 4.86%) had more than 100 reviews. We did not manually scrape those reviews because our pre-processing pipeline requires an API-exclusive variable (see details below).

In Table 1, we report some descriptive summary statistics of the extracted reviews. One notable feature is the relation between vocabulary size and the number of words. The median vocabulary size (the number of unique words that appear in each review) was only slightly lower than the number of total words, reflecting a low tendency to repeat words

Figure 2

A flowchart illustration of the present study's methodological approach and key descriptive statistics.



and a considerable amount of information contained in the reviews. Additionally, the median playing time before writing a review was 11.90 hours, suggesting that reviewers had some considerable experience with the games before writing a review.

For our subsequent analyses, we needed to identify the reviews that were displayed in the main bar and in the side bar at the time each of the reviews in our database was composed. We had to reverse-engineer the algorithm that populates the review bars with recent and most helpful reviews because Steam does not provide this information via its API. To reconstruct the side-bar content, where recency-sorted reviews are displayed, we simply obtained the most recent reviews (relative to the time when the target review was written), excluding reviews already shown in the main-bar section of the web page. As the reviews in the side bar are ordered according to their recency, we were able to reconstruct the order with which they were displayed to each user. There is no minimum threshold for the number of reviews displayed on the side bar, but the maximum number of reviews displayed is set to 10. To validate our method for reconstructing contents of the side-bar, we randomly selected 20 games and correlated the results of our extraction with the true results visible on the website (currently). For ten out of the 20 games, all

Table 1

Descriptive statistics of the reviews used in the analyses.

Item	Summary statistic		
	Mean	Standard deviation	Median
Vocabulary size	35.57	64.79	12
Number of words	50.73	117.8	13
Number of reviews per game	1576	6291	24
Number of reviews per reviewer	1.53	1.61	1
Time spent playing the game when writing review (in hours)	60.50	297.39	11.90
Upvotes received	5.28	72.54	1

reviews were present in our validation sample, and only for three of the games, fewer than 5 reviews were present in the validation sample. The order of reviews that were present in the validation sample was perfectly reconstructed for all but two games.

In case of the main bar, we attempted to reconstruct its contents using the Steam-provided ‘weighted_vote_score’. Note that the weighted vote score is not the same as the number of helpfulness votes received by each review. This score is accessible through the official API but it is not directly visible on the Steam web pages. Whenever there are enough reviews to fill the main bar (i.e., at least 10 reviews) that have been composed within the past 30 days and have obtained at least one ‘helpfulness’ vote by other community members, the weighted vote score provides a perfect measure of the order of reviews at the time of display.

If there were not enough reviews published in the last 30 days to fill the main bar, we expanded our research under the assumption that Steam uses an extended window of 30–90 days to select most helpful reviews. If at this stage there are still not enough reviews to be displayed, the same procedure is applied to reviews written in the 90–180 days period, after which all reviews that are older than 180 days are used.

We validated the reconstructed contents of the main bar using the same 20 games that we used to validate the reconstructed contents of the side bar. For all but two of the 20 games, our algorithm retrieved at least 70% of the games that were displayed in the main bar in real time. The order of reviews that were present in the validation sample was perfectly reconstructed for all but three games.

We removed all games from the analysis for which the algorithm resulted in fewer than 10 reviews that would be displayed in the main or the side bar (249,259 or 6.9%), after which 3,388,574 reviews from across 868 games remained.

Finally, to determine the control reviews, we identified the 10 most recent reviews written within 30 days before the target review was written and that were neither part of the main-bar nor the sidebar. We excluded a small proportion of reviews (123,631; 3.6%) for which there were fewer than 10 reviews written within 30 days in addition to those displayed on the main review page, resulting in a review count of 3,264,943 across 717 games. We further removed 183,791 (6%) of these reviews because they appeared on multiple pages (e.g., when games are parts of different bundles), which resulted in a final review count of 2,897,361 across 694 games.

Text mining and statistical analysis

We pre-processed the reviews for the purpose of subsequent analyses (Kannan et al., 2014). Steam automatically censors selected profanities in reviews by replacing them with heart (♥) or asterisk (*) symbols. We relied on a community-compiled list of hypothesized censored profanities (Steam Developer Community, 2021) to convert censored words to their original profane text by matching the contents in this list to the length of the censored words. Next, we converted emojis and emoticons back into their original meanings using the `emot` package for Python. In the next step, we stripped the reviews of stop words (such as “is” or “are”) and used lemmatization in combination with grammatical tagging to increase the running speed of subsequent analyses (Loper & Bird, 2002; Plisson et al., 2004; Walkowiak et al., 2018).

To represent the reviews as vectors in a vector space (Bhatia, 2017) we used the pre-trained `fastText` embeddings (Athiwaratkun et al., 2018; Joulin et al., 2016). We selected `fastText` for two main reasons. First, compared to purely metric-based techniques, `fastText` considers the contextual semantics, in addition to the word meanings themselves. Specifically, purely metric-based text embeddings typically assign weights to individual n-grams with minimal consideration of the semantic meaning and relationships between the words (Kasumba & Neumann, 2022; van Tussenbroek, 2020). Second, `fastText` is better able to handle unseen words (Athiwaratkun et al., 2018; Won et al., 2021). `fastText` works by breaking down each word into sub-word units (also known as vectors of character n-grams). Given that unseen text (e.g., short non-english terms) is expected to

Table 2

Illustration of the similarity score and the effect sizes observed in the study. The comparison reviews' similarity scores are displayed with respect to the target review. All reviews were generated artificially to reflect a representative sample of a very similar review (#1), two reviews that reflect the average observed similarity scores in the data (#2 and #3), and one review that is dissimilar to the target review (#4). All reviews were pre-processed according to the pre-processing pipeline used for our main analyses.

	Target review: "Levels are well designed, offering a great playground for frantic gun battles."	
#	**Comparison review**	**Similarity score**
1	"Doom's levels are well designed, offering a great playground for frantic gun battles."	.95
2	"Doom is a power fantasy come true, letting you unleash hell on demons in meticulously designed environments."	.58
3	"A visceral and satisfying exploration of pure, unadulterated action, Doom will leave you wanting more."	.51
4	"git gud."	.19

occur frequently in video-game reviews, `fastText` will still be able to generate a reliable representation by summing up the vectors of its character n-grams.

To compute the similarity between the to-be-written reviews and the vector representations of the visible reviews, we relied on cosine similarity. Formally, cosine similarity $S_{i,j}$ between two vectors i and j is given by

$$S_{i,j} = \frac{V_i \cdot V_j}{||V_i|| \cdot ||V_j||} = \frac{\sum_{k=1}^{n} (V_i)_k \cdot (V_j)_k}{\sqrt{\sum_{k=1}^{n} (V_i)_k^2} \cdot \sqrt{\sum_{k=1}^{n} (V_j)_k^2}},$$

where $S_{i,j} \in [-1, 1]$, V is the vector of each review with elements k. Similarity scores of 1 reflect perfect similarity, whereas those with a score of -1 reflect semantically most distant concepts/terms. See Table 2 for an illustration. For each review, we calculated all 30 similarity scores between the target review and the 10 main-bar reviews, the 10 side-bar reviews, and the 10 control reviews.

For our statistical analysis, we relied on a 3 (salience: main bar vs. side bar vs. control) by 10 (order: 1 to 10, from top to bottom) repeated-measures ANOVA with the similarity score as the dependent variable. The similarity score was obtained by computing the similarity between the target review and the review at the respective position on the page. For this analysis, we aggregated data within each cell of the experimental design for each reviewer who wrote more than one review. This reduced the number of reviews to 1,897,898. The results do not change qualitatively without the aggregation and are provided in the output of the code (Spektor et al., 2024). Due to the large number of observations included in the analysis, we will rely on visual inspection and standardized effect sizes (η_p^2) in addition to formal significance testing.

Results

With respect to our hypotheses, a 3 (salience: main bar vs. side bar vs. control) by 10 (order: 1 to 10, from top to bottom) repeated-measures ANOVA revealed a main effect of salience, ($F(2, 3'795'794) = 169'202.66$, $p < .001$, $\eta_p^2 = .082$), a main effect of display order ($F(9, 17'081'073) = 431.50$, $p < .001$, $\eta_p^2 < .001$), and an interaction effect of the two factors ($F(18, 34'162'146) = 395.97$, $p < .001$, $\eta_p^2 < .001$).

In terms of the main effect of salience, post-hoc t-tests revealed that all groups (main bar, side bar, control) differed significantly from one another. However, the difference between control and side bar was negligible ($d = 0.001$), whereas the main bar had moderately higher values than both the side bar ($d = 0.172$) and the control reviews ($d = 0.174$). The effect sizes are illustrated in Table 2, reviews #2 and #3.

To characterize the interaction, separate one-way repeated-measure ANOVAs were run for each of the three salience conditions separately. The effect of order was only significant in the main bar ($F(9, 17'081'073) = 1'532.19$, $p < .001$, $\eta_p^2 = .001$), but not in the side bar ($F(9, 17'081'073) = 1.46$, $p = .156$, $\eta_p^2 < .001$) and not for the control reviews ($F(9, 17'081'073) = 0.222$, $p = .992$). The latter of which is noteworthy, since this null effect would have been highly unlikely if our algorithms of reconstructing reviews from the three categories had a high rate of mis-classifications; After all, the control reviews were not visible on the main review page so that order should not play a role. The statistical analyses and effect sizes confirm what can be seen in Figure 3: There is a modest effect of salience, such that people's reviews are more similar to reviews displayed in the main bar, and only in the main bar is there a small effect of order, such that reviews are most similar to the reviews displayed at the top of the page.

As can be seen from Table 1, the number of reviews per game is extremely positively skewed. Very few games have many reviews, whereas most games have only very few reviews. Considering that the ANOVAs presented above are representative of the total distribution of reviews, the reviews of games that have many reviews are more frequent in the data set, thus driving the results to a large extent. To rule out that some idiosyncratic properties of those few games with the most reviews create a spurious effect, we investigated the proportion of games in which the observed effects occurred.

This analysis confirmed the main effects of salience: The main-bar similarity score was higher than the side-bar similarity and the control similarity scores for 72.0% and 71.9% of the games, respectively, and the side-bar similarity score was higher than the control similarity score for 55.9% of the games. In a next step, we fit a linear regression with the similarity score as the dependent variable and the order as the only predictor variable for each game and salience condition separately. We found that the slope of order in the main bar was negative for 69.5% of the games and deviated significantly from zero, $t(693) = -6.840$, $p < .001$. The slope of order in the side bar was negative for 54.0% of the games and did not differ significantly from zero, $t(693) = 0.308$, $p = .758$. The slope of order in the control condition was negative for 52.3% of the games and did not differ significantly from zero, either, $t(693) = 0.514$, $p = .607$.

The results so far suggest the content of a newly written review is most similar to the review that is presented most prominently, namely in the main bar and in the top position, and that is at the same time the review that has been rated as the most helpful by other users. In the following analysis, we asked whether imitating the most successful review at the time is a good strategy for writing a review that itself will become successful. To answer this question, we used a linear regression to predict the Z-standardized number of helpfulness votes that a review obtained as a function of the similarity between the top-most review from the main bar and the time stamp at which the review was created (to control for the fact that earlier reviews have had more opportunities to be rated as helpful). This analysis revealed a modest but positive effect of similarity score (standardized $\beta = .019$) and a modest but negative effect of time (standardized $\beta = -.015$). In other words: For each standard deviation above the mean degree of similarity between reviews, the number of helpfulness votes that a review receives increases by 1.9% of its standard deviation.

Discussion

The present study investigated review-writing behavior on a large digital storefront for video games. We hypothesized that customers are influenced by the reviews they see on the screen at the time of composing their own review, such that their review will be similar to salient reviews that are most easily accessible. Our results supported both of these hypotheses, so that successful and salient reviews displayed in the center of the web page (the "most helpful" reviews published in the last 30 days) had the largest influence on to-be-written reviews. A follow-up analysis showed that reviews that imitate these most helpful reviews tend to be rated as more helpful themselves, reflecting a downstream effect of particularly 'successful' reviews.

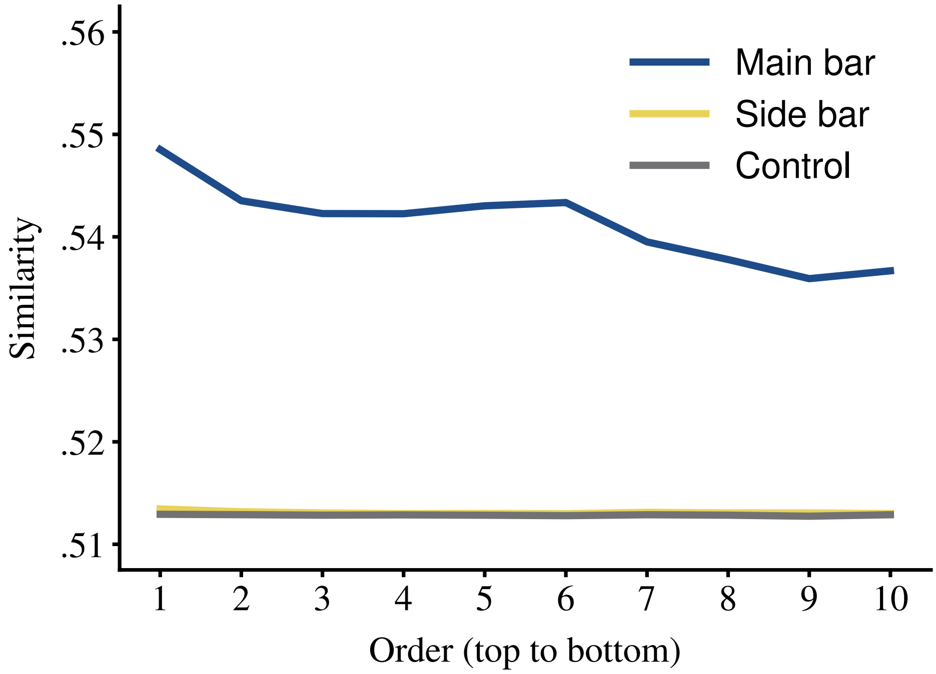
Our results corroborate past findings highlighting the influence of salience (Buscher et al., 2009; Faraday, 2000; Roth et al., 2013; Shomstein et al., 2019) and ordering (Asad et al., 2021; McCarthy, 2013; Nielsen, 2010) on the attentional allocation of consumers. Our study goes beyond what was previously shown by demonstrating how the increased attentional allocation translates into behavior. One way to interpret the results is that customers writing their reviews do not disregard the information on the screen but rather compose their reviews in a similar fashion to what they see. In other words, to understand and quantify the information content of reviews, it is crucial to consider the context within which it was written. Both positive and negative reviews that were written within a narrow time window could reflect the imitation process studied here rather than the true opinion of the reviewers. If the influence of visible elements was purely a bottom-up effect, then one would expect both the main-bar reviews and side-bar reviews to exert an influence on the review contents. In contrast, there was virtually no difference between the influence of reviews displayed in the side bar and reviews that were written in the same time frame but that were *not* displayed on the review page. This suggests a directed attempt at imitating successful reviews but ignoring reviews that have not yet received helpfulness ratings. The main effect of order that was only of a somewhat noteworthy size for the main-bar reviews further corroborates this interpretation, as the review displayed at the very top of the main-bar usually corresponds to the most helpful one.

Although we interpret these results as attempts to mimic successful reviews (and we found that reviews that are more similar to successful reviews tend to be more successful themselves), we acknowledge that we cannot be certain about people's motivation. It is possible that reviewers are selectively influenced by the content of the main bar when composing their own review, instead of trying to imitate their popularity.

We believe that our approach of aggregation across various features of the reviews and games (e.g., sub-genres of games, positivity/negativity of reviews, absolute level of helpfulness, etc.) provides a robust investigation of the qualitative patterns: While we implicitly control for them by comparing the similarity of the visible reviews to reviews that were not directly visible at the time of writing, the observed effect sizes are likely to be attenuated by not explicitly im-

Figure 3

Main results of the study. Similarity scores reflect the per-reviewer average of the similarity between their reviews and the reviews at the corresponding position on the web page, as a function of salience (main bar vs. side bar vs. control) and the display order (from top to bottom). See Figure 1 for an illustration of the web page format. Error bars are omitted due to the sample size (i.e., the range of the confidence interval is virtually zero).



plementing these factors in our analyses. Future studies can apply our methodology to investigate the moderating cognitive and situational factors behind review imitation.

Our results are based on semantic similarity obtained from a large pre-trained language model. This measure is suitable for capturing a variety of similarities between two texts in their semantic content. For example, two reviews would be more similar, using our metric, if they both focus on the quality of graphics in a given shooter game, rather than if one covers graphical fidelity, but the other elaborates on the game's controls. Future research could explore the conditions under which imitation is more prevalent, including factors associated with the products themselves (e.g., life-service shooters vs. single player games) or other extraneous factors (e.g., times when games receive critical updates). Beyond semantic similarity, imitations could also vary as a function of the review's content (e.g., based on the topic structure of a given review, it's length, or its valence (positive vs. negative)).

In sum, the results of our study can be translated into practical implications for commercial game developers, videogame enthusiasts, and researchers alike. Particularly salient and helpful reviews influence the to-be-written reviews by increasing the tendency of other reviewers to write similar reviews. This imitation is not without consequences, as these new review are more likely to become salient and helpful in the future. Developers may want to try and boost their sales by exploiting the effect. For example, they could ensure that prominently displayed reviews are particularly positive, which could result in a 'ripple-like' effect on the spread of positive reviews (Gremler & Brown, 1999). On the flip side, consumers should be careful in inferring the quality of a product based on the most prominent reviews, as they are likely to be, at least partly, imitations of one another. This effect might impair the accumulation of knowledge, and future research should investigate it further.

Data and Code Access Statement

Data used for this study were retrieved using the Steam API. Commercial restrictions on the usage and distribution of Steam's content was abided to in this study. The API's terms of use can be found at https://steamcommunity.com/dev/apiterms. Code that scrapes data and runs all analyses reported in the manuscript is publicly available on the Open Science Framework (Spektor et al., 2024). Running the code will naturally yield data that differ from those used in the present study, as new games are released, new reviews are written, and existing reviews are edited and/or receive votes from other users. The raw data used in the present study will be provided in case of legitimate interest.

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