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Online Review Updating: Prevalence and Implications for Platforms and Businesses

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Online Review Updating: Prevalence and Implications for Platforms and Businesses

Abstract

This study documents the existence and prevalence of the “review updating” phenomenon, where consumers change the ratings and content of their existing reviews, and examines its implications for platforms and businesses. Using both primary and secondary data, a dataset comprising 3 million reviews of 50,000 companies from a large global online review platform, text analysis methods, and staggered adoption design models, the research shows that consumers update between 5% and 30% of their existing reviews across various platforms. Consumers are motivated by the desire to provide more accurate and updated information, and are especially likely to update existing reviews with extreme and/or negative ratings. The updates tend to mitigate the extremity of the review ratings and content: 77.2% of extremely negative ratings increase by an average of 1.83 stars post-update, and the content of updated reviews becomes less emotionally extreme, overall more net positive, and richer in cognitive content. Consumers also rate the same reviews as more helpful post-update. Importantly, the research shows that low-cost, unincentivized platform solicitations can directly increase the likelihood of review updating, suggesting a novel managerial tool to mitigate the undesirable impacts of extreme and negative reviews. The findings contribute to the literature on online reviews by challenging the implicit assumption that reviews remain static in content and ratings post-creation and propose that review updates can benefit consumers, businesses, and platforms.

JEL-Codes: E310, F320, Q430, C330.

Keywords: online reviews, online review updating, online review dynamics, online review extremity, user-generated content, e-word of mouth.

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1 Introduction

Online reviews provide consumers with valuable information about companies, products, and services and impact a wide array of economic outcomes, including product demand, sales, and business reputation (Pocchiari, Proserpio, & Dover, 2024). However, the review creation process often leads to polarization and extremity, with extremely negative and highly positive review scores posted more frequently than moderate ones. The prevalence of extremity and polarization in ratings and content can reduce the informativeness of reviews and the extent to which they accurately represent underlying consumer opinions (Karaman, 2021; Schoenmueller, Netzer, & Stahl, 2020). Furthermore, extremely negative reviews can have particularly concerning consequences for the reviewed businesses, as consumers tend to overweight negative information when making decisions (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001; Chevalier & Mayzlin, 2006; Ito, Larsen, Smith, & Cacioppo, 1998). In fact, even a single negative review can significantly diminish the likelihood of a purchase. In cases where a product page only displays negative feedback, purchase probabilities can drop to zero (Varga & Albuquerque, 2023).

Recent research has investigated the drivers of review extremity and approaches to mitigate its negative consequences (Brandes, Godes, & Mayzlin, 2022b; Schoenmueller et al., 2020). These approaches focus on creating new reviews that compensate for the problems caused by existing ones, likely based on the assumption that once reviews are published, they remain unchanged (Proserpio & Zervas, 2017). For instance, Brandes et al. (2022b) and Karaman (2021) propose that soliciting additional reviews could help reduce extremity by activating reviewers with more moderate experiences, while Mayzlin, Dover, and Chevalier (2014) show that companies purchase additional positive reviews to compensate for existing negative reviews. However, soliciting and purchasing new reviews may not always be possible. For example, third-party platforms cannot solicit consumers who did not leave a review about their experience, and purchasing promotional reviews is an unethical practice resulting in welfare losses for platforms and consumers (Mayzlin et al., 2014).

In this study, we document and examine an overlooked phenomenon: review updates. We

show that *existing* online reviews receive *updates* to both content and ratings after being posted, and that this phenomenon occurs on most major online review and e-commerce platforms, including Amazon, Trustpilot, Yelp, Goodreads, and Alibaba. Furthermore, we demonstrate that review updates can help mitigate the extremity of review ratings and content – especially when the initial reviews are extremely negative – without relying on the creation of new reviews. In particular, we show that updates to existing reviews result in more moderate content and ratings, especially in the case of initially extreme and negative reviews. In addition, other consumers find the same reviews relatively more helpful after an update. Finally, we show that platforms can increase the incidence of review updates through a low-cost solicitation intervention targeting existing reviewers, opening up new possibilities for platforms and businesses to manage extreme and polarized reviews.

Our study of review updates combines several sources of information and data. The primary source and empirical context is PissedConsumer.com, a global online review platform with more than 1.8 million reviewers from over 100 countries, and one of America’s fastest-growing platforms in 2024 (Financial Times, 2024). Our unique proprietary dataset comprises more than 3 million public reviews of 50,000 companies posted by 2 million consumers between 2007 and 2022. Consumers on this platform typically write reviews about companies and service providers, similar to reviews on Trustpilot, Yelp, and Tripadvisor. Therefore, consumers use this platform to share public opinions and complaints about firms through online reviews, which include 1- to 5-star ratings and free-form text. Although consumers may choose to write both positive and negative reviews, most describe negative experiences and provide negative feedback – resulting in polarized and extreme reviews skewed toward negative ratings.

Negative reviews about firms on online review platforms might share some similarities with customer complaints described in the service marketing literature – for instance, both focus on negative feedback and may be addressed to specific companies. However, they differ in a key aspect: negative reviews are publicly available and influence other consumers (Pocchiari et al., 2024), whereas the majority of customer service complaints typically remain private within the internal channels of a company (Wirtz & Lovelock, 2021). This difference makes the

phenomenon of review updates particularly relevant to public online reviews, where changes in ratings and content can directly affect other consumers. Thus, PissedConsumer.com is an ideal setting to study how, when, and why reviews – especially extreme and negative ones – are updated, as these updates can impact both the reviewed companies and the decisions of future consumers.

In addition to data from PissedConsumer.com, our study includes review updating information from 19 major online reviews and e-commerce platforms, data from 3 additional online review platforms (i.e., Goodreads, Trustpilot, and a platform of employer reviews), and primary data from an exploratory online survey.

Our results show that more than 150,000 existing online reviews on PissedConsumer.com have been updated in ratings and/or content. Moreover, the frequency of review updates has steadily increased in recent years, highlighting its growing use by consumers. The incidence of review updates has increased from 2.8% in 2011 to 5.7% in 2021, with a peak of 8.3% in 2020. Most of these updates (69.4%) were created by consumers before receiving any solicitation from the platform. A similar or even larger fraction of consumers have updated their existing reviews on other major online review platforms. For instance, we find that consumers have updated 4% of their online banking reviews on Trust Pilot, 9% of their reviews on a major employer review platform, and 31% of their book reviews on Goodreads. Furthermore, 35% of the respondents in our exploratory survey ($N = 591$) have seen updated reviews on online reviews and social media platforms such as Google Reviews and Facebook, as well as e-commerce platforms such as Amazon, Taobao, and Alibaba. Additionally, 22% of respondents have updated their own reviews, motivated by a desire to improve the accuracy of their existing feedback and to add novel information and context about their interactions with the reviewed company.

In addition to documenting the prevalence and drivers of the review updating phenomenon, we find that review updates can help manage existing online reviews that exhibit extreme and negative ratings and content. Our results show that reviews with extremely negative ratings are more likely to be updated than moderate reviews, and that reviews with initially extreme and negative ratings become more positive and less extreme after an update. Specifically, we find

that 77.2% of extremely negative ratings increase, on average, by 1.83 stars post-update. The potential to mitigate extremity is even more pronounced for negative reviews related to issues that consumers considered “resolved”. In terms of content, updated reviews are, on average, less emotionally extreme, overall more net positive, and suggest that consumers engage in more cognitive processing after the update. Using crowd-sourced metrics of review helpfulness, we find that consumers consider the same reviews relatively more helpful after an update.

Finally, we assess the effect of a platform intervention that solicits review updates on Pissed-Consumer.com, using design-based staggered adoption models (Athey & Imbens, 2022; Roth & Sant’Anna, 2021). We find that review platforms can use unincentivized update solicitations to directly increase the likelihood of updates to existing reviews, from an average of 0–1 daily updates to 3–4 daily updates, with the positive effect persisting for 3–4 days. Furthermore, reviews with initially extreme and negative ratings become significantly more moderate following a solicited update, with an average increase of 2.1 stars post-update (compared to 1.77 stars for unsolicited updates).

Overall, the results of this study indicate that consumers spontaneously update their existing reviews across major online review and e-commerce platforms. These review updates can help mitigate the issue of review extremity, especially when the existing reviews are extreme and negative, and when the updates complement company efforts to resolve consumers’ issues and complaints. Furthermore, low-cost solicitations from review platforms can effectively increase the number of review updates, thereby fostering desirable changes to extreme and negative reviews without raising common ethical concerns.

Platforms that aggregate consumer opinions can use these findings to (i) design systems that allow consumers to change their existing feedback, (ii) encourage consumers who left extremely negative reviews to re-evaluate their experiences, and (iii) potentially mitigate the widespread issue of extremity in review ratings and content. Additionally, review update solicitations are particularly useful for third-party review platforms. These platforms may not be able to solicit new (and more moderate) reviews, as they may not have access to internal company records of consumers who purchased but did not review. In such cases, review updates could effectively

mitigate extremity concerns even for platforms without access to internal company information.

The results are also encouraging for companies facing negative reviews, particularly those that have taken actions to resolve consumer concerns. For example, we find that between 20 and 107 companies with exclusively negative ratings pre-update gained at least one positive rating post-update, depending on whether the updated reviews were “unresolved” or “resolved”. These results have potential economic implications for businesses, as consumers are unlikely to purchase from companies with exclusively negative ratings on their online review pages (Vana & Lambrecht, 2021; Varga & Albuquerque, 2023).

Furthermore, the downstream consequences of negative review extremity can threaten both the profitability and reputation of affected businesses. In response, some businesses may resort to ethically questionable and often ineffective practices to manage negative electronic word-of-mouth (eWOM). These tactics include purchasing promotional reviews, threatening legal action against negative reviewers, manipulating or fabricating reviews, and incorporating contractual clauses designed to discourage unfavorable feedback (He, Hollenbeck, & Proserpio, 2022; Luca & Zervas, 2016; Mayzlin et al., 2014; Proserpio & Zervas, 2017). Our study shows that review updating and the solicitation of review updates could provide low-cost solutions to the extremity of existing negative reviews and offer an additional way to manage negative reviews without compromising ethical standards.

This study primarily contributes to the literature on the dynamics and extremity of online reviews. Previous research has largely focused on the dynamics of online reviews in the review creation stage (e.g., Brandes et al. 2022b; Godes and Silva 2012; Karaman 2021, 2024; Moe and Trusov 2011) without examining whether and how existing reviews may change at later stages of the review process. We extend this literature by considering changes in review content and ratings *after* the review creation stage, exploring the dynamics in the later stages of the review process. We also contribute to the literature on negative consumer feedback (e.g., Colmekcioglu, Marvi, Foroudi, and Okumus 2022; Esmark Jones, Stevens, Breazeale, and Spaid 2018; Pee 2016; Varga and Albuquerque 2023), and the management of eWOM and user-generated content (e.g., Esmark Jones et al. 2018; Sen and Lerman 2007; Varga and Albuquerque 2023). To the best of

our knowledge, this study is the first to establish, characterize, and quantify dynamics in *existing* online reviews, challenging the prevailing implicit assumption that existing online reviews do not change over time, even when platforms allow updates. We propose that studying the dynamics of existing online reviews opens promising avenues for future research – including the broader impact of review updates on consumer attitudes and purchase intentions, and the potential of review updates to reflect a “lifecycle” of consumer opinions online more transparently.

The rest of the paper is organized as follows. Section 2 describes the empirical context and the data from PissedConsumer.com. Sections 3–5 document the overlooked phenomenon of review updates across platforms and present the results, key managerial insights, and causal evidence of the effectiveness of update solicitations. Section 6 concludes.

2 Empirical Context

The main source of data for this study is PissedConsumer.com, a large online review platform where users publicly share their experiences through online reviews, access insights into peer opinions and issues, and gather information about companies across many industries (PissedConsumer.com, 2023). Established in 2006, the platform has accumulated a substantial volume of user-generated content (including reviews, ratings, and accompanying media and documents) and was included in the list of America’s fastest-growing companies of 2024 by the Financial Times (Financial Times, 2024).

The proprietary data provided by the company consists of 3,147,668 public online reviews created by 1,814,004 users between February 2007 and November 2022. Users on the platform write reviews about 53,771 companies and businesses – similar to TripAdvisor, TrustPilot, Glassdoor, and Yelp, where consumers review companies and service providers. The reviews concern companies in 156 product categories.¹ These reviews were created by users from 253 locations, including countries, island nations, and other territories.

¹We map the companies and their product categories in the data to 20 major NAICS codes by company name (see Online Appendix A for details).

2.1 Platform Functionalities

The nature and primary focus of PissedConsumer.com, which positions itself as “a place for consumers to voice their issues,” tend to attract predominantly negative reviews (average rating = 1.8 stars, standard deviation = 1.18, minimum rating = 1, maximum rating = 5). Apart from the negative average review ratings, the reviews and functionalities of the website are virtually identical to those found on other major review platforms like Yelp and Trustpilot.

Users can access publicly available customer reviews categorized by industry and company name, similar to platforms like Trustpilot, TripAdvisor, and Yelp. At the time of data collection, the typical review page on PissedConsumer.com included the review ID, title, text, rating, creation date, reviewer’s username, and the reviewed company’s name. The interface could also display additional optional fields, such as the company’s public contacts, any monetary loss incurred by the reviewer (in USD), any “pros and cons” about the company shared by the reviewer, crowd-sourced helpfulness metrics (upvotes and downvotes), and whether any issue raised in the review was resolved by the reviewed company.

Negative reviews shared on eWOM platforms such as PissedConsumer, Trustpilot, TripAdvisor, and Yelp allow consumers to share their concerns and complaints with companies and the public. While acknowledging the service marketing literature on customer complaints – processes through which consumers reach out to companies to get redress and restore a sense of justice (Wirtz & Lovelock, 2021) – we note several key differences between negative online reviews on platforms like PissedConsumer.com and customer service complaints.

First, the overwhelming majority of customer service complaints are typically delivered through the company’s internal channels or directly to customer service representatives (Wirtz & Lovelock, 2021). In contrast, the reviews in this context are exclusively public online reviews and numerical ratings posted on a third-party review platform. As such, the content of customer service complaints tends to remain private within the internal service channels. Reviews on platforms such as PissedConsumer.com, by contrast, are posted publicly and are most similar to other forms of public negative eWOM, such as complaints and negative experiences shared

on social media to vent anger or frustration (Wirtz & Lovelock, 2021).

These distinctions highlight that review updates are primarily relevant in the context of online reviews rather than customer service complaints shared directly with companies. Negative reviews serve as “public complaints” affecting not only the company but also future customers, influencing their decisions. In contrast, private customer service complaints do not directly affect other consumers. Therefore, review updates are particularly significant in the context of public online reviews, where the visibility of feedback and its changes over time can shape consumer behavior.

Similar to TrustPilot, TripAdvisor, and Yelp, PissedConsumer.com also provides users with an overview of the company’s publicly available contacts but does not enable direct contact between the company and the consumers on the platform. Like most online review platforms, businesses that receive a negative review on PissedConsumer.com can create a profile and reply to address the negative content, but there is no direct correspondence between platform users and consumer service identifiers. For these reasons, we consider the eWOM shared on PissedConsumer.com to be online reviews with potentially negative content and ratings (which allow consumers to complain) instead of customer service complaints, and the website itself as an online review platform instead of a complaint management service.

PissedConsumer.com’s rating distribution makes it an ideal setting to study review updates – particularly in the context of extreme and/or negative reviews, which have attracted substantial attention in marketing literature. As previously outlined, research has consistently shown that online review platforms exhibit extremity (Karaman, 2021; Schoenmueller et al., 2020) and that negative information and experiences have a stronger impact on individuals’ perceptions and behaviors than positive ones (Baumeister et al., 2001; Ito et al., 1998). Similarly, prior studies on online reviews have demonstrated that the detrimental effects of negative reviews typically outweigh the benefits of positive ones (e.g., Chevalier & Mayzlin, 2006; Colmekcioglu et al., 2022; Esmark Jones et al., 2018; Pee, 2016; Varga & Albuquerque, 2023), and that platforms and companies should strive to mitigate review extremity (Karaman, 2021). This extant research has established the substantial influence of extreme and negative reviews on

consumer behavior but has neglected the fact that existing negative online reviews can change, and that these dynamics could contribute to mitigating extremity on review platforms.

2.2 Review Creation

To create a review on PissedConsumer.com, consumers must select a company to review and write a minimum of 100 characters describing their experience. Similar to most online review platforms, consumers on PissedConsumer.com can assign numerical star ratings to their reviews. Ratings are not compulsory, and range from 1 star (most negative) to 5 stars (most positive). At the time of data collection, consumers were required to evaluate various dimensions of their consumption experience on a 1–5 scale to create an average company rating. These dimensions include, for instance, value for money, product quality, location, and customer service – see Appendix [A](#), Figure [10](#) for details.

Importantly, the average of all sub-ratings would result in the overall 1–5 review rating shown on the review page. For example, a review with 3 sub-ratings of 1 star, 3 stars, and 5 stars would have an average review rating of 3 stars.^{[2](#)}

Between 2011 and 2022, consumers created an average of 711.8 new reviews per day on the platform, with an average growth in the volume of annual reviews of 31%. In 2019, the most recent year before any potential disruptions related to the COVID-19 pandemic, consumers created an average of 669 reviews per day, with a minimum of 295 daily reviews created on April 21, 2019 (Easter Sunday) and a maximum of 1,120 reviews created on December 16, 2019.

2.3 Review Updating

Since 2011, platform users have been able to update and make changes to the content and ratings of their existing reviews. During the updating process, they can modify the review text, for instance, to describe any interactions with the company that occurred after posting the

²In contrast, the average rating *for a company* is calculated as the average of *all the average review ratings* associated with that company. So, for instance, a company with 3 reviews with average ratings of 1 star, 3 stars, and 5 stars, would have an overall company rating of 3 stars.

initial review. Appendix [B](#) shows that users share a variety of topics in their review updates and that the content is not limited to redress and problem resolution. Reviewers share updates about new actions taken by the company, details on communication procedures, waiting times, existing or new issues with products and services, and lastly, details on the resolution of their original problems.

Following an update, the review interface displays an indicator showing that the existing review was changed, along with the date of the most recent update. Therefore, review updates and their history are visible to other consumers.

The data include detailed information on review creation and updates, such as a review update identifier, an identifier for the original review, a chronological record of update timestamps, a log of changes to the review text, and the total count of updates at the time of data collection. Additionally, the data contain timestamped updates to numerical ratings.³

2.4 Update Solicitations

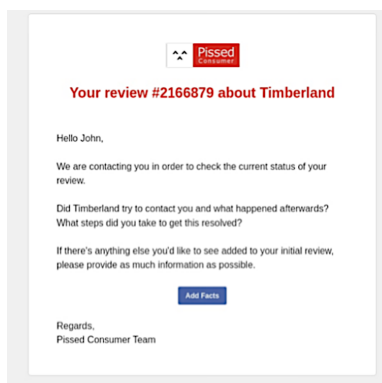
Thirty days after a review is created, the platform sends an unincentivized solicitation email to the reviewer, inviting them to update their existing review (Figure [1](#)). The solicitation is always sent thirty days after a review is created and is sent to all reviewers who created a review thirty days prior, without any specific targeting criteria.

This email encourages reviewers to revisit their existing contribution through several prompts: (1) report any interactions with the company since the review was created, (2) detail any actions the reviewer took to seek resolution, and (3) provide additional facts and context to the existing review content.

The solicitation emphasizes the importance of sharing as much information as possible. Notably, when requesting updates, the solicitations primarily focus on revising the review content, placing less emphasis on changing the review ratings, which can affect whether consumers change their ratings at all after the solicitation.

³Recall that users are required to assign ratings across various dimensions. To update their average rating, users must update each sub-dimension separately.

Figure 1: E-mail copy of the unincentivized solicitation to update sent to online reviewers.



2.5 Review Updates, Extremity, and Resolution

We investigate systematic differences in updates to existing reviews across several managerially relevant dimensions.

First, we assess whether review updating differs across existing reviews with different initial review ratings and content, specifically distinguishing between extreme and moderate existing reviews. Online review platforms are often characterized by extremity in ratings and content, with problematic implications for the unbiased representation of consumer experiences (Karaman, 2021; Pocchiari et al., 2024; Schoenmueller et al., 2020). We expect that updates to initially extreme reviews could result in more moderate ratings and content. For instance, as the memory of a very negative or very positive experience fades, consumers might be more likely to share moderate opinions about the same experience in an update compared to their original review. Similarly, research has shown that positive aspects of an experience are easier to recall when considering events that occurred further in the past (Huang, Burtch, Hong, & Polman, 2016) – suggesting that updates might mitigate negative extremity. Furthermore, extreme outcomes in consumer-firm interactions may be more likely to be followed by less extreme outcomes in subsequent interactions, resulting in less extremity after an update (Le Mens, Kovács, Avrahami, & Kareev, 2018). Therefore, updates could help platforms mitigate extremity issues, and help businesses mitigate the undesirable effects of extremely negative reviews on their reputation and performance.

Second, we investigate how much review updating differs between “resolved” and “unre-

solved” reviews. Consumers can flag their reviews as “resolved” at any time, usually if their issues have been addressed. The “resolved” flag typically follows additional actions undertaken by companies to resolve the complaints raised in the negative reviews. We expect that updates to “resolved” reviews may mitigate the negativity and/or extremity of existing reviews since they might complement additional efforts by the reviewed company – with positive potential implications for both the reviewed company and the quality of information shared on the review platform.

2.6 Construction of Samples for Analysis

The dataset used in this study includes reviews created between 2011 (the year in which review updates were first introduced on the platform) and 2022. The 2011–2022 dataset includes 3,077,874 reviews created by 1,774,402 users, reviewing 51,428 companies in 156 product categories and 20 NAICS categories.

To maintain computational tractability, we estimate the models of update solicitation effectiveness on two subsets of data. The first subset consists of online reviews created between January and December 2019. The second subset includes online reviews created between January and June 2019. We use the second subset only when estimation on the first subset is computationally unfeasible. We selected 2019 to estimate the causal effects of solicitations to avoid any idiosyncratic shocks to updating propensities due to COVID-19.

Additionally, we only evaluate the effect of the solicitation intervention on reviews marked as “unresolved” to ensure that the updates reflect primarily changes in consumer opinions and evolving issues, rather than predominantly problem resolution. This subset is organized in a panel format at the review-day level. Specifically, we track each review daily – from day 1 to day 90 post-creation⁴ – and measure whether a review was updated on any given day based on the update timestamp. We also vary the post-creation window length for robustness, including 40 and 60 days post-creation.

Table 1 provides a summary of the characteristics of the datasets used in the analyses.

⁴98% of the updates in 2019 occurred within the first 90 days post-creation

Table 1: Summary statistics

	2011–2022			January–December 2019			January–June 2019		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
N. Reviews	3,077,874	-	-	241,794	-	-	108,605	-	-
N. Reviewers	1,774,402	-	-	170,632	-	-	75,605	-	-
N. Companies	51,428	-	-	14,189	-	-	9,915	-	-
N. Product Categories	156	-	-	156	-	-	156	-	-
N. Reviews Resolved	23,577	-	-	-	-	-	-	-	-
Ratings	1,437,903	1.81	1.18	134,993	1.78	1.20	55,989	1.85	1.22
Reviews per User	-	1.73	894	-	1.42	156	-	1.44	110
Reviews per Company	-	59.8	657	-	17	121	-	11	76.1
Reviews per Day	-	712	683	-	662	151	-	600	129

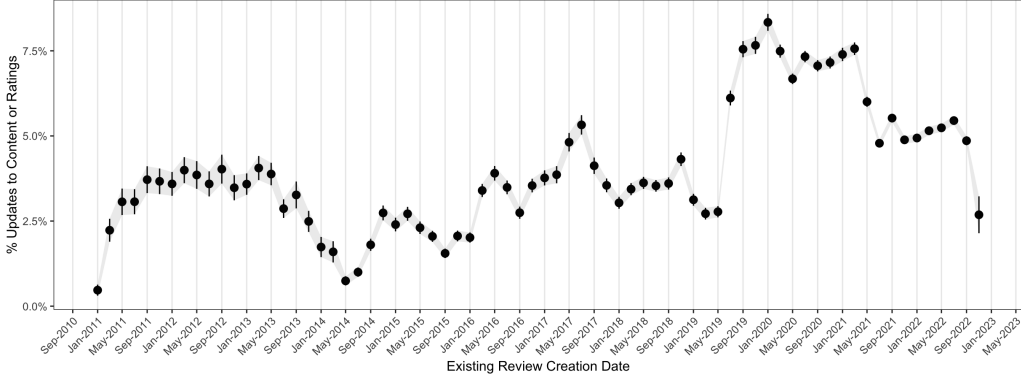
3 How Much do Consumers Update Their Existing Reviews and Why?

We begin by documenting and quantifying the phenomenon of review updates in the main empirical context, PissedConsumer.com. Between March 2011 and November 2022, consumers made 154,821 updates to either the content or the ratings of their existing reviews, representing an 11-year average update incidence of 4.95%. Most of these were updates to the content of the existing reviews (150,315 content updates), rather than updates to the review ratings (9,058 rating updates). One possible explanation for this pattern is that rating is not compulsory, and even when a rating exists, the platform requires users to update each rating sub-dimension separately (see Section 2) to change the overall review rating. These extra steps may discourage consumers from updating their ratings on PissedConsumer.com.

The volume and percentage of updates to existing reviews have increased over time, rising from 1,370 updates to content or ratings in 2011 (2.81%) to 35,753 in 2020 (7.24%) and 41,104 (5.69%) in 2021. The highest monthly incidence of review updating was recorded in January 2020 (8.33%, Figure 2). This trend suggests that a substantial number and share of existing reviews have been updated in content and/or ratings, potentially impacting the opinions and choices of the consumers exposed to these changes.

The content of most updated reviews was changed only once (single updates cumulatively account for 73% of the content updates) or twice (cumulatively 89% of the content updates), while all updated ratings were changed only once. On average, consumers made their first change to the content of a review after 18 days. However, most of the content updates (62%)

Figure 2: Incidence of Updates to Existing Reviews (2011-2022).

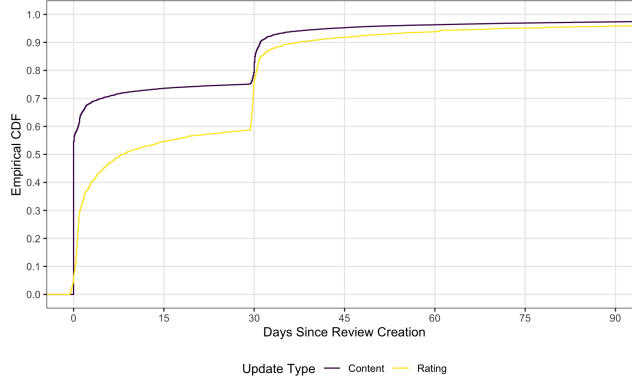


occurred within the first 24 hours after the creation of the review. The text shared in these early updates tends to be shorter (13 words on average) than updates created later (48 words on average). These early content updates typically involve small additions to the original review, factual corrections, pleas for help, or corrections to typos (see Online Appendix). Figure 3 shows that 17% of the content updates occurred between day 1 and day 29 – before receiving an update solicitation from the platform – and the remaining 21% of the content updates took place on day 30 or later (see Appendix Table 6 for the yearly prevalence of updates by update timing).

In terms of ratings, 31% of the rating updates occurred within the first day of review creation, 28.3% occurred between day 1 and day 29, and the remaining 40.7% occurred on day 30 or later (Figure 3). Respectively, 95% of the updates to content and ratings occurred within 43 and 62 days since the original review creation. These statistics suggest that a substantial proportion of consumers update their reviews and ratings spontaneously, but also that consumers may be potentially responsive to an unincentivized solicitation to update their existing reviews.

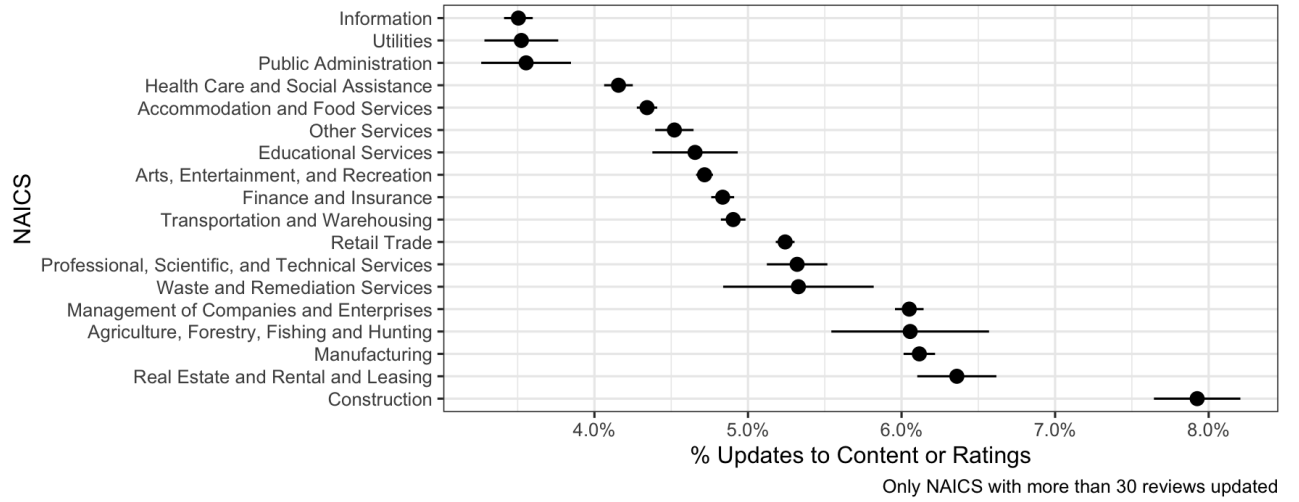
Finally, the likelihood of updating existing reviews is heterogeneous across companies' NAICS sectors. Companies operating in construction, real estate services, and manufacturing received the most updates to their reviews (between 6% and 8% in 2011–2022), while companies in information services, utilities, and public administration saw the fewest updates (around 3.5% on average in 2011–2022, Figure 4). While we cannot extrapolate deeper insights from this heterogeneity, this distribution suggests that reviews about companies offering

Figure 3: Empirical cumulative distribution function of review update timing since review creation (2011-2022).



physical products (e.g., housing and home improvement, product manufacturing) might receive more frequent updates than companies offering services (e.g. information, utilities, and public administration).

Figure 4: Likelihood of Updating Existing Reviews across NAICS Product Categories (2011-2022).



Our findings so far suggest that (i) a substantial number of existing reviews on the focal platform receive both spontaneous and solicited updates to content and ratings, confirming the relevance of the overlooked phenomenon of review updates; (ii) the incidence of updates to reviews is heterogeneous across companies and increases around the solicitation; and (iii) consumers continue to update their reviews for several days after the time of the solicitation.

3.1 Review Updates Across Platforms and Reasons to Update

Next, we assess whether the phenomenon of review updates is generalizable across platforms – thus, whether consumers update their existing reviews on other major online reviews and e-commerce platforms in addition to PissedConsumer.com – and, if so, what are some of the main reasons to update their reviews.

To answer these questions, we collected publicly available information and data about 19 major online reviews and e-commerce platforms⁵, including Amazon, Yelp, and Trustpilot. Additionally, we conducted an exploratory online survey with 600 university students (591 valid responses, see Online Appendix C for details on the survey design and sample).

Table 2 shows that updates to existing reviews are pervasive across major online reviews and e-commerce platforms. Eleven out of 19 major platforms enable updates to existing reviews, including Google, Amazon, Yelp, and Goodreads. Of these, 10 allow users to revise their existing numerical ratings in addition to changing the review content. Based on the data that include review update timestamps, we quantify that the incidence of review updating ranges between 4% (based on a sample of 20,000 online banking reviews on Trustpilot) and 31% (based on a sample of 15 million reviews on Goodreads).⁶ The updating incidence on other platforms aligns with or exceeds the incidence in our main empirical context (5% on average across 11 years, and between 5% and 8% in 2020–2022).

The exploratory survey results reveal that 35% of respondents (205 out of 591) have encountered an updated online review at least once. Respondents encountered updated reviews across online reviews and social media platforms like Google Reviews and Facebook, as well as e-commerce platforms like Amazon, Taobao, and Alibaba. Furthermore, among respondents who wrote online reviews (69%), 21% have updated their reviews at least once.

Survey respondents who indicated that they had updated an existing review in the past were also asked to explain their motivations for doing so. Eighty-five participants shared non-null responses. Figure 5 shows the 50 most frequently used words, revealing that respondents

⁵We based the data collection on the list of online reviews and e-commerce platforms in Schoenmueller et al. 2020, see Online Appendix B for details on the data sources.

⁶These data do not distinguish between content and rating updates.

Table 2: Review updating prevalence and incidence on major online review and e-commerce platforms.

Platform	Updates Allowed ^a	Updates Disclosed	Rating Updates Allowed	Update (vs. Text) ^b	Time-stamp Inferred from	% Updates	Notes on Sample
Airbnb	Before host reviews, and within 14 days from check-out	No	No	✗		-	Data unavailable
Amazon	Yes	No	Yes	✗		-	Data unavailable
BlaBlaCar	No	-	-	-		-	-
Booking.com	Within 30 days from checkout	No	Yes	✗		-	Data unavailable
Edmunds	No	-	-	-		-	-
Expedia	No	No	-	-		-	-
Glassdoor	Within 30 days unless the employer has responded or they have been marked helpful	No	Yes	✗		-	Data unavailable
Goodreads	Yes	Yes	Yes	✓		31% ^c	Sample of 2M books, 15M reviews
Google	Yes	No	Yes	✗		-	Data unavailable
Employer Review Platform	Yes	Yes	Yes	✓		9%	Sample of 150,000 reviews
IMDB	Yes	No	Yes	✗		-	Data unavailable
Indeed	No	-	-	-		-	-
Metacritic	No	-	-	-		-	-
MovieLens	No	-	-	-		-	-
Pissedconsumer.com	Yes	Yes	Yes	✓		4.95%	2011-2022
Rotten Tomatoes	No	-	-	-		-	-
Tripadvisor	No	-	-	-		-	-
Trust Pilot	Yes	Yes	Yes	✓		4%	Sample of 20,000 online banking reviews
Yelp	Yes	Yes	Yes	✗		-	Data unavailable
Total with Updates	11						
Total Platforms	19						
% with Updates	58%						

Notes:

(a) Sources of information regarding platform review updating functionalities: Booking.com: [Source 1](#), [Source 2](#); Airbnb: [Source 1](#), [Source 2](#); Amazon: [Source](#); Glassdoor: [Source](#); Goodreads: [Source](#); Google: [Source](#); IMDB: [Source](#); Tripadvisor: [Source](#); Trustpilot: [Source](#); Yelp: [Source](#).

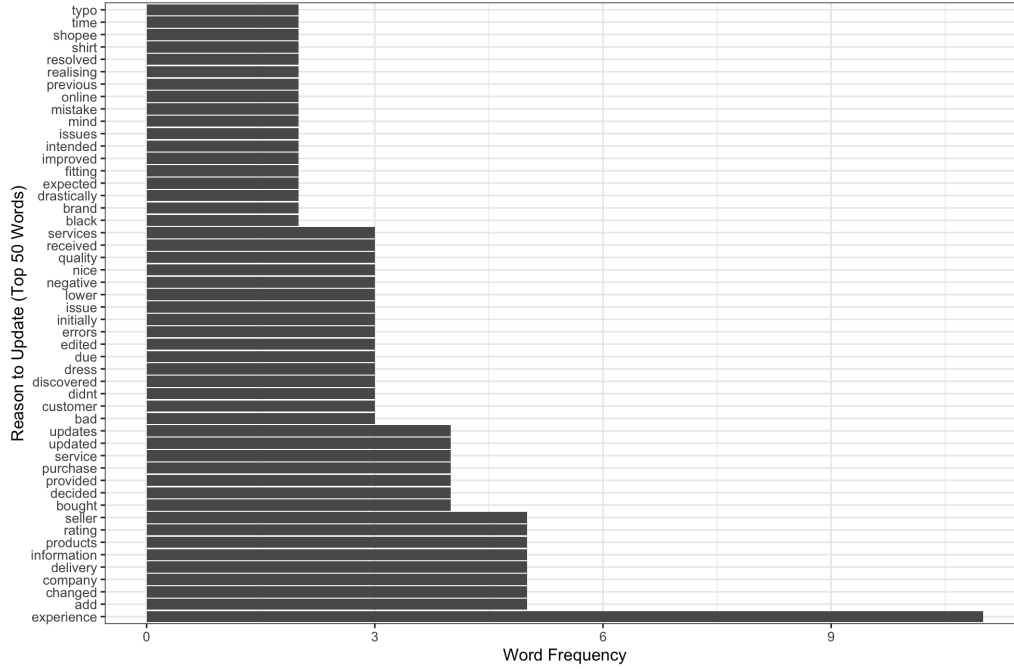
(b) “Inferred from text” refers to cases where the dataset for the focal platform lacks timestamps of review updates, and updating incidence can be inferred solely from the text. This is possible only if users self-report updates in the updated review text (e.g. “Edit: changed rating to 3 stars”). Additional information on the sources of the sample datasets is reported in Online Appendix B.

(c) The updating incidence on Goodreads is conservatively based on reviews updated at least 1 day post-review creation, to exclude updates addressing typos or accidental mistakes. If we consider all updates, the incidence of review updating on the Goodreads sample exceeds 60%.

primarily updated their reviews to add new information, describe changes in their experience (i.e., with the product or company), revise the initial star ratings, correct errors and typos, and follow up on issues that were ultimately resolved. We also use ChatGPT-4o, a state-of-the-art Large Language Model (LLM), to analyze and classify the motivations for updating into themes. This analysis reveals themes broadly consistent with the desire to share new information, describe changes in product performance, and fix initial errors (see Online Appendix for the prompt and more details on the analysis).

Finally, in addition to the insights from the survey, we use our main dataset from Pissed-Consumer.com to extract additional drivers and content of the review updates. Specifically, we fit an LDA topic model on the text of the review updates to assess the motivations, information, and experiences consumers disclose in these updates. Appendix [B](#) shows that reviewers share a variety of topics in their review updates. In particular, they describe actions undertaken by the

Figure 5: Top 50 words explaining the reasons driving review updating decisions among survey respondents.



company since they posted the original review (Topic 1), provide details on processes related to solving the issue at hand (Topics 2–3), describe issues that emerged over time (Topics 4–7), and provide information on the resolution of their original issues (Topic 8).

In sum, the evidence gathered from major online reviews and e-commerce platforms and an exploratory survey demonstrates that review updating occurs frequently across platforms and product categories, often at rates similar to or higher than in our empirical context – suggesting that review updating is a phenomenon relevant across major platforms that occurs at a non-negligible rate. We find that consumers update their reviews for various reasons – ranging from improving the accuracy of the initial review to adding new information about their experience with the products or companies. Additionally, we find that the content of review updates can provide important insights into the customer-firm interactions that took place after the creation of the original review, the status of the original issues, the progression of problem-solving processes, and the new developments that emerged since the original review was posted.

4 How do Consumers Update Their Existing Reviews?

Review Updating, Extremity, and Resolution

So far, we have demonstrated that consumers update their existing reviews on most major online reviews and e-commerce platforms, including PissedConsumer.com. Next, we investigate *how* consumers change the ratings and content of their existing reviews depending on the initial review properties. In particular, we assess whether updates can help platforms mitigate the extremity of review ratings and content, and how updates differ depending on the companies’ efforts to resolve customers’ complaints.

4.1 Review Updating Mitigates Review Rating Extremity

The prevalence of extreme reviews is a common issue that affects most online reviews and e-commerce platforms, including the empirical context of this study. Several recent papers investigated the prevalence of extremity in review ratings and tested various interventions to reduce the extremity of new ratings (Brandes et al., 2022b; Karaman, 2021; Schoenmueller et al., 2020). Mitigating the extremity of online review ratings is desirable for both platforms and consumers, as it can increase the informational value that these ratings and contents provide (Schoenmueller et al., 2020). Since consumers can use updates to change the content of their reviews and adjust their ratings, we explore the relationship between review rating extremity and review updating and whether updating can help platforms mitigate the extremity of existing reviews.

Following Brandes, Godes, and Mayzlin (2022a), we consider ratings as “extreme” depending on the distribution of ratings on the platform. Brandes et al. (2022a) propose that 50%–65% of the ratings on a platform constitute extreme ratings. In our case, we consider ratings as extreme if they are equal to 1 (“extremely negative”), or 4 and 5 (“extremely positive”) after rounding to the nearest half. In this way, “extreme” reviews account for 65% of all the ratings, in line with the suggested share in Brandes et al. (2022a) (see Online Appendix A for the full

rating distribution after rounding).

Our data suggest that, among the reviews that received updates, reviews with extremely negative and extremely positive ratings are updated more frequently (N=8,454 ratings, 1% incidence) than moderate ratings (N=3,438 ratings, 0.7% incidence, p-value < 0.001).⁷ Interestingly, the likelihood of updating extremely positive and extremely negative ratings is not symmetric – consumers are more likely to update extremely positive ratings (1.14%) than extremely negative ones (0.86%, t-value = -9.87, p-value < .001). We also note, again, that the incidence of updates to ratings is low on this platform, likely due to the platform design hurdles described in Section 2.

Furthermore, Figures 6 (a) – (d) show that both positive and negative extreme ratings become more moderate after updates, while the changes to initially moderate ratings are very small. The vast majority of the extremely negative ratings (5,194 ratings, 77.2%) increase on average by 1.83 stars post-update. The increase is even larger for updates created 30 or more days after review creation, and hence after receiving a platform solicitation to update (Figure 6 panel b, average rating score change post-solicitation = 2.1, average rating score change unsolicited = 1.77, t-value = 7.64, p-value < .001).

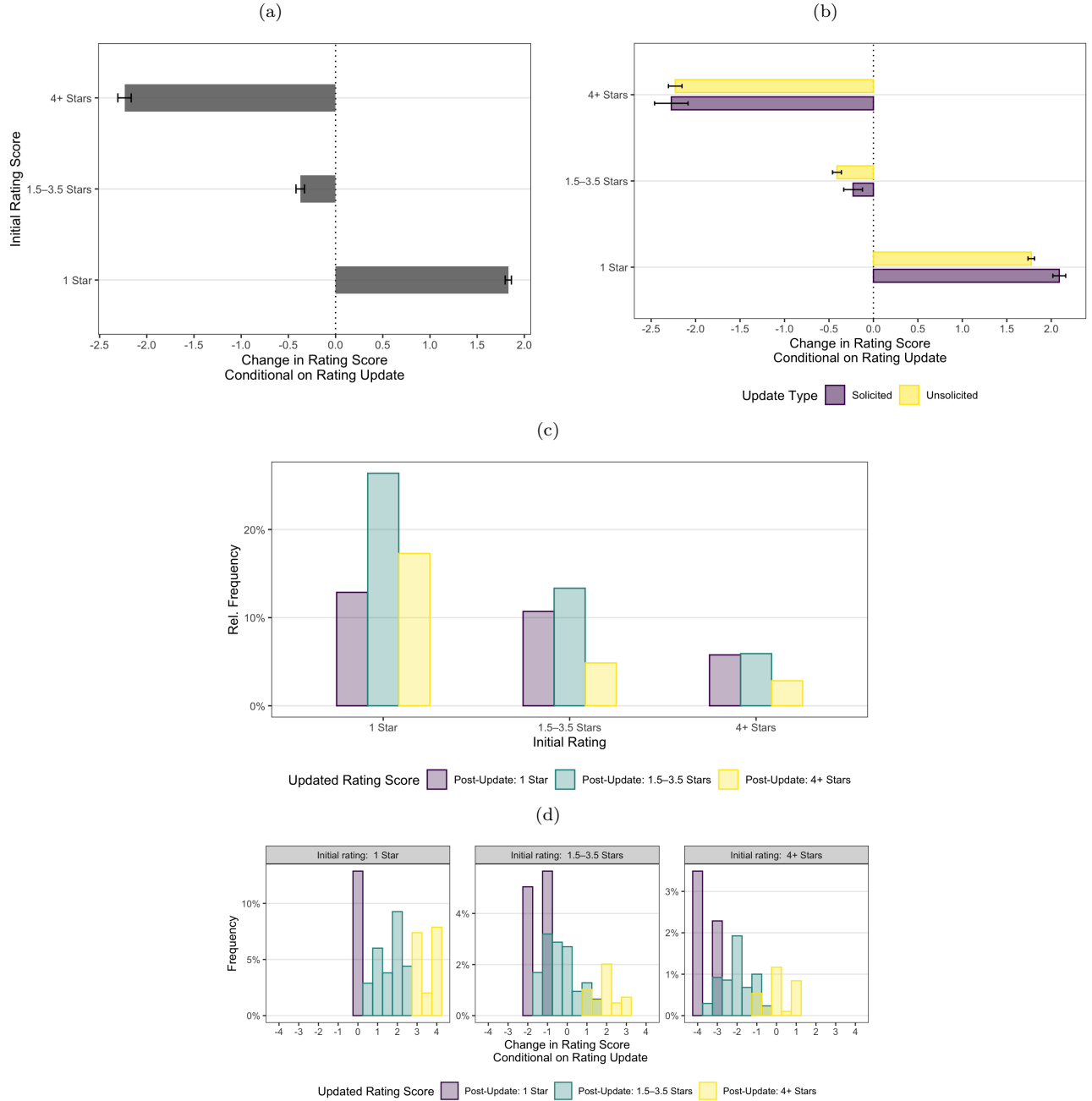
On average, conditional on updating, 85.5% (1,478) of the extremely positive ratings decrease by -2.24 stars after an update, with no significant difference based on the timing of the update (unsolicited vs. 30+ days post-creation, t = -0.43, p-value = 0.67). Over 90% of moderate reviews either increase or decrease post-update, with the average rating change being negative but very small (-0.37 stars). The decrease in average ratings is even smaller for solicited updates to moderate reviews (-0.41 average unsolicited change, -0.23 average solicited change, t-value = 3.05, p-value = 0.002).

Across all the review ratings that received updates on the platform, the increase in extreme and negative ratings outweighs the decrease in extremely positive ratings (Figure 6 panel c). Specifically, 43.13% of all updated review ratings on the platform were initially extremely

⁷In all cases, over 80% of the rating updates are unsolicited (85.1% for 4+ star reviews, 80.2% for moderate reviews, and 82.7% for 1-star reviews).

negative, and increased post-update. Finally, among ratings with updates, the post-update distribution is noticeably more moderate than before the updates (45.1% ratings post-update are moderate, compared to 26.9% pre-update – Figure 6 panel d).

Figure 6: Change in Ratings Conditional on Initial Rating Scores (2011-2022).



These results, demonstrating that updates could effectively mitigate the extremity of existing reviews, are encouraging for platforms that seek to manage the issue of rating extremity,

especially in the case of extremely negative ratings. Although the incidence of rating updates is low on this platform (likely due to platform design) reviews with extreme ratings receive more updates, and the updates make the ratings less extreme – especially following a platform solicitation. Extremely negative ratings increase by 1.8 stars on average after a spontaneous update, and by more than 2 stars after a solicited update. Extremely positive ratings also become more moderate post-update regardless of whether the update was solicited. Although this result may be desirable for review platforms and consumers, it may also have more nuanced managerial implications for the reviewed companies.

4.2 Review Updating and Review Content

Most prior research evaluated review extremity in terms of rating scores (Brandes et al., 2022b; Karaman, 2021; Schoenmueller et al., 2020). However, the positive or negative valence of an online review is also expressed through its content and language (Pocchiari et al., 2024). We rely on the widely used 2022 Linguistic Inquiry and Word Count dictionary (LIWC, Pennebaker, Boyd, Jordan, and Blackburn 2015) and the Evaluative Lexicon 2.0 (Rocklage, Rucker, & Nordgren, 2018) to assess the relationship between review content and review updating. Using LIWC, we measure the percentage of negative, positive, and angry words in each review, as well as the net positive percentage (the difference between percentages of positive and negative words). To further characterize the review content, we also assess the percentage of words referring to morality, economic concerns (money), and cognitive processes.

We complement these measures with metrics for content valence and positive dichotomy from the Evaluative Lexicon 2.0 (Rocklage et al., 2018). Content valence in Rocklage et al. (2018) is calculated as the difference between the weighted average positive and negative deviation from the midpoint of the valence scale of the words in the review content. This measure creates a continuum from negative to positive average valence of the review content. Finally, positive dichotomy indicates the percentage of reviews that contain only positive words.

Figure 7 shows that existing reviews with above-median content in most dimensions (posi-

tive, negative, anger, morality, and money) receive more updates to content and ratings than reviews with below-median content in those dimensions. In contrast, existing reviews with above-median cognition words receive relatively fewer updates than reviews with low cognition content. Furthermore, Table 3 suggests that post-update, reviews contain more positive and negative words (but relatively more positive than negative, resulting in higher net positive scores and higher positive dichotomy scores), more moderate content valence, more words related to cognitive processes and monetary concerns, and fewer words related to morality. Appendix Table 7 demonstrates the relationship between initial rating extremity, content extremity, and content updates.

Figure 7: Review Updates by Initial Review Content

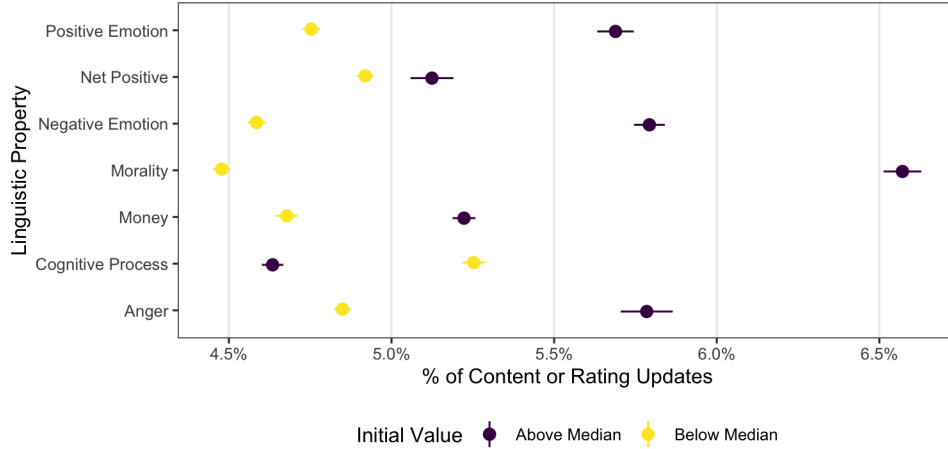


Table 3: Pre-Update vs. Post-Update Average Content Properties

Content Property	Avg. % Words Pre-Update	Avg. % Words Post-Update	T-value	P-value	95% C.I. Lower Bound	95% C.I. Upper Bound
Positive emotion	0.35	0.57	-18.29	< 0.001	-0.25	-0.20
Negative emotion	0.52	0.57	-3.40	< 0.001	-0.07	-0.02
Net positive emotion	-0.18	0.01	-9.89	< 0.001	-0.22	-0.14
Anger	0.13	0.13	0.93	0.35	-0.01	0.02
Cognitive processes	10.09	11.14	-23.13	< 0.001	-1.15	-0.97
Money	3.91	4.01	-3.98	< 0.001	-0.15	-0.05
Morality	0.43	0.37	6.35	< 0.001	0.04	0.08
Content valence continuum	-0.91	-0.66	-12.98	< 0.001	-0.29	-0.21
Positive dichotomy	0.19	0.30	-18.64	< 0.001	-0.12	-0.10

In sum, the results presented so far suggest that review updates can be useful for platforms in better managing the issue of review extremity, both in terms of ratings and in terms of review content, especially in the case of extremely negative reviews. In terms of content, updated

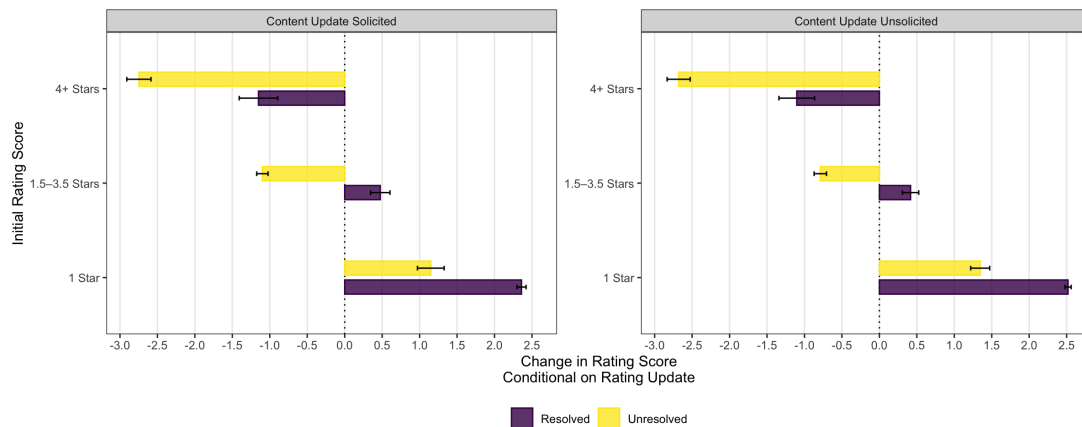
reviews are less emotionally extreme, overall more net positive, more moderate in valence, and contain more words related to cognitive and information processing.

4.3 Review Updating and Review Resolution

Consumers on Pissedconsumer.com can flag their existing reviews as “resolved” at any point, especially when their issues, complaints, or suggestions have been addressed.

The data indicate that the likelihood of updating an existing review marked as “resolved” is extremely high (90.5% updating incidence, versus 4.1% for “unresolved” reviews). In addition, Figure 8 shows that “resolved” reviews with initially extreme ratings become significantly more moderate post-update than “unresolved” extreme reviews. Importantly, reviews with positive extreme ratings (4+ stars) become more moderate post-update both when they are “resolved” and “unresolved” – however, the initially positive rating decreases relatively less for “resolved” reviews than for “unresolved” ones. These desirable patterns persist regardless of whether the review updates are spontaneous or solicited.

Figure 8: Review Updates by Review Resolution Status and Review Update Timing



To summarize, reviews with extreme ratings and reviews marked as “resolved” receive more updates, and these updates make the ratings less extreme for both “resolved” and “unresolved” reviews. However, the potential to reduce extremity is more pronounced for “resolved” reviews. While extremely positive ratings become more moderate (or less positive) post-update regardless of the resolution status, they remain more positive when the review is marked as “resolved.”

Furthermore, the aggregate increase in extremely negative ratings outweighs any decrease in positive ratings. These results could mitigate managerial concerns around the decrease in extremely positive ratings post-update. Therefore, review updates could be powerful tools to manage online reputation, particularly when combined with other efforts to address consumers' issues and complaints, while simultaneously mitigating concerns around review extremity.

4.4 Review Updating and Other Business Implications

Our findings suggest that review updates can help mitigate review extremity, with potential implications for the informativeness of the reviews and their representativeness of evolving consumer opinions. However, the implications of the review updating phenomenon extend beyond changes in the rating and content distributions on online review platforms. In particular, reductions in extreme negative reviews may have downstream consequences, including a potential impact on the purchase likelihood of future consumers.

Recent results from [Vana and Lambrecht \(2021\)](#) and [Varga and Albuquerque \(2023\)](#), respectively, demonstrate the marginal impact of exposure to a single review with positive (versus negative) ratings on purchase likelihoods. More specifically, both papers exploit platform design features that change the order of the reviews on a review page and argue that the resulting changes in review ratings displayed to consumers (from more negative to more positive in [Vana and Lambrecht \(2021\)](#) and vice versa in [Varga and Albuquerque \(2023\)](#)) could directly impact purchase likelihoods. This implies that there could be an important effect on the purchase of updated reviews that change to be more positive or more negative, post-update.

For example, our data suggest that between 20 and 107 companies with exclusively negative review ratings pre-update, gained at least one positive review post-update, depending on whether the updated reviews were “unresolved” or “resolved.” This change of the negative-to-positive ratio of reviews on company pages could potentially impact consumers' purchase likelihood.

Furthermore, in the Online Appendix, we provide suggestive evidence that the phenomenon

of review updates could have implications for the generation of revenues from the reviewed companies. In particular, to get a rough simulated estimate of the impact on revenues - we use information from [Vana and Lambrecht \(2021\)](#) and [Varga and Albuquerque \(2023\)](#), average industry benchmarks for conversion rates and industry-specific average order values, and calculate the potential change in revenues associated with higher or lower review ratings post-update. This analysis cautiously suggests that “unresolved” reviews that change from negative to positive post-update, under our simplistic assumptions, could be associated with an average \$4,626.37 increase in monthly revenues across product industries. The potential increase in average monthly revenues, under these assumptions, could further rise to \$11,327.67 in case of negative-to-positive updates to “resolved” reviews. However, the interpretation of these results should consider that the sources of information on industry benchmarks do not directly refer to the companies in our data and that quantifying the causal effects of review updates on revenues is beyond the objectives of this paper.

Beyond the potential effects on purchase likelihood, our findings suggest that updated reviews may also be perceived as more helpful by consumers, as updates often include additional information and corrections to mistakes. Review helpfulness is frequently determined through crowd-sourcing, where users can vote on whether the review is helpful (upvote) or not (downvote) ([Pocchiari et al., 2024](#)). Most online review platforms, including Yelp, Tripadvisor, Trustpilot, and PissedConsumer.com enable their users to crowd-source review helpfulness through voting systems.

Using the detailed log of upvotes and downvotes for reviews on PissedConsumer.com, we determine whether users perceive reviews as more or less helpful after an update. We consider “upvotes” as crowd-sourced votes for “helpfulness” of the reviews. Table [4](#) shows that among the reviews that received votes, consumers rate reviews as relatively more helpful after an update. Conditional on reviews receiving votes, consumers also voted updated reviews as relatively more helpful than reviews without updates. The perceived helpfulness of review updates applies to both updates to ratings and content. We also note that reviews that received updates were rated as relatively more helpful even before the update occurred. This suggests that reviewers who

update their reviews may have a stronger intrinsic “commitment” to writing helpful reviews from the start, but that the update makes the review even more helpful. The commitment might also be another subtle driver of review updating, in addition to the motivations already highlighted in Section 3.

Table 4: Perceived Helpfulness of Reviews. The % helpfulness of a review is calculated as the number of upvotes over the total number of upvotes and downvotes received by the review. The table refers to reviews that received at least one vote between 2011 and 2022.

Update Type	Vote Creation Time	% Helpfulness	2.5% C.I.	97.5% C.I.	N. Votes	N. Reviews	Std. Error
Updates to Rating	Before Update	77.24	71.98	82.49	317	231	0.02
Updates to Rating	After Update	84.59	82.94	86.24	4115	1468	0.01
Updates to Content	Before Update	78.34	77.43	79.25	21079	6649	0.00
Updates to Content	After Update	80.43	79.84	81.02	61784	12436	0.00
No updates	-	76.36	76.27	76.45	2827840	656799	0.00

5 Effectiveness of Unincentivized Solicitation to Update

So far, we have shown that consumers change the content and ratings of their existing reviews. Many of these changes happen spontaneously, and updated reviews exhibit desirable managerial outcomes for both companies and platforms, especially in the case of extremely negative reviews.

The results described so far have concerned many “endogenous”, spontaneous updates and provided descriptive evidence that consumers may be responding to platform solicitations to update their existing reviews. Next, we provide causal evidence for the effectiveness of a platform intervention soliciting unincentivized updates to existing review content. If solicitations have a positive effect, platforms could design low-cost interventions to manage the spontaneous dynamics of existing online reviews.

5.1 Quantifying the Effectiveness of Update Solicitations

The panel structure of the data from PissedConsumer.com enables the analysis of review update solicitations as staggered interventions, administered by the platform to cohorts of reviewers. Based on the timing of a platform intervention, all reviewers who posted a review on the same day would also simultaneously receive an unincentivized solicitation email 30 days later, forming

a cohort (Athey & Imbens, 2022). Under this solicitation schema, on any day of the panel, we observe cohorts that are (1) “early treated” (the review was posted at least 30 days prior and already received a solicitation at that point), (2) “late treated” (the review was posted less than 30 days prior and will receive a solicitation later in the panel), and (3) “not yet treated in the current panel” reviews (the review was posted less than 30 days prior and will receive a solicitation only *after* the end of the observation period).

More formally, consider any review r created by user i on day d . Any user $i \in N$ who created r on day d will receive a solicitation to update their review, $D_{r[i]t}$, on day $d + 30$. We denote binary indicator $D_{r[i]t} = \mathbf{1}_{d+30 \leq t}$ as equal to 1 if the solicitation date $d + 30$ precedes day t .

From this design, it follows that all reviewers who posted a review on the same day d receive the solicitation email on the same day $d + 30$ and form a cohort, N_d (in Section 2, we demonstrated that, on average, between 600 and 700 users create a review on the same day). Therefore, for any day $t \in T$ in the panel, we observe cohorts of “early solicited” (received the solicitation on or before day t), “late solicited” (did not receive the solicitation by day t but will receive it by the end of the panel), and “not solicited yet” reviews (posted a review after $T - 30$, and therefore would not receive a solicitation during the observation period in the current panel). In a matrix format, this can be represented as:

$$\mathbf{D}_{N \times T} = \begin{pmatrix} 1 & 2 & 3 & 4 & \dots & & T & \text{(time period)} \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & \text{(not solicited yet)} \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 1 & \text{(late solicitation)} \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 1 & \\ 0 & 0 & 0 & 0 & 1 & 1 & \dots & 1 & \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \\ 0 & 1 & 1 & 1 & 1 & 1 & \dots & 1 & \text{(early solicitation)} \end{pmatrix}$$

In this setting, following Athey and Imbens (2022), we estimate the effect of solicitations (τ) on the likelihood of updating review $r[i]$ on day t ($Y_{r[i]t}$) using a two-way fixed-effects regression (TWFE) logit regression model with control variables ($X_{r[i]}$) and fixed effects. The control

variables include the review creation date, a company identifier, the reasons for creating the initial review, the initial average review rating, the product category, and the number of prior contacts with the company at the time of review creation. In particular, we specify the following model:

$$Y_{r[i]t} = \alpha_i + \beta_t + \tau D_{r[i]t} + \gamma X_{r[i]} + \varepsilon_{r[i]t} \quad (1)$$

where $Y_{r[i]t}$ is the binary variable for whether review r written by individual i was updated at time t , α_i is a vector of fixed effects to control for unobserved, time-invariant characteristics of individual reviewers, β_t is a vector of time fixed effects at the day-level to account for any shocks or trends that are common across individuals over time, τ is the treatment effect of solicitation $D_{r[i]t}$, and $X_{r[i]}$ is a matrix of time-invariant covariates for review r written by individual i . $\varepsilon_{r[i]t}$ is an i.i.d. error term, which we assume follows a logistic distribution.

5.1.1 Identification Assumptions

The identification of $\hat{\tau}_{t,dd'}$ relies on several important assumptions from [Athey and Imbens \(2022\)](#).

The first assumption is that, from the perspective of platform users with similar pre-treatment variables, the timing of the update solicitation is (conditionally) random. Note that we do not assume that the timing of *review creation* is random. Users self-select into review creation, as is typical on most online review platforms. We also note that users who posted a review on the same day may share similar pre-treatment characteristics and unobserved idiosyncrasies. Instead, we assume that the unobserved factors driving the *review platform's choice* of a 30-day solicitation threshold are mostly uncorrelated with the unobserved idiosyncrasies driving an individual user's decision to create a review on day t . While this assumption is not testable, representatives of PissedConsumer.com confirmed that the decision about the 30-day threshold was taken at the start of the review updating program, and that the threshold has never changed. The original decision was based on expectations of the time it would take for

companies to see the online review, and not on users’ propensity to update. Therefore, concerns about the systematic violation of this assumption by all individuals in our panel are minimal.

The second assumption is that platform users did not anticipate receiving a solicitation, such that anticipation did not affect their likelihood of updating a review (*No Anticipation*). This assumption is plausible in our empirical setting, given that over 95% of the users only write one review, and that the solicitation is not advertised on the platform. This information minimizes both the concern that users strategically timed their review creation based on the expected time of solicitation, and that their likelihood of updating changes as a result of anticipation.⁸

The third assumption is that on day t , the likelihood of updating is not affected by the reception of a solicitation earlier versus later in the panel, as long as the solicitation occurred before or on day t (*Invariance to History*).

Finally, the fourth assumption is that once a reviewer receives the reminder, they are considered “treated” throughout the rest of the periods in the panel.

Under these assumptions, $\hat{\tau}_{t,dd'}$ is identified from variation generated from cohorts of reviewers who created a review on the same date $d < t$, and from cohorts of reviewers who created reviews on $d' \geq t$, given that different cohorts are similar on pre-treatment covariates.

5.1.2 Time-Varying Effectiveness of Review Update Solicitations

To capture time dynamics in the effectiveness of review update solicitations, we re-estimate the model in Eq. 1 using Roth and Sant’Anna (2021)’s staggered rollout design. This alternative specification allows for the estimation of treatment effects that vary by day. Furthermore, this specification relies only on the first two assumptions discussed above and relaxes the third (and strongest) assumption. Therefore, this additional analysis also tests the robustness of the baseline estimates.

We estimate the staggered rollout effect τ_t at the daily level with the *staggered* package (Roth & Sant’Anna, 2023). As required in Roth and Sant’Anna (2021), we use a balanced

⁸Atthey and Imbens (2022) also suggests that if the no-anticipation assumption holds, the assumption of conditionally random solicitation date could be relaxed.

Table 5: Estimates from the SAD Regression of update solicitations on updating likelihood. The unincentivized update solicitation significantly increases the likelihood of updating existing reviews.

	Likelihood of Updating (τ)		
	(1)	(2)	(3)
Days since Review Creation	[1-90]	[1-60]	[1-40]
Unincentivized Solicitation	8.634*** (0.157)	11.450*** (0.210)	12.098*** (0.210)
Controls	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
User FE	Yes	Yes	Yes
Deviance	25116.31	22913.10	28579.90
Num. obs.	338840	234639	200332

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Estimates are expressed in log-odds units. Estimation subsample: January – December 2019. Days since review creation: (1) [1-90] days; (2) [1-60] days; (3) [1-40] days. Model specification: $Y_{r[i]t} = \alpha_i + \beta_t + \tau D_{r[i]t} + \gamma X_{r[i]t} + \varepsilon_{r[i]t}$. Control variables: review creation date, company identifiers, original review motives, review rating, and number of prior contacts with the company at the time of review creation.

panel of reviews created in the first six months of 2019. A balanced panel implies that update values are missing in periods preceding the day of review creation, as users would never be able to update the reviews in periods when the review did not yet exist. As [Roth and Sant’Anna \(2021\)](#) recommend, we impute missing pre-creation update values using two criteria. First, we impute “potential updates” as random draws from a Bernoulli distribution with probability equal to the updating incidence in the estimation panel. In other words, we impute the missing outcomes assuming that reviews would have been updated at the same rate as usual during the imputation period. Second, for robustness, we impute values of “potential updates” to 0 – however, we note that this imputation method may result in overestimated causal effects.

5.2 Results of the Solicitations

Table [5](#) demonstrates that solicitations significantly increase the likelihood of updates to existing review content. This effect is robust to different samples that vary by length of the panel, and it is stronger when the post-creation windows are shorter, suggesting that solicitations may be most effective closer to the intervention, with diminishing effectiveness over time.

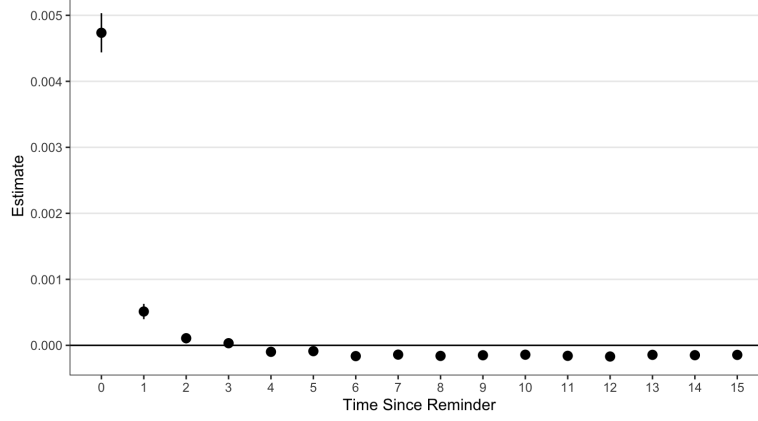
The coefficient estimate for τ in column (1) in Table 5 corresponds to a 0.51% average treatment effect (ATE) of the unincentivized solicitation. Recall that the platform sends a solicitation to all users 30 days after the creation of their original review. On average, in the panel, 664 reviews are created every day, and reviews receive an unincentivized update every 7 days (0.02% likelihood of updating reviews before day 30).

With a 0.51% ATE, if the platform is reaching out to 662 reviewers on an average day, 3-4 more reviews might be updated daily than without the solicitation. Considering that the solicitation is unincentivized, the increase in updating likelihood can be achieved without direct costs in addition to the cost of sending the solicitation email. The solicitation intervention could generate positive business value if the cost of implementing the solicitation is low relative to the value of the updating – and this value could be especially high for initially extreme and negative reviews. Furthermore, the intervention could lead to a significant impact on platforms where users share a larger number of reviews per day – for instance, Amazon sells over 12 million products that receive an average of 1-2 reviews per day (Buck, 2024; Trowbridge, 2024), resulting in a massive potential pool of reviewers to solicit.

We further explain the time dynamics in the effectiveness of the platform intervention using a staggered rollout design from Roth and Sant’Anna (2021). This alternative specification confirms that solicitations are most effective on the first day of the intervention, and remain effective for 3–4 days (Figure 9). These results are robust to different outcome imputation criteria (Appendix C). Furthermore, the magnitude of the effect sizes (around 0.5% on the first day and around 0.1% later) is roughly comparable to the ATE calculated using the TWFE coefficients (0.51%), which confirms the robustness of the results in Table 5 after relaxing stronger identification assumptions.

To sum up, consumers spontaneously update their existing reviews in ways that result in less extreme review content and ratings, and they also respond positively to low-cost review update solicitations from the review platform. The unincentivized solicitations to update are most effective on the same day of the intervention and remain effective for 3–4 days. These findings are encouraging for platforms and businesses aiming to proactively manage review

Figure 9: Staggered rollout estimates τ_t , over the 15 days following the reception of the solicitation. Error bars report the 95% confidence intervals of the estimates. The solicitation is most effective on the day of the reception and remains effective for approximately two days. Estimation subsample: January – June 2019.



updates by directly soliciting consumers to re-evaluate their existing contributions, without raising immediate ethical concerns.

6 Conclusions

This study established and investigated the important – yet previously under-researched – phenomenon of updates to existing online reviews. The insights from this study reveal that a significant proportion of mainstream online review platforms and e-commerce platforms allow users to change their existing reviews. Despite the prevalence of review updates, there is still little insight into this phenomenon.

In the study’s empirical context, the findings reveal that 5%–8% of the existing reviews received at least one update, and the changes occurred in both review ratings and content. These updates led to less extreme content and ratings, especially in the case of initially extreme and negative reviews, and when companies have taken steps to resolve the issues raised in the initial review. Consumers also consider the same reviews to be relatively more helpful after an update. Updates to existing reviews occur both spontaneously and in response to solicitations from the review platform. The results of a causal analysis of a platform intervention that solicits review updates demonstrate that low-cost update solicitations are effective in directly

increasing the rate of review updating from an average of 0–1 daily updates to 3–4 daily updates and that the intervention remains effective for 3–4 days. In addition to increasing update rates, solicitations could further help reduce the extremity of initially negative ratings, as solicited updates to negative reviews exhibit more moderate ratings compared to unsolicited ones.

Consumers’ ability to change their existing online reviews has important consequences for the management of eWOM, especially extreme and negative reviews. Prior studies on the tactics to manage negative reviews and ratings have generally implicitly assumed that negative reviews cannot change. As a consequence, businesses may feel “forced” to adopt potentially ethically questionable management tactics, such as purchasing positive promotional reviews, writing fake reviews, or preventing consumers from leaving negative feedback in the first place. Similarly, prior research on review platforms has investigated the issue of review extremity assuming that existing extreme reviews cannot change and that the issue could be addressed primarily by soliciting new reviews from previously “silent” consumers who tend to have moderate experiences. Our study challenges this prevailing implicit assumption and demonstrates that review updates are effective and inexpensive tools to manage negative and extreme consumer reviews. These insights suggest that review platforms can use this novel management tool to reduce extremity in both content and ratings, and therefore improve the quality of the information generated on the platform (Karaman, 2021; Schoenmueller et al., 2020). Similarly, businesses could foster their online reputation by simply asking dissatisfied reviewers to revisit their existing contribution, especially when the business has addressed the underlying issues.

This study has several limitations but also opens new avenues for research. From the standpoint of data, using only one platform as our empirical context may limit the generalizability of our results. While we provided evidence of review updating across most major online review and e-commerce platforms, including Trustpilot and Goodreads, and showed that review updating rates in our empirical context are very similar to those measured on other online platforms, future research should study review updating in different contexts. Moreover, the data provided to us did not allow us to explore the behavioral mechanisms driving the results. Potential explanations for the results we measured might include, for instance, the protocols of

company-consumer interactions following the creation of the initial review. We encourage future research to explore other factors in the online review process that could explain systematic differences in review updating and the psychological mechanisms that drive review updates and responses to update solicitations. Another limiting factor is the platform design feature, specific to our empirical context, which required reviewers to update multiple rating sub-dimensions to update the overall review rating. This design feature might have discouraged consumers from updating their review ratings more frequently, resulting in an under-estimated potential of review updates to reduce rating extremity. Future research should evaluate review updating on platforms where updates to review ratings are more immediate and less “costly” for the consumer. A final data-related limitation is that we were unable to study the relationship between solicitations to create new reviews and to update existing reviews. There could be both synergies and drawbacks to combining the two approaches. For instance, soliciting new reviews, which tend to be more moderate, in combination with updates to existing reviews, which tend to reduce extremity, could further enhance the informativeness and representativeness of the review ratings and content. However, receiving multiple solicitations might discourage consumers from engaging with the company in the future (Ferecatu, De Bruyn, & Mukherjee, 2024). Furthermore, soliciting new reviews can backfire, potentially leading to a reduction in future expenditure from solicited reviewers, particularly among those who are dissatisfied (Karaman, 2024). In that case, solicitations to update existing reviews could be a better choice to mitigate extremity among dissatisfied consumers and avoid the loss of future sales.

Methodologically, our models might underestimate the effects of update solicitations, as most reviewers in the empirical context only updated once. In the current approach, any decision *not to update* after the initial revision is interpreted by the models as potential ineffectiveness of the solicitation. Future research employing similar models should account for the fact that the likelihood of subsequent updates may inherently decrease after the first revision, irrespective of the effectiveness of the intervention, if most users only create one update.

Finally, the platform intervention in this study solicited all reviewers after a fixed interval (30 days) following the creation of their review. Consequently, the current models cannot account

for dynamics in the timing of the solicitation and its effectiveness. We encourage future research to run field experiments to test the effectiveness of solicitations sent at different times. This would provide more managerial guidance for companies and platforms implementing update solicitation strategies.

The study establishes the significance of the overlooked phenomenon of review updates and demonstrates its prevalence and relevance for digital platforms and companies. However, it also raises additional open questions about review updating. For instance: What are the platform-level consequences of introducing updates to existing reviews? What psychological mechanisms motivate different consumers to revise their existing reviews, and how can this inform the design of review solicitation programs? Do the reviewers' identity and the characteristics of their consumption experience influence the likelihood of review updating? What are the effects of review updates on consumers who are exposed to them? Are updated reviews perceived as more trustworthy compared to those that were never updated? Do consumers change their beliefs, perceptions, attitudes, and willingness to transact with a company after reading a consumer review that received a (favorable or unfavorable) update? Finally, do spontaneous review updates potentially reflect an underlying "consumer opinion lifecycle", where consumer opinions about firms change (relatively frequently) over time?

In sum, to the best of our knowledge, this is one of the first studies to demonstrate that existing online reviews change over time, potentially reflecting consumers' evolving opinions, experiences with products and firms, and relationships with companies. This is also one of the first studies to demonstrate that changes in existing online reviews can help manage negative and extreme eWOM. We achieve these goals using extensive and novel data from multiple sources (including a large, global online review platform, mainstream review, and e-commerce platforms, and an exploratory survey) and employing diverse and robust causal methodologies. We hope that future research will continue investigating review updating as an important phenomenon in marketing, management, and information sciences, and assess its potential to shape the landscape of online reviews and customer-relationship management in the future.

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A Additional Tables and Figures

A.1 Review Rating Sub-Dimensions

When assigning a star rating to their review, users on the focal platform must rate several rating sub-dimensions separately. Then, the star rating of their review will be calculated by PissedConsumer.com as the simple average of the ratings assigned to the sub-dimensions. Finally, the average rating of a company or product on PissedConsumer.com is calculated as the average of these review-level average ratings.

Figure 10: Users on PissedConsumer.com Rate Companies, Products, and Services Along a Varying Number of Criteria, Depending on Product Category.



A.2 Percentage of Updates per Year and Type of Update

Table 6: Number and Percentage of Updates per Year by Type of Update. (Potentially) solicited updates are created 30+ days after posting the initial review. Spontaneous updates are created less than 30 days after posting a review. Updates marked as “solicited” may also be

Year	N. Reviews	% Updates	N. Updates	% Updates by Creation Time w.r.t. Initial Review	
				30+ days	< 30 days
2011	48692	2.814	1370	49.854	50.146
2012	57100	3.746	2139	57.223	42.777
2013	70377	3.387	2384	47.106	52.894
2014	92655	1.646	1525	34.230	65.770
2015	163709	2.143	3509	26.161	73.839
2016	196564	3.167	6226	16.013	83.987
2017	157307	3.201	5035	17.736	82.264
2018	246905	3.390	8370	41.075	58.925
2019	247993	5.000	12400	25.105	74.895
2020	494079	7.118	35170	17.529	82.471
2021	722136	5.602	40456	16.883	83.117
2022	631418	5.025	31731	17.910	82.090

A.3 Pre- and Post-Update Content by Initial Ratings

Table 7: Content Extremity: Pre-Update vs. Post-Update by Initial Rating

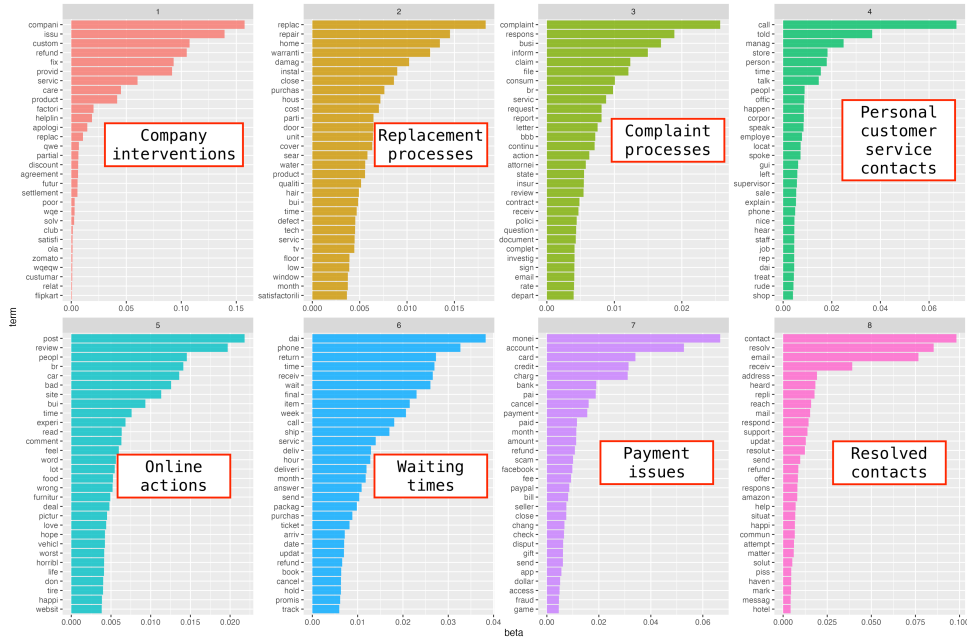
Content Property	Initial rating	Avg. % Words Pre-Update	Avg. % Words Post-Update	T-value	P-value	95% C.I. Lower Bound	95% C.I. Upper Bound
Positive emotion	Extreme negative (≤ 1 star)	0.24	0.40	-10.58	0.00	-0.19	-0.13
Positive emotion	Moderate (2-3 stars)	0.32	0.42	-6.17	0.00	-0.14	-0.07
Positive emotion	Extreme positive (4+ stars)	0.56	1.23	-5.68	0.00	-0.90	-0.44
Negative emotion	Extreme negative (≤ 1 star)	0.52	0.46	3.43	0.00	0.03	0.10
Negative emotion	Moderate (2-3 stars)	0.51	0.47	2.44	0.01	0.01	0.08
Negative emotion	Extreme positive (4+ stars)	0.48	0.51	-0.31	0.75	-0.15	0.11
Net positive emotion	Extreme negative (≤ 1 star)	-0.28	-0.06	-9.26	0.00	-0.27	-0.17
Net positive emotion	Moderate (2-3 stars)	-0.19	-0.04	-6.02	0.00	-0.19	-0.10
Net positive emotion	Extreme positive (4+ stars)	0.07	0.72	-4.74	0.00	-0.91	-0.38
Anger	Extreme negative (≤ 1 star)	0.14	0.12	1.31	0.19	-0.01	0.04
Anger	Moderate (2-3 stars)	0.12	0.12	0.76	0.45	-0.01	0.02
Anger	Extreme positive (4+ stars)	0.09	0.10	-0.26	0.79	-0.04	0.03
Cognitive processes	Extreme negative (≤ 1 star)	9.92	10.31	-5.31	0.00	-0.54	-0.25
Cognitive processes	Moderate (2-3 stars)	10.15	10.88	-8.83	0.00	-0.90	-0.57
Cognitive processes	Extreme positive (4+ stars)	9.98	10.64	-2.45	0.01	-1.19	-0.13
Money	Extreme negative (≤ 1 star)	3.78	4.21	-8.64	0.00	-0.52	-0.33
Money	Moderate (2-3 stars)	3.35	3.70	-6.91	0.00	-0.44	-0.25
Money	Extreme positive (4+ stars)	3.60	3.63	-0.22	0.83	-0.36	0.29
Morality	Extreme negative (≤ 1 star)	0.48	0.37	7.32	0.00	0.07	0.13
Morality	Moderate (2-3 stars)	0.35	0.32	1.92	0.06	-0.00	0.06
Morality	Extreme positive (4+ stars)	0.36	0.26	2.52	0.01	0.02	0.18
Content valence cont.	Extreme negative (≤ 1 star)	-1.09	-0.70	-10.75	0.00	-0.47	-0.33
Content valence cont.	Moderate (2-3 stars)	-0.80	-0.65	-3.60	0.00	-0.22	-0.07
Content valence cont.	Extreme positive (4+ stars)	-0.19	0.46	-5.45	0.00	-0.89	-0.42
Positive dichotomy	Extreme negative (≤ 1 star)	0.15	0.29	-13.32	0.00	-0.17	-0.12
Positive dichotomy	Moderate (2-3 stars)	0.19	0.30	-8.62	0.00	-0.14	-0.09
Positive dichotomy	Extreme positive (4+ stars)	0.40	0.57	-4.16	0.00	-0.25	-0.09

B Updated Review Text

We fit an LDA topic model on the text of the updated reviews to better understand what type of information or experiences consumers choose to share in a review update (Blei, Ng, & Jordan, 2003). We find an optimal 8-topic solution based on quantitative criteria from Arun, Suresh, Veni Madhavan, and Narasimha Murthy (2010); Cao, Xia, Li, Zhang, and Tang (2009); Deveaud, SanJuan, and Bellot (2014); Griffiths and Steyvers (2004).

Figure 11 shows that reviewers share a variety of topics in their review updates: they describe actions undertaken by the company (Topic 1), details on processes related to handling the issue at hand (Topics 2 and 3), any existing or additional issues emerged between the time of review creation and the creation of an update (Topics 4–7), and information on the prospects of resolving their issues (Topic 8).

Figure 11: An LDA 8-topic solution on updated review text reveals what consumers discuss in review updates.

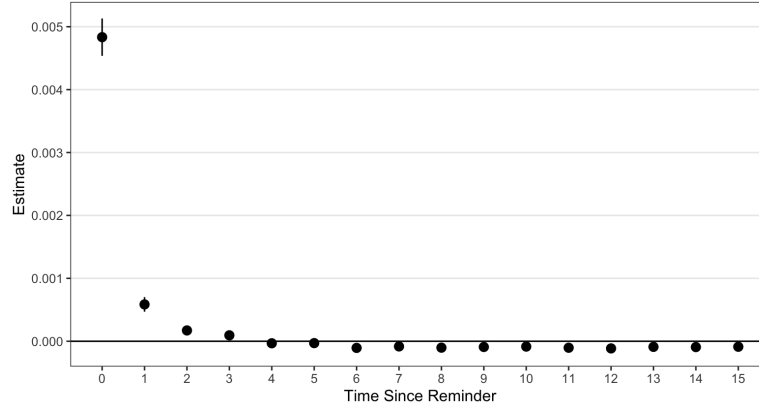


C Staggered Rollout with Alternative Imputation

The staggered rollout design proposed by Roth and Sant'Anna (2021) requires that the estimation panel be balanced. In the empirical setting, this requirement implies that outcome values for $Y_{r[i]t}$ be

imputed in the time periods preceding the creation of review $r[i]$. In the main analyses, imputed as a random draw from a Bernoulli distribution, with probability equal to the incidence of review updates in the balanced panel. Here, we impute values of the “potential updates” preceding review creation to 0. Figure 12 demonstrates the results, and suggests that the effects are substantially robust to alternative imputations.

Figure 12: DID estimates for solicitation effectiveness with imputation to zero.



Web Appendix to “Online Review Updating: Prevalence and Implications for Platforms and Businesses”

Martina Pocchiari*

Verena Schoenmueller*

Yaniv Dover[†]

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Web Appendix Disclosure Statement

These materials have been supplied by the authors to aid in the understanding of their paper. The AMA is sharing these materials at the request of the authors.

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A Additional Tables and Figures

Figure 1: Distribution of rating scores on PissedConsumer.com

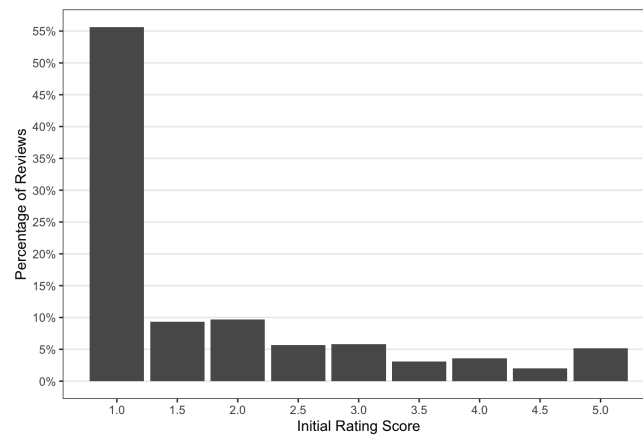


Table 1: NAICS codes and product categories

NAICS	Product Category
Accommodation and Food Services	Beverages
Accommodation and Food Services	Cafes, Restaurants and Bars
Accommodation and Food Services	Coffeehouses and Bakeries
Accommodation and Food Services	Dairy Foods
Accommodation and Food Services	Fast Food
Accommodation and Food Services	Fast Food
Accommodation and Food Services	Food
Accommodation and Food Services	Food Delivery
Accommodation and Food Services	Food Manufacturers
Accommodation and Food Services	Hosting
Accommodation and Food Services	Hotels and Resorts
Accommodation and Food Services	Kitchen and Cooking
Agriculture, Forestry, Fishing and Hunting	Animal Services
Agriculture, Forestry, Fishing and Hunting	Animals
Agriculture, Forestry, Fishing and Hunting	Breeders
Agriculture, Forestry, Fishing and Hunting	Hunting, Fishing and Camping
Arts, Entertainment, and Recreation	Adult Entertainment
Arts, Entertainment, and Recreation	Arts and Fine Arts
Arts, Entertainment, and Recreation	Astrology
Arts, Entertainment, and Recreation	Cards
Arts, Entertainment, and Recreation	Cinemas and Theaters
Arts, Entertainment, and Recreation	Dating and Social Networking
Arts, Entertainment, and Recreation	Entertainment
Arts, Entertainment, and Recreation	Event Venues
Arts, Entertainment, and Recreation	Events
Arts, Entertainment, and Recreation	Gambling and Lotto
Arts, Entertainment, and Recreation	Games and Movies
Arts, Entertainment, and Recreation	Media
Arts, Entertainment, and Recreation	Music stores
Arts, Entertainment, and Recreation	Periodicals & Publishing
Arts, Entertainment, and Recreation	Periodicals & Publishing
Arts, Entertainment, and Recreation	Photography
Arts, Entertainment, and Recreation	Sport
Arts, Entertainment, and Recreation	Sport Equipment and Accessories
Arts, Entertainment, and Recreation	Theme Parks
Arts, Entertainment, and Recreation	Tickets
Arts, Entertainment, and Recreation	Travel
Arts, Entertainment, and Recreation	Travel Agencies
Arts, Entertainment, and Recreation	Weddings
Construction	Chimneys and Fireplaces
Construction	Construction and Repair
Construction	Decks, Fencing and Gates
Construction	Flooring and Tiling
Construction	Home Builders
Construction	Landscaping and Gardening
Construction	Painting And Wallpapering
Construction	Paving

Construction	Plumbing
Construction	Restoration, Renovation and Remodeling
Construction	Roofing, Siding and Masonry
Construction	Windows and Doors
Educational Services	Courses and Trainings
Educational Services	Education
Educational Services	Kindergartens and Nurseries
Educational Services	Universities, Colleges and Schools
Finance and Insurance	Banks
Finance and Insurance	Cash Services
Finance and Insurance	Collection Agencies
Finance and Insurance	Dealers
Finance and Insurance	Financial Services
Finance and Insurance	Gift Cards, Rewards and Cashbacks
Finance and Insurance	Insurance
Finance and Insurance	Liquidators and Closeouts
Finance and Insurance	Loans and Mortgages
Finance and Insurance	Taxes
Health Care and Social Assistance	Beauty Salons and Spas
Health Care and Social Assistance	Cosmetics and Personal Care
Health Care and Social Assistance	Dentistry
Health Care and Social Assistance	Dentistry
Health Care and Social Assistance	Fitness Centers
Health Care and Social Assistance	Health and Beauty
Health Care and Social Assistance	Hospitals, Clinics and Medical Centers
Health Care and Social Assistance	Medical Supplies and Equipment
Health Care and Social Assistance	Pet Medicine and Veterinary Clinics
Health Care and Social Assistance	Pharmacy
Health Care and Social Assistance	Vitamins and Supplements
Health Care and Social Assistance	Weight Loss, Diets and Training
Information	IT Services and Solutions
Information	Review Websites and Directories
Information	Telecommunications
Management of Companies and Enterprises	Accounting
Management of Companies and Enterprises	Advertising
Management of Companies and Enterprises	Auctions and Marketplaces
Management of Companies and Enterprises	Consulting
Management of Companies and Enterprises	PR and Marketing
Management of Companies and Enterprises	SEO and Reputation Management
Manufacturing	Appliances and Electronics
Manufacturing	Blinds, Curtains and Shutters
Manufacturing	Building Products
Manufacturing	Cigarettes and Tobacco
Manufacturing	Equipment
Manufacturing	Furniture and Decor
Manufacturing	Gadgets and Accessories
Other Services	Background and People Search
Other Services	Cleaning Services
Other Services	Flowers / Florist
Other Services	Funerals

Other Services	Household Services
Other Services	Investigation
Other Services	Job Search and Employment
Other Services	Luggage
Other Services	Miscellaneous
Other Services	Non Profit Organizations
Other Services	Packaging and Packing
Other Services	Security and Protection Services
Other Services	Service Centers and Repairs
Other Services	Staff
Other Services	Talent and Modeling Agencies
Other Services	Writing and Editing Services
Professional, Scientific, and Technical Services	Gutters and Carpentry
Professional, Scientific, and Technical Services	Heating, Cooling and Air Conditioning
Professional, Scientific, and Technical Services	Lawyers and Legal Services
Professional, Scientific, and Technical Services	Locksmiths
Professional, Scientific, and Technical Services	Mechanical Engineering
Professional, Scientific, and Technical Services	Professional Services
Professional, Scientific, and Technical Services	Software
Professional, Scientific, and Technical Services	Web Design and Development
Public Administration	Governmental Organizations and Politics
Public Administration	Passports and Visas
Public Administration	Post
Real Estate and Rental and Leasing	Real Estate
Real Estate and Rental and Leasing	Rentals
Retail Trade	Beauty Supplies and Equipment
Retail Trade	Bed and Bath
Retail Trade	Carpets, Rugs and Mats
Retail Trade	Craft Supplies and Tools
Retail Trade	E-commerce
Retail Trade	Fashion
Retail Trade	Food Stores
Retail Trade	Footwear and Clothing
Retail Trade	Household Essentials
Retail Trade	Jewelry and Accessories
Retail Trade	Kids
Retail Trade	Kids' Stores
Retail Trade	Party Supplies
Retail Trade	Pawnshops
Retail Trade	Pet Stores
Retail Trade	Pools, Spas and Plumbing Supplies
Retail Trade	Printing
Retail Trade	Supermarkets and Malls
Retail Trade	Weapons
Transportation and Warehousing	Airlines and Air Transport
Transportation and Warehousing	Auto
Transportation and Warehousing	Auto Parts and Accessories
Transportation and Warehousing	Bicycles and Skateboards
Transportation and Warehousing	Buses
Transportation and Warehousing	Cruises and Ships

Transportation and Warehousing	Motorcycles and ATVs
Transportation and Warehousing	Moving and Storage
Transportation and Warehousing	RVs, Motorhomes and Trailers
Transportation and Warehousing	Trains
Transportation and Warehousing	Transport
Transportation and Warehousing	Transportation and Logistics
Utilities	Utility
Waste and Remediation Services	Pest Control and Services
Waste and Remediation Services	Waste And Recycling Services
Waste and Remediation Services	Water Transport
Wholesale Trade	Food Wholesalers and Distributors

B Additional Data Sources

To assess the presence and incidence of review updates on other major review platforms, outside of our empirical context, we collected information and public data from various sources. Information on updating was retrieved from the Booking Partner Hub ([Booking.com](#), 2023) and [Mondello \(2023\)](#), the Goodreads user forum ([Goodreads](#), n.d.), the IMBD support page ([IMDB](#), n.d.), the Google ([Google](#), n.d.), Trustpilot ([Trustpilot](#), 2018), Yelp ([Yelp](#), n.d.), Airbnb ([Airbnb](#), n.d.), Amazon ([Amazon](#), n.d.), and Glassdoor support websites ([Glassdoor](#), n.d.). We obtained sample data from [Wan and McAuley \(2018\)](#) and [Wan, Misra, Nakashole, and McAuley \(2019\)](#) (Goodreads), [Maksi and Trustpilot \(2022\)](#) (Trustpilot), [Fred \(2018\)](#) (Yelp), and proprietary data from an online review platform dedicated to employer reviews that requested to remain anonymous.

C Exploratory Survey on Review Updating

We conducted an exploratory survey among a sample of students enrolled in a prominent university in Asia (IRB code BIZ-MKT-23-0906) to measure: (1) the frequency with which respondents wrote online reviews, (2) how frequently respondents updated their existing online reviews and why, and (3) how often they encountered updated or edited online reviews during their internet browsing, and if yes, on which websites.

For question (1), we asked “How often do you write online reviews following your consumption experiences?”, and measured reviewing frequency on a 5-point scale ranging from “Never” to “Always”. For question (2), we asked “Have you ever edited or updated an online review yourself? If yes, why?”. This question was presented solely to respondents who did not select “Never” in response to question (1). Finally, for question (3), we asked “Have you ever seen an updated or edited online review? If yes, on which website?”. For both questions (2) and (3), respondents were given the possibility to elaborate on their response in a free-text form. For question (2), respondents could elaborate on the motivations that led them to update their existing reviews. For question (3), respondents were asked to share the platforms where they had witnessed review updating.

The survey was conducted between October 9 and October 23, 2023, and was administered to the students through an internal university platform. 600 students enrolled to take the survey, and we recorded 591 valid responses. 97.6% of the respondents were aged 18-24, 51.6% were female, 47.2% were male, and the remaining 1.2% identified as non-binary or preferred not to disclose their gender. Students received 0.5 course credits for their participation in the survey. Table 2 shows that over 69% of the respondents reportedly write online reviews at least sometime after their purchases or consumption experiences. Among those who engage in reviewing, 21% have also updated or edited their own existing reviews. Finally, 34.7% of the respondents reported having encountered an edited or updated online review in the past.

Table 2: Results of the exploratory survey

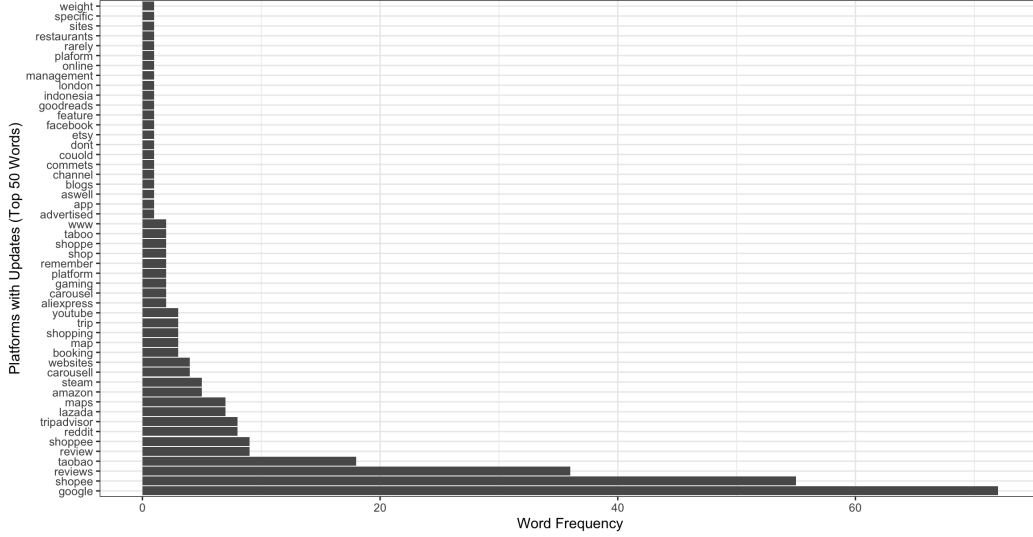
	N. responses	Percentage (%)
<i>How often do you write online reviews following your consumption experiences?</i>		
Always	4	0.68
Most of the time	20	3.38
About half the times	63	10.66
Sometimes	322	54.48
Never	182	30.8
<i>Have you ever edited or updated an online review yourself? If yes, why?</i>		
No	323	78.97
Yes	86	21.03
<i>Have you ever seen an updated or edited online review? If yes, on which website?</i>		
No	386	65.31
Yes	205	34.69

N=591

Respondents who indicated that they had seen an updated or edited review were asked to specify the websites or platforms where they observed review updates. Google is most frequently mentioned by respondents, followed by major online shopping platforms such as Shopee, Taobao, Amazon, Lazada, and Aliexpress. Respondents

also reported encountering updates to consumer reviews on entertainment and social networking platforms like YouTube, Reddit, and Steam. Finally, Figure 3 shows the most common pairs of words mentioned as motivation to update an existing review.

Figure 2: Histogram of the top 50 words describing the websites or platforms where respondents have seen updates to existing reviews.



C.0.1 LLM Theme Analysis

To extract more insights about the motivations that drive review updating decisions, we also asked ChatGPT 4o, a state-of-the-art Large Language Model (LLM) to analyze the text of the responses to question 2 (“Have you ever edited or updated an online review yourself? If yes, why?”).

The prompt we used to instruct the LLM was as follows: “I will upload a dataset. The column ”text” includes participants’ responses to why they chose to update an existing review. Remove missing values in the column ”text”. Analyze the text in the column ”text” and classify people’s responses into themes. A response can fall into more than one theme. Identify a parsimonious number of themes. Identify the number of instances for each theme and give a description of the themes.”

The LLM identified 7 themes in the respondents’ free text answers: Improved Customer Experience (15 responses), Received Compensation or Incentives (10 responses), Change in Product Performance or Quality (20 responses), External Influence (Friends, Family, or Social Circle) (7 responses), Error or Clarification in Initial Review (12 responses), Product Return or Exchange (8 responses), New Information or Updates about the Product (13 responses).

Table 3 summarises the themes and provides examples taken from the respondents’ answers to question (2).

Figure 3: Reasons driving review updates – Top 50 Bigrams.



Table 3: Themes Identified in Participant Free-Text Responses to Question 2

Theme	Description	Example	Number of Responses
Improved Customer Experience	Participants updated their reviews due to positive changes in customer service or receiving better support after their initial feedback.	"They had provided me with better customer service."	15
Received Compensation or Incentives	Participants updated their reviews because they received a refund, discount, or other forms of compensation from the seller or company.	"The seller offered a partial refund."	10
Change in Product Performance or Quality	Participants indicated a change in their evaluation after experiencing a product differently over time, either positively or negatively.	"Change of mind" or "I used the product longer and had a different experience."	20
External Influence (Friends, Family, or Social Circle)	Participants mentioned updating their review due to the opinions or needs of others, such as friends or family.	"It was for my friend's shop."	7
Error or Clarification in Initial Review	Participants updated their reviews to correct a mistake, clarify their thoughts, or provide additional context that was initially missing.	"I realized I made an error in my first review."	12
Product Return or Exchange	Participants mentioned revising their reviews after returning or exchanging a product, which influenced their perception or experience.	"I had to return the product and wanted to update the review accordingly."	8
New Information or Updates about the Product	Participants updated their reviews after receiving new information, such as new product features or updates that changed their initial opinion.	"The product was updated, and I had a better experience."	13

D Sample Texts of Unresolved Reviews Updated Within 24 Hours

The Results Section in the paper demonstrated that reviews updated within 24 hours since review creation are significantly shorter than reviews updated at least 24 hours post-creation. In this appendix, we report 10 examples of review update texts, focusing on reviews updated less than 24 hours post-creation. The examples are sampled at random from reviews in Sample A that received an update within 24 hours, were not empty, and that did not repeat the original review text without any change. Review 1457086 illustrates that the updating function was used to fix a typo in the original text. Review 1531615 reports that within the past 24 hours, the consumer tried to reach the company again. The other reviews reiterated and emphasized the requests already made in the original review, with small additions for emphasis or urgency.

Table 4: Samples from 10 Review Updates Shared Less than 24 Hours Since Review Creation.

Review Id	Hours Since Review	Update Text
1457086	0.14	Meant to say omw to file complaint with [Redacted]. Danm auto correct!! FYI: Even if a company is not accredited with [Redacted] you can still file a complaint which they will address resolution with the company before filing a complaint, but they will address the Company directly. [Redacted] has obvious issues with customer care and resolutions and we who have experienced their lack of integrity and professionalism should pursue remedy to possibly prevent someone else from this awful experience
1531615	0.55	Update: Called again and was told they have a 60-day warranty and it was out of warranty. They said they had no record of anyone calling about the item. I gave them the ticket number (from my daughter's conversation with them) and said I had the emails and video my daughter had sent them I could provide as well. then they said they would look into getting me a new one or a refund. They are sending me a new replacement so hopefully this one last longer.
1534537	15.08	No
1542938	0.20	[Redacted Name]
1640837	0.18	I just need you to have a conversation with your employee [Redacted]. As an employee who discusses too many of the company's policies and codes for securities
1642896	0.19	Never will go back! Food and service was bad no napkins dry food wait time was crazy and the place not full oof people.
1669340	0.25	I have notable documentation on what had been discussed per our conversation
1703558	20.88	Just the argument at the time
1719968	0.08	I hope someone can get back to me about this issue
1721616	0.18	I need help in recovering my funds. Sonthat i can file charges and move past this in order to move forward and get my bills paid..and soon cause they were due on the 1st and i have n9bgrace period. So each day that passes i am one dqy closer to utilitoes cut off and mortgage going into default!!!!

Note: The review update text was reported verbatim, and therefore, it has not been redacted for typos, punctuation, or inappropriate content. Company names, employee names, and personal information have been redacted. The content of this text does not reflect the views of the researchers. The text was selected at random from the dataset of non-empty review update texts, referring to reviews updated within 24 hours since review creation. For random sampling reproducibility, we set a seed equal to 100.

E Potential Business Implications of Review Updates

In this section, we provide suggestive evidence that updates to existing reviews might potentially affect the business performance indicators of the reviewed companies, and specifically the purchase likelihood of consumers exposed to the updated reviews.

Data Sources We base the suggestive evidence on several sources of data and information. First, we obtain figures on the marginal effects of exposure to a new positive or negative review on purchase likelihoods from recent marketing literature. [Vana and Lambrecht \(2021\)](#) estimate that exposure to a 5-star instead of a 1–4-star review increases purchase probability by 1.58 percentage points. On the other hand, [Varga and Albuquerque \(2023\)](#) measure that exposure to a 1–3-star instead of a 4–5-star review decreases baseline conversion rate by 41.8%.

Second, we rely on recent industry reports to obtain the average baseline conversion rate across 14 industries, which is estimated at around 2.9% in 2024 ([Rigby, 2024](#)).

Third, we collect information on average order volume per industry from industry reports by [Oberlo \(n.d.\)](#) and [Doofinder \(2024\)](#). We manually matched the industries from the reports to the corresponding NAICS industries in our data sets.

Finally, we use the PissedConsumer data to estimate the monthly visitors to the online review page for each company and the resolution status of the reviews. Specifically, we take the “lifetime” page views per company over 11 years, and divide them equally by 132 months to capture the average company review page views per month. Lastly, we use the “resolved” field in the data to classify the reviews into “resolved” and “unresolved”.

Classifying Changes in Review Valence and Net Valence Changes We classify all updated reviews by whether their valence changed post-update, and in which direction (positive vs. negative) in two ways. The first way is based on the 5-star threshold for valence from [Vana and Lambrecht \(2021\)](#), implying that a review is negative if it has a rating of 1–4 stars, and positive if it has a 5-star rating. Therefore, according to the [Vana and Lambrecht \(2021\)](#) threshold, a negative review with a 1–4-star rating pre-update would become “positive” if the post-update rating was 5 stars.

The second way is based on the 3-star threshold for valence from [Varga and Albuquerque \(2023\)](#), implying that a review is negative if it has a rating of 1–3 stars, and positive if it has a rating of 4–5 stars. Similarly, according to the [Varga and Albuquerque \(2023\)](#) threshold, a negative review with a 1–3 star rating pre-update would become “positive” if the post-update rating was 4 or 5 stars.

With this method, we calculate two metrics of “net change” in review valence per company page, depending on whether initial review valence and post-update valence changes were calculated based on [Vana and Lambrecht \(2021\)](#) or [Varga and Albuquerque \(2023\)](#) thresholds. The “net change” post-update measures the difference between the number of reviews that turned from negative to positive (positive change in valence) and the number

of reviews that changed from positive to negative (negative change in valence).

These metrics will provide the basis to calculate the potential impact of positive and negative review updates on conversion likelihood among the monthly visitors of the companies’ review page.

Measuring Potential Impact Based on the changes to purchase probability estimated by Varga and Albuquerque (2023) (for negative review updates) and Vana and Lambrecht (2021) (for positive review updates), we estimate that the baseline conversion rate of 2.9% would increase by 1.58% when a review goes from negative to positive, and decrease by 1.19% when a review goes from negative to positive.

Then, the number of additional potential purchases per single updated review is calculated as the number of monthly visits to the review page times the change in conversion rate implied by the scenarios above (1.58% or -1.19% depending on the change in valence).

It follows that the *total* number of additional potential purchases is equal to the number of additional potential purchases per single updated review times the absolute value of the “net change” post-update. For instance: if a company has 2 positive-to-negative reviews, 4 negative-to-positive reviews post-update, and 100 monthly page visits, then it could expect the total additional potential purchases on an average month to be $(100 \times 1.58\%) \times |2| = 3.16$.

The revenue impact of this change is then calculated as the total additional potential purchases times the average order value per product industry. For instance, if the company in the example above had an AOV of \$100, it could expect a revenue change of $3.16 \times 100 = \$316$ per month, potentially attributable to the net change in company review valence from negative to positive.

E.1 Results for Review Ratings Distributions

Unresolved Reviews We consider 405 companies that received updates to 8,615 reviews classified as “unresolved”. Among these reviews, 40 (0.46%) turned from negative to positive using the 5-star threshold from Vana and Lambrecht (2021), and 95 (1.1%) turned from negative to positive using the 3-star threshold from Varga and Albuquerque (2023).

Over 405 companies with “unresolved” review updates, 24 (5.9%) company review pages with exclusively negative reviews had at least one positive review post-update, using the 5-star threshold from Vana and Lambrecht (2021) (20 companies using Varga and Albuquerque (2023) thresholds).

Resolved Reviews Next, we consider the 352 companies that received updates to 3,702 reviews classified as “resolved” by the consumers. Among these reviews, 281 (7.59%) turned from negative to positive using the 5-star threshold from Vana and Lambrecht (2021), and 988 (26.69%) turned from negative to positive using the 3-star threshold from Varga and Albuquerque (2023).

Among the 352 companies with “resolved” review updates, 104 (29.55%) company review pages with exclusively negative reviews had at least one positive review post-update, using the 5-star threshold from [Vana and Lambrecht \(2021\)](#) (107 companies using [Varga and Albuquerque \(2023\)](#) thresholds).

E.2 Results for Potential Changes in Revenue

Using the metrics explained above, Table [5](#) demonstrates that for companies with net positive rating changes post-update, the increase in review ratings could imply an average revenue increase of \$4,626.36 (unresolved reviews) and \$11,327.67 (resolved reviews) across industries. On the other hand, the decrease in review ratings for companies with net negative rating changes due to updates could imply a revenue loss of \$-870.36 (unresolved reviews) and \$-335.24 (resolved reviews) across industries.

Table 5: Potential Changes in Average Monthly Revenue Implied by the Net Changes in Review Ratings Post-Update.

		Estimated Revenue Change (\$)				
Net Valence Change	Resolution	Mean	SD	Min.	Max.	N
Negative	Unresolved	-870.36	5650.36	-86789.65	0	390
Negative	Resolved	-335.25	3282.09	-48070.52	0	223
Positive	Unresolved	4626.37	11547.95	71.56	65722.77	33
Positive	Resolved	11327.67	59706.92	27.97	691399.9	138

Finally, Tables [6](#) (unresolved reviews) and [6](#) (resolved reviews) show similar insights, but illustrate the heterogeneity in revenue changes within product industries.

Table 6: Potential Changes in Average Monthly Revenue Implied by the Net Changes in Unresolved Review Ratings Post-Update – By Industry.

	Estimated Revenue Change (\$) – Unresolved Reviews				
NAICS Industry	Mean	SD	Min.	Max.	N. Companies
Accommodation and Food Services	55.57	1511.78	-3040.57	10753.73	61
Arts, Entertainment, and Recreation	-51.59	1068.26	-4233.50	5675.77	59
Construction	0.80	160.67	-354.86	363.65	11
Educational Services	0	-	0	0	1
Finance and Insurance	-292.79	2641.60	-15483.88	4866.36	39
Health Care and Social Assistance	288.63	818.56	-351.94	2574.33	21
Information	-2154.01	11347.96	-48070.52	16401.95	21
Management of Companies and Enterprises	-7977.10	21128.64	-86789.65	10687.66	19
Manufacturing	1284.31	9489.75	-4382.61	65722.77	49
Other Services	0	0	0	0	15
Professional, Scientific, and Technical Services	-183.09	448.49	-1098.57	0	6
Public Administration	0	-	0	0	1
Real Estate and Rental and Leasing	-79.17	193.92	-475.01	0	6
Retail Trade	-549.76	3239.06	-25407.01	2253.96	81
Transportation and Warehousing	-123.79	578.80	-2287.21	539.97	31
Utilities	2039.90	-	2039.90	2039.90	1
Waste and Remediation Services	0	-	0	0	1

Table 7: Potential Changes in Average Monthly Revenue Implied by the Net Changes in Resolved Review Ratings Post-Update – By Industry.

NAICS Industry	Estimated Revenue Change (\$) – Resolved Reviews				
	Mean	SD	Min.	Max.	N. Companies
Accommodation and Food Services	4362.58	18209.83	-811.72	109049.63	36
Arts, Entertainment, and Recreation	979.20	3122.38	-892.20	17027.31	60
Construction	328.99	657.97	0.00	1315.95	4
Educational Services	0.00	-	0.00	0.00	1
Finance and Insurance	5127.48	10343.62	-5448.06	33138.42	28
Health Care and Social Assistance	683.31	1782.51	0.00	6803.47	16
Information	655.84	11637.47	-48070.52	25982.81	25
Management of Companies and Enterprises	41158.40	149726.91	-6871.18	691399.93	21
Manufacturing	1674.91	5457.67	-3833.54	32861.39	43
Other Services	142.88	571.53	-864.38	1200.90	14
Professional, Scientific, and Technical Services	539.83	1079.67	0.00	2159.33	4
Public Administration	0.00	-	0.00	0.00	1
Real Estate and Rental and Leasing	256.74	513.48	0.00	1026.95	4
Retail Trade	1891.92	6413.23	-2339.03	37658.89	74
Transportation and Warehousing	463.50	830.40	-104.58	2963.61	27
Utilities	0.00	-	0.00	0.00	1
Waste and Remediation Services	3194.42	4517.59	0.00	6388.83	2

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