# Navigating the Sea of Reviews: Unveiling the Effects of Introducing AI-Generated Summaries in E-Commerce

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## Abstract

Amidst the burgeoning incorporation of generative AI into commercial realms, numerous companies are exploring ways to leverage technological advancements. Despite companies actively adopting generative AI tools in practice, there is still a lack of empirical evidence to support their effectiveness. Responding to the need for scientific inquiry, our paper explores how AI-generated summaries (AIGS), a relatively new generative AI tool, influence consumer review behavior. It may seem logical to assume that AI-generated content could replace user-generated content, thus diminishing users' incentive to contribute. Surprisingly, our research reveals that the introduction of AIGS actually leads to an increase in the volume of consumer reviews. This positive effect is more pronounced among products that are well-reviewed (vs. under-reviewed) and polarizing (vs. non-polarizing). A more fine-grained linguistic analysis, utilizing both the computerized text analysis tool and traditional statistical techniques, reveals the influence of AIGS on the content of subsequent reviews. Specifically, reviews subsequent to the introduction of AIGS are more externally focused, socially relevant, and assertive in tone. They also display enhanced content richness and reduced mentioning of AI-generated product attribute keywords. These findings corroborate our hypothesis that AIGS positively influences consumer review behavior by enhancing the perceived social impact of their reviews. Furthermore, our study identifies a potential challenge of introducing AIGS: a Matthew effect in sales dynamics, where top-ranked products benefit more substantially from AIGS than their lower-ranked counterparts. These findings advance our understanding of how AI integration influences consumer review behaviors in e-commerce and offer valuable practical guidance for business strategies on employing generative AI.



**Keywords**: generative AI, AI-generated summary, AI-generated content, e-commerce, consumer review, natural experiment


## 1. Introduction

Recent advances in generative artificial intelligence (AI) have significantly enhanced its ability to produce novel and human-like texts, audios, images, videos, and other formats of creation, making this technology a prominent and engaging topic across a wide range of industries (Bail 2024; Epstein et al. 2023). The commercial potential of generative AI has been widely recognized, prompting substantial investments from various companies. For instance, since 2019, Microsoft has invested over $13 billion in OpenAI, incorporating generative AI tools across its extensive product portfolio, including the Bing search engine, Microsoft 365 applications, the Edge web browser, and Windows operating systems (Novet 2023; Warren 2024). More recently, Amazon has committed a total of $4 billion to Anthropic, the startup developing the generative AI model Claude (Amazon 2024). Additionally, knowledge sharing platforms based on user-generated content, such as Reddit and Stack Overflow, have announced their partnership with OpenAI (Reddit 2024; Stack Overflow 2024).

Generative AI technology is transforming how businesses interact with customers. Popular applications include customer service chatbots and AI-generated knowledge and product recommendation lists (Campbell et al. 2022; De Freitas et al. 2023). These tools, typically based on AI-generated content (AIGC), are rapidly gaining popularity. However, their benefits are not always guaranteed. For example, previous research has indicated that disclosing the AI identity of a customer service chatbot before interaction may decrease purchase rates (Luo et al. 2019). Therefore, it is imperative to deepen our understanding of generative AI applications in business and to provide valuable practical guidance.

## 1.1 Motivations

In the current era of information explosion, effectively delivering useful information to target audiences is a growing challenge. To address this issue, companies started to leverage the advanced capabilities of generative AI in creating, analyzing, and summarizing texts. Consequently, AI-generated summaries (AIGS) tools are now increasingly used to highlight key points of existing content for customers and users. For example, Gannett, a major US media conglomerate that owns hundreds of newspapers, has incorporated AIGS featuring bulleted points at the beginning of journalists' articles (Sato 2024). Likewise, Google has introduced an AIGS feature that displays summarized results at the top of search responses (Pierce 2024). Similar to these changes, e-commerce companies are now employing AIGS tools on their platforms.

For e-commerce platforms, consumer reviews have long been a valuable content source that they actively manage to present better to potential buyers (Mudambi and Schuff 2010; Park et al. 2023). Widely regarded as trustworthy and user-oriented, consumer reviews play a crucial role in shaping purchasing decisions in today's digital marketplace (Archak et al. 2011; Chevalier and Mayzlin 2006; Schoenmueller et al. 2020). Surveys have shown that potential buyers not only trust consumer reviews but also actively seek them out for guidance (Bruce 2021). Even the mere presence of reviews can boost conversion rates across diverse product categories (PowerReviews 2022). However, the vast number of reviews on the platforms, such as tens of thousands for popular products like the Amazon Fire TV Stick, often leads to information overload, preventing thorough analysis by consumers (Jones et al. 2004). Typically, consumers scan only a handful of reviews to quickly form product perceptions (Jabr and Rahman 2022). The challenge of information overload is likely to be exacerbated by the rise of mobile e-commerce, where smaller displays of smartphones and even smartwatches limit information intake (Furner and Zinko 2017). To tackle this issue, AIGS is increasingly adopted across e-commerce platforms to help consumers quickly digest the most relevant insights. In May 2023, Microsoft Store launched the AIGS feature that displays a concise paragraph summarizing key consumer opinions derived from existing reviews (Sardo 2023). Not long thereafter, Amazon and Yelp also introduced AIGS on their platforms in a similar manner (Saldanha 2024; Schermerhorn 2023).

In contrast to broader AIGC, which is trained on a diverse range of Internet content and designed to generate novel, human-like creations, AIGS targets content specifically related to certain topics of interest, such as news articles, search queries, or products and services (Pierce 2024; Sato 2024; Schermerhorn 2023). Typically, the input sources of AIGS content are easily recognizable due to its focused scope. Specifically in the context of consumer reviews, AIGS aims to help potential consumers by synthesizing and condensing existing reviews into comprehensive overviews that facilitate decision-making. This focused application of generative AI in e-commerce is relatively new and its impacts and effectiveness are yet to be fully explored. Our study seeks to deepen understanding of AIGS applications and their potential effects for both practitioners and researchers.

### 1.2 Research Questions and Contributions

With the rapid rise of generative AI applications in business, there is a growing academic interest in how generative AI can reshape dynamics in e-commerce. Previous research has primarily focused on the impact of AIGC implementations, such as AI-powered chatbots and AI-generated commercials, on user perceptions and reactions (Campbell et al. 2022; Kumar and Kapoor 2023; Luo et al. 2019). Our study explores a novel application—AIGS—where the generative AI technology is used to summarize and condense existing consumer reviews into concise paragraphs and bulleted points that aid purchasing decisions. These summary contents are typically placed prominently on the product pages, before the original consumer reviews. This approach to integrating generative AI into e-commerce platforms provides a unique context for studying its impact on consumer review contributions.

One possibility is that AIGS might reduce consumer-contributed reviews. To illustrate, if potential contributors believe the summaries generated by AI can already address other consumers' informational needs, they may perceive further consumer-contributed reviews will add little value (Schoenmueller et al. 2020). Thus, it is possible that AIGS could lead to reduced consumer engagement in review contributions. Conversely, it is also possible that AIGS could motivate potential contributors to write reviews. By prominently featuring insights from consumer reviews, AIGS can shift potential buyers' attention to these concise summaries. This enhanced visibility may lead potential contributors to perceive that their opinions will be incorporated into AI summaries, thereby influencing a larger number of potential buyers' decisions. Given that helping other consumers is a major motivation for writing reviews (Cheung and Lee 2012; Hennig-Thurau et al. 2004), increasing the visibility and perceived social influence of their reviews could enhance consumers' willingness to contribute. Therefore, our first research question arises: (1) *What is the impact of introducing AI-generated summaries on subsequent consumer contributions to reviews?*

We explore this inquiry by analyzing data collected from Amazon, which announced the introduction of a generative AI-powered feature on August 14, 2023.[1] Following this announcement, Amazon began gradually displaying a concise paragraph clearly marked as "AI-generated from the text of customer reviews" on product pages. This paragraph summarizes key product features and consumer

[1] See https://www.aboutamazon.com/news/amazon-ai/amazon-improves-customer-reviews-with-generative-ai, accessed on May 26, 2024.

opinions derived from existing reviews. Notably, this feature was not uniformly applied to products on Amazon.com all at once, allowing us to employ a difference-in-differences (DID) analysis to assess the impact of AIGS on subsequent consumer review behavior. Our findings show a significant increase in the volume of subsequent consumer reviews following the AIGS introduction, suggesting that AIGS encourages rather than discourages consumer contributions to reviews. Given the novelty and growing popularity of AIGS features, these findings provide critical insights for e-commerce platforms considering AIGS as a tool to enhance the management and presentation of consumer reviews.

To gain a deeper understanding of the observed effect and possible underlying mechanism, we probe into the heterogeneity of the AIGS' impact on subsequent consumer review behavior in e-commerce through the lens of social influence theory (Dholakia et al. 2004). As previously argued, AIGS could lead potential contributors to believe that their feedback is more likely to influence potential buyers' decisions, thereby motivating consumers to write reviews (Hennig-Thurau et al. 2004). Based on this, we expect that the effectiveness of AIGS in motivating consumer review contributions is dependent on its ability to enhance the perceived social influence of each review. Accordingly, we consider two critical factors that might influence the extent of this enhancement and moderate the observed effect: the volume of existing reviews and the dispersion of ratings. Formally, we posit our second research question as follows: (2) *Does introducing AI-generated summaries have heterogeneous effects across products, particularly with different levels of existing review volume and rating dispersion?*

Our empirical results show that AIGS has a more pronounced positive effect on the subsequent consumer review volume for products with higher (vs. lower) accumulated review volumes and dispersed (vs. non-dispersed) ratings. Prior to the introduction of AIGS, individual reviews of products with a high volume of existing reviews generally had minimal impact. This is often due to potential buyers facing information overload when navigating through numerous reviews, which causes a single review to go unnoticed in a vast sea of information (Jabr and Rahman 2022; Jones et al. 2004; Zhou and Guo 2017). AIGS potentially mitigates information overload by making the digestion process of reviews more manageable. As such, AIGS may significantly elevate the perceived visibility and social influence of a review that will be incorporated into AIGS content. Conversely, for products with fewer reviews, each review already stands out. For these products, AIGS does not markedly change their social influence.

The influence of AIGS on the perceived social influence of a new review also varies with different levels of rating dispersion. Dispersed ratings, which reflect greater controversy in product evaluations, create uncertainty and ambiguity for potential buyers during their decision-making process (Li 2018; Liu and Karahanna 2017). In situations of conflicting opinions, potential buyers often seek more guidance and social validation (Lee et al. 2021). AIGS content can provide guidance by prominently featuring a summary paragraph that highlights the most prevalent opinions and sentiments. For potential contributors, the visibility of AIGS underscores that their reviews may be prominently featured and integrated into the AIGS content. This could make their opinions more likely to gain social attention and affect the social validation process, thereby encouraging consumers to contribute their own insights. In contrast, non-dispersed ratings, which indicate a consensus and higher certainty, limit the additional social influence the AIGS can provide for a new review. Our empirical results demonstrating the greater positive effects of AIGS on the subsequent consumer review volume for products with higher accumulated review volumes and more dispersed ratings further support the increased perceived social influence as the underlying mechanism.

Beyond mere volume, consumer review content also provides rich insights into the motivations and deliberate efforts of review contributors (Brandes and Dover 2022; Ludwig et al. 2013). This richness of data can facilitate a deeper understanding of the observed effects and the underlying mechanism. Therefore, we formulate our third research question: (3) *How does the introduction of AI-generated summaries influence subsequent review content?* We first investigate changes in the textual features of subsequent consumer reviews following the introduction of AIGS. Utilizing the Linguistic Inquiry and Word Count (LIWC) tool (Pennebaker et al. 2022), we analyze textual features indicative of the review contributors' intentions to influence potential buyers, specifically focusing on *Clout*, *Social*, and *Certitude*. These dimensions respectively represent the review contributors' external focus, social reference, and expressed assertiveness. Additionally, we also examine review content richness as the dependent variable, measured by review length and sentence count. Given that product reviews are a unique discourse form that effectively conveys detailed product attribute information (Qiao and Rui 2023), exploring how AIGS influences the discussion of product attributes is valuable. In our context, we explore the relationship between review content and AIGS content, specifically examining whether consumer reviews posted after the introduction of AIGS cover more or fewer product attribute keywords highlighted by AIGS.

Our empirical analysis reveals that the introduction of AIGS positively affects scores across the *Clout*, *Social*, and *Certitude* dimensions, suggesting an increase in external focus, social reference, and expressed assertiveness in subsequent consumer reviews. An increase in these textual features indicates that review contributors are more inclined to influence potential buyers through their reviews. Moreover, our findings indicate that the AIGS introduction also enhances the richness of review content. This increased richness is likely due to contributors more extensively discussing product information that is not summarized by AIGS, as consumer reviews following the AIGS introduction include fewer product attributes highlighted by AIGS. These analyses provide valuable insights concerning how AIGS influences the content of consumer reviews. The findings are also consistent with our proposed mechanism that increased expected social influence of writing a review may be the reason why AIGS motivates consumer review contributions.

After investigating the effects on consumer reviews, we take a step further to explore how AIGS impacts product sales dynamics, with a particular focus on the fairness of the AI integration policy. AI fairness has long been a critical and controversial topic, encompassing discussions from systemic biases in AI models (Forbes Technology Council 2023; Satell and Abdel-Magied 2020) to fairness issues arising from AI applications in practice (Agrawal et al. 2023; Noy and Zhang 2023). Prior research has shown that technological shifts could either narrow or widen the gap between large and small businesses and between popular and non-popular products (Brynjolfsson et al. 2010; Elberse 2008; Gu et al. 2013). On one hand, the rise of e-commerce enables niche products to become more visible and capture a larger share of sales, an effect known as the "long tail," a concept initially termed by Anderson (2004) and widely adopted in subsequent research (e.g., Brynjolfsson et al. 2003; Oestreicher-Singer and Sundararajan 2012). On the other hand, empirical findings indicate that distributing through e-commerce platforms with selection and search functions can widen the disparity between popular and non-popular products, leading to a "rich-get-richer" effect, also known as the Matthew effect (Elberse 2008; Gu et al. 2013).

In our research context, it is crucial to examine whether AIGS enhances fairness by providing all sellers equal opportunities to present high-quality product-related information to potential buyers, or if they inadvertently favor dominant players by significantly boosting their visibility and consumer reach. This consideration leads us to formulate our fourth research question: (4) *What is the impact of introducing AI-generated summaries on sales? Does it result in a Matthew effect or a long-tail effect?* Our empirical findings indicate a fairness issue in applying AIGS: top-ranked products disproportionately benefit from AIGS compared to their lower-ranked counterparts, suggesting a Matthew effect rather than a long-tail effect. An alternative explanation might be that top-ranked products are more likely to be included in the treatment group (products with AIGS), thereby resulting in a disproportionate benefit observed for these top-ranked products. We rule out this alternative explanation by conducting a robustness check with the matched sample derived by the Coarsened Exact Matching (CEM) technique. We obtain the same findings when the difference in product sales rank between the treatment (products with AIGS) and the control groups (products without AIGS) is insignificant. This finding regarding product sales dynamics highlights a challenge of adopting AIGS for e-commerce platforms. In platform economies, the vitality of small businesses plays a crucial role in fostering innovation and employment within the economic ecosystem. Therefore, the dynamics of equality between large and small businesses deserve careful attention. This uneven impact of AIGS could potentially undermine the viability of small businesses on the platform, posing a challenge to the ecosystem of the e-commerce platform.

To the best of our knowledge, this research is the first exploration into the influence of introducing AIGS on e-commerce platforms. Our findings, which uncover both benefits and potential risks associated with AIGS, contribute valuable insights to both theory and practice. Theoretically, our research echoes the burgeoning academic interest in the consequences of employing generative AI across digital platforms (Wessel et al. 2023). Whereas prior research predominantly examined the influence of AIGC applications on user perceptions and reactions (e.g., Campbell et al. 2022; Kumar and Kapoor 2023; Luo et al. 2019), our investigation centers on AIGS—a distinct generative AI tool—highlighting its unique characteristics and impacts compared to AIGC. We explore the differences between the two forms of generative AI applications in terms of their input sources and objectives, with a specific focus on their role in enhancing the perceived social influence of e-commerce reviews. Our empirical tests provide evidence that AIGS increases the volume of subsequent consumer reviews by enhancing their expected social influence. Furthermore, our research extends to discuss fairness concerns within AI applications, revealing a potential risk: AIGS may exacerbate disparities between high- and low-ranked products, leading to a Matthew effect where "the rich get richer and the poor get poorer."

In addition to theoretical contributions, our study also offers practical insights. Despite the rapid expansion of AIGS applications, their impacts remain insufficiently examined. Our research thus provides essential practical guidance for managers considering the integration of AIGS into their platforms. Specifically, our findings indicate a positive influence of introducing AIGS on subsequent consumer review behavior, which is moderated by the existing volume of consumer reviews and dispersion of ratings. Moreover, our analysis informs managers of a potential risk associated with deploying AIGS: a Matthew effect of AIGS on product sales, which could adversely affect the sustainability of small businesses on their platforms. These insights offer practical, actionable recommendations for e-commerce platform managers who consider employing AIGS in their platforms.

## 2. Literature Review

In this section, we review and summarize prior studies and theories that closely align with our research. We specifically delve into both theoretical frameworks and empirical findings related to AIGC and AIGS, as well as scholarly works on the role that perceived social influence plays in consumer review behaviors. Additionally, we analyze how our research stands in relation to the existing literature, highlighting the unique contributions and distinct position of our work in the field.

### 2.1 AIGC and AIGS

In recent years, the landscape of AI has witnessed transformative growth, particularly in the realm of generative AI. Built on large language models and massive databases, techniques such as ChatGPT, Bard, and Midjourney exhibit impressive ability for reading, analyzing, and creating content, and have rapidly gained immense popularity (Burtch et al. 2023; OpenAI 2023; Susarla et al. 2023). AIGC refers to materials produced using advanced generative AI techniques rather than human authors, primarily automating the creation of large volumes of content more rapidly and cost-effectively (Cao et al. 2023). The application of AIGC entails utilizing algorithms to generate or assist in the production of diverse content that previously required human efforts—ranging from texts and images to audios and videos—typically tailored to specific user requirements and inputs (De Freitas et al. 2023; Kumar and Kapoor 2023). The advanced capacities of generative AI have prompted businesses to explore innovative ways to leverage AIGC in interactions with consumers. For example, customer service chatbots fueled by generative AI, such as Carrefour's Hopla and Taobao's WenWen, are utilized to answer questions and offer personalized suggestions (Carrefour 2023; De Freitas et al. 2023; Staiirs 2023). Moreover, AIGC is increasingly adopted to effectively generate a wide range of content displayed to consumers, including brand product sheets, high-quality product page content, and advertising materials for special events such as holidays (Westmoreland 2024).

Our research focuses on AIGS, an increasingly popular application of generative AI. This technology has been adopted by digital platform giants such as Amazon, Microsoft, and Yelp to provide users with concise summaries of original consumer reviews, condensing them into short, informative paragraphs. The key distinction between AIGS and broader AIGC lies in their foundational relationships with their source inputs and objectives. AIGS are typically crafted by analyzing and condensing specific, existing content—for example, consumer reviews—into brief overviews that maintain the essence of the original content. This process is tightly bound to the content of the source input and its context.

In contrast, broader AIGC, although also trained with human-created datasets, is often designed to produce entirely new outputs that might not have direct equivalents in the training data (Cao et al. 2023; Epstein et al. 2023). This includes generating novel text, art, or music that mimics human creativity but is not necessarily a direct summary or condensation of specific content. Thus, while both use human-created data, AIGS serves a distinct purpose: facilitating understanding of existing information rather than creating new, original content. This difference between AIGC and AIGS is particularly important in understanding the unique influence of AIGS, especially in our research context where content contributors have motives to influence viewers. Specifically, AIGS based on consumer reviews can serve as a signal to consumers that their contributions can directly influence the AIGS content presented to potential buyers and help shape purchase decisions, which is considered a crucial altruistic motivation for consumers to write product reviews (Cheung and Lee 2012; Hennig-Thurau et al. 2004).

### 2.2 Social Influence Process and Its Impact on Consumer Review Behavior

Online consumer reviews play an increasingly important role in shaping the landscape of e-commerce by influencing purchase decisions and guiding the strategic directions of businesses (Ananthakrishnan et al. 2023; Jiang and Guo 2015). The existing body of literature emphasizes not only the direct impact of consumer reviews on sales (e.g., Babić Rosario et al. 2016; Zhu and Zhang 2010) but also explores the motivations behind why consumers choose to contribute reviews (Hennig-Thurau et al. 2004). Particularly, consumers' belief that their feedback can help others make better purchasing decisions adds a significant altruistic dimension to the act of writing a review.

Consumers are often motivated to write reviews by the perceived impact their contributions can have on future potential buyers (Cheung and Lee 2012; Hennig-Thurau et al. 2004). This perceived social influence is likely to be enhanced by platform features that highlight the usefulness of reviews to others, such as votes for "helpfulness" from other users. Such features not only validate the review contributor's effort but also emphasize other users' appreciation of their contributions, enhancing the perceived value of contributing reviews. Literature on social influence processes in virtual communities also highlights that the perceived value of giving and receiving useful information to make decisions (i.e., purposive value) fosters a sense of belonging and purpose within the community. This enhances shared group norms and social identity, which in turn motivates contributions (Dholakia et al. 2004).

However, the sheer number of reviews can lead to information overload and consequently information breakdown, making a single review less effective and influential (Jones et al. 2004). Platforms started to adopt policies to present AIGS that summarize key points from numerous existing reviews, helping consumers quickly grasp the overall sentiment and main ideas. By condensing existing consumer reviews directly into brief overviews that maintain the essence of the original content, AIGS increases the likelihood that original consumer reviews will make a greater impact on potential buyers. We posit that this increased sense of social influence can boost users' desire to contribute to product reviews.

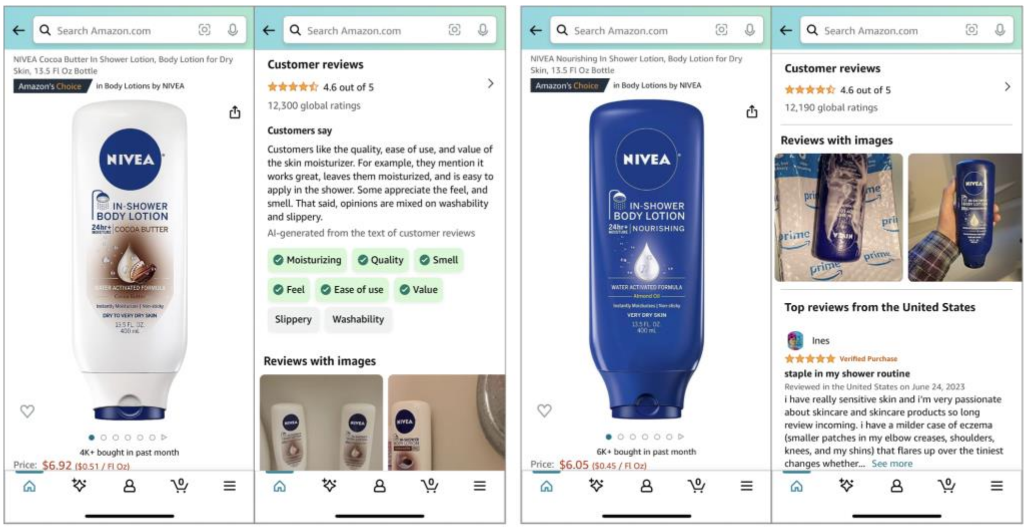
## 3. Data and Descriptive Statistics

We investigate the research questions using data gathered from Amazon.com, one of the largest e-commerce platforms in the US. Our research leverages a new feature announced by Amazon on August 14, 2023, which utilizes generative AI to provide a brief paragraph on product pages.[2] This paragraph presents product attributes and consumer opinions that are frequently mentioned across existing reviews. We take advantage of the fact that the policy has been gradually implemented for products on the Amazon US website (i.e., Amazon.com). In other words, this is a case of staggered adoption. The AIGS feature was not introduced to all products simultaneously; some received it earlier, while others received it later. For products that are affected by the policy, a summary of reviews generated by AI is prominently displayed at the top of the customer review section and is clearly marked as "AI-generated from the text of customer reviews." In contrast, for products not affected by this policy, the customer reviews sections remain unchanged. Figure 1 presents real-world examples from the two product categories: those that are affected by the policy and those that are not. This specific feature of the policy provides a natural experiment setting, allowing us to examine the influence of introducing AIGS (the products in the treatment and control groups could be very similar, see Figure 1 below). In our analysis, the treatment group consists of products displaying AIGS following the policy implementation, while the control group comprises products that remain without AIGS.

Our study period spans from May to October 2023, covering approximately three months both before and after the policy launch. We limit our dataset to products listed before May 2023 to ensure a consistent review panel across pre- and post-treatment periods. We initially select a random sample of

[2] See https://www.aboutamazon.com/news/amazon-ai/amazon-improves-customer-reviews-with-generative-ai, accessed on May 26, 2024.

products within this timeframe in Amazon's Beauty & Personal Care department and then focus on active products with at least one review before and at least one review after the policy launch. This approach results in a total of 3,014 products for our main dataset. Since Amazon's sales data are not publicly available, we use sales rank data as a proxy for sales, a well-established approach in previous research (e.g., Park et al. 2023; Sun 2012). Definitions and summary statistics for the key variables in our main dataset are presented in Table 1.




(a) a product that is affected by the policy (b) a product that is unaffected by the policy

**Figure 1: Real-world Examples of Products Affected and Unaffected by the Policy**

**Table 1. Definitions of Variables and Summary Statistics**

| Variable | Definition | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| RevVolume | the number of reviews for a product in a week | 1.28 | 2.91 | 0 | 72 |
| AISummary | whether a product has AIGS (1: Yes; 0: No) in a week | 0.31 | 0.46 | 0 | 1 |
| Rank | the sales rank of a product at the end of a week | 97,582.00 | 135,969.50 | 3 | 1,540,145 |
| Price | the price of a product, averaged through a week | 40.36 | 148.71 | 0.90 | 5,999.00 |
| AveClout | the average Clout scores of reviews for a product in a week | 16.05 | 21.75 | 1.00 | 99.00 |
| AveSocial | the average Social scores of reviews for a product in a week | 5.23 | 6.59 | 0.00 | 100.00 |
| AveCertitude | the average Certitude scores of reviews for a product in a week | 1.32 | 3.30 | 0.00 | 100.00 |
| AveLenRev | the average character count of reviews for a product in a week | 178.10 | 168.59 | 0.00 | 4,132.00 |
| AveNumSent | the average number of sentences of reviews for a product in a week | 2.96 | 2.05 | 0.00 | 43.00 |

Notes: SD is for standard deviation; Min is for minimum; Max is for maximum.

## 4. Empirical Analysis

This section presents the results of our empirical analysis. Our examination starts with the impact of AIGS on subsequent consumer review volume. Afterward, we carry out a series of checks to support the robustness of our main findings. To gain a more comprehensive understanding, we probe into the heterogeneity of effects across different products, underscoring how existing consumer review volume and rating dispersion moderate these effects. We also conduct a granular review content analysis to understand how AIGS impacts the content of subsequent reviews. Finally, we analyze the effects of AIGS on sales dynamics on the platform, offering deeper insights into the theoretical and managerial implications of integrating AI into e-commerce.

### 4.1 Main Analysis

We first apply the two-way fixed effects model to examine how introducing AIGS affects the volume of subsequent consumer reviews. Consistent with previous research (Liu and Cong 2023; Shan and Qiu 2023), we analyze the change in consumer review volume following the introduction of AIGS, utilizing the following DID regression specification:

$$\log(RevVolume_{it}) = \beta_0 + \beta_1 AISummary_{it} + X_{i,t-1} + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

The dependent variable, $RevVolume_{it}$, represents the volume of consumer reviews for product $i$ during week $t$. The independent variable, $AISummary_{it}$, is a dummy variable denoting the presence of AIGS on the product page of the product $i$ up to week $t$. We add $X_{i,\,t-1}$ to denote control variables. In line with previous research (Li et al. 2022; Pu et al. 2023; Yazdani et al. 2018), our control variables include $\log(Price_{i,\,t-1})$ and $\log(Rank_{i,\,t-1})$, respectively corresponding to the price and sales rank of product $i$ during the preceding week $t-1$. We further include product fixed effects, $\mu_i$, to control for any inherent differences in product attributes, as well as weekly fixed effects, $\delta_t$, to control for potential temporal variations.

The findings of the main analysis are presented in Table 2. Columns (1) and (2) respectively display the results of the regressions without and with the inclusion of control variables. The coefficients of

$AISummary_{it}$ are consistently positive across the analysis. Specifically, introducing AIGS results in about a 6.8% ($= e^{0.066} - 1$) increase in subsequent consumer review volume for a product. The results indicate that introducing AIGS increases the volume of subsequent consumer reviews. Addressing our first research question, the results add to the understanding of how AI integration influences consumer review behavior, showing that the introduction of AIGS can be beneficial to consumer contributions to product reviews.

**Table 2. Impact of AIGS on Consumer Review Volume**

| Variables | (1) log(RevVolume) | (2) log(RevVolume) |
|---|---|---|
| AISummary | $0.071^{***}$ | $0.066^{***}$ |
| | (0.009) | (0.009) |
| Control variables | No | Yes |
| Product FE | Yes | Yes |
| Weekly FE | Yes | Yes |
| Observations | 69,322 | 69,322 |

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; Robust standard errors clustered at the product level are in parentheses; FE stands for fixed effect.

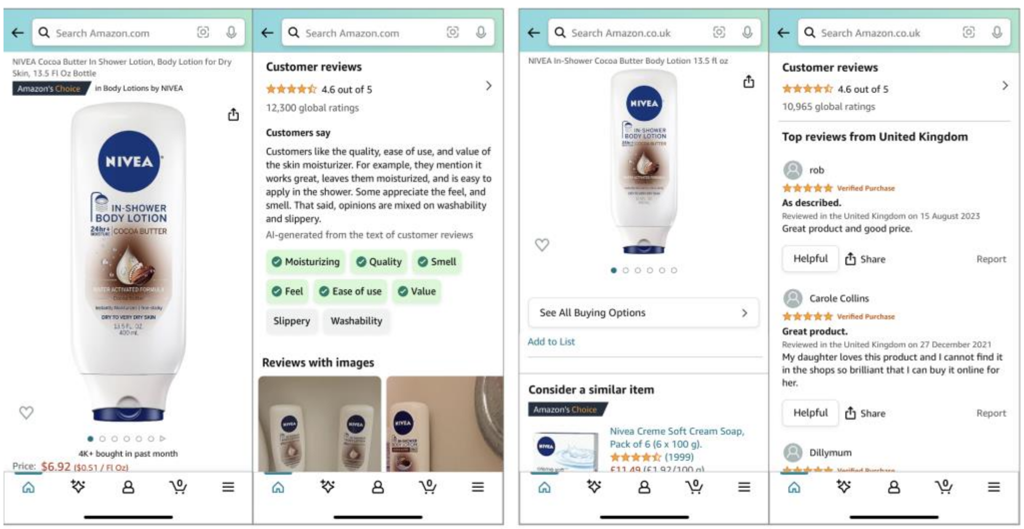
## 4.2 Robustness Checks

In Section 4.1, we show that introducing AIGS on e-commerce platforms significantly increases the volume of subsequent consumer reviews. To strengthen the robustness of our findings, we conduct a series of robustness checks using different empirical techniques. These checks are summarized in Table 3. For the final robustness check, we use Amazon UK as a control group since it has not implemented AIGS during our observation period. We compile a matched-products dataset by pairing products from the treatment group on Amazon US with their identical counterparts on Amazon UK. This matching is done using the ASIN, Amazon's unique identifier for products. In the DID analysis based on this dataset, the products listed on Amazon US serve as the treatment group, while those listed on Amazon UK serve as the control group (The treatment and control groups consist of essentially identical products, see Figure 2 below).

**Table 3. Overview of Robustness Checks**

| Empirical Methods | Description | Primary Takeaways |
|---|---|---|
| Relative Time Model (RTM) | We use RTM to test whether the parallel trends assumption is satisfied. | Our results confirm that the parallel trends assumption holds, suggesting that pretreatment trends do not confound the observed effect. |
| Coarsened Exact Matching | We use CEM to construct a control | Our results remain robust after |

| | | |
|---|---|---|
| (CEM) | group more comparable to the treatment group to address the concern of selection bias. | adjusting for the variations related to observable factors between the treatment and control groups. |
| Goodman-Bacon Decomposition | We use Goodman-Bacon Decomposition to alleviate potential biases that may arise from differences in treatment timing. | Our results remain robust after problematic comparisons in the DID estimation are removed. |
| Poisson Quasi-Maximum Likelihood Estimation (QMLE) | We use Poisson QMLE to estimate the treatment effects to reduce potential concerns associated with log-like transformations. | Our results remain robust when using an alternative analysis method that mitigates the bias of log-like transformation related to zero values. |
| Analysis with the Matched Products from Amazon UK | We match products in the main dataset with those from Amazon UK and create a subset of products sold on both platforms to make control and treatment units more comparable. | Our results are consistent with the findings from the main dataset. |




(a) an affected product on Amazon US (b) the same product on Amazon UK

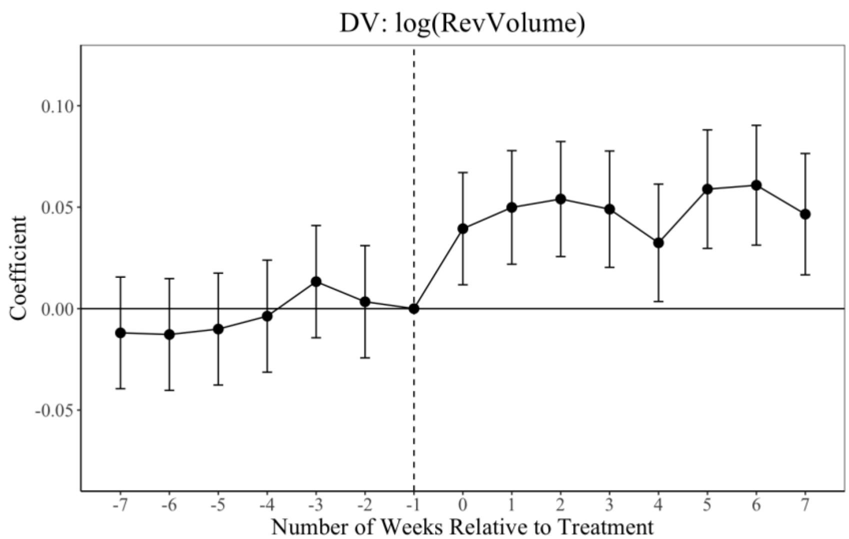
**Figure 2: Examples of Matched Products on Amazon US and Amazon UK**

### *4.2.1 Relative Time Model*

In DID analysis, a foundational assumption is the parallel trends assumption, which necessitates that, prior to the introduction of AIGS, the trends in the volume of consumer reviews should be similar for treatment and control groups. Following the methodologies of previous studies (Autor 2003; Park et al. 2021), we employ the RTM method to verify this assumption by including relative time terms in the model. The parallel trends assumption is considered satisfied if the relative time terms are insignificant prior to the introduction of AIGS, indicating that the treatment and control groups are on comparable trends in the absence of treatment (Angrist and Pischke 2008). Specifically, we establish Equation (2) by replacing $AISummary_{it}$ in Equation (1) with a vector of relative time dummy variables, $RelaWeek_{it}^{\tau}$, which indicates the chronological distance between week *t* and the week of treatment.

$$\log(RevVolume_{it}) = \beta_0 + \sum \beta_\tau RelaWeek_{it}^{\tau} + X_{i,t-1} + \mu_i + \delta_t + \varepsilon_{it} \tag{2}$$

Here, $\tau \in \{-7, \dots, -2, 0, \dots, 7\}$, with the last pretreatment week ($\tau = -1$) serving as the baseline week. The variable $RelaWeek_{it}^{\tau}$ is assigned a value of 1 if week $t$ represents the $\tau$th week relative to the baseline group, and is assigned a value of 0 otherwise. The coefficients of the relative time terms that represent the week-to-week shifts prior to the introduction of the AIGS, i.e., $\beta_{-7}$ to $\beta_{-2}$, are all insignificant, indicating that the parallel trends assumption is satisfied (Li et al. 2022). Consequently, we cannot ascribe the observed effect to differences in pretreatment trends between treatment and control groups, mitigating concerns of non-parallel trends as a confounding factor. Figure 3 visually displays the results of the RTM analysis.




Notes: Error bars show 95% confidence intervals.

**Figure 3. Impact of AIGS on Consumer Review Volume Over Time**

### *4.2.2 Coarsened Exact Matching*

Although utilizing the DID method could mitigate some selection bias with the inclusion of fixed effects, our findings are not entirely free from endogeneity concerns. A potential issue with our results can arise from the fact that Amazon determines which products are assigned to AIGS. One could argue that the feature assignment might be non-random and lead to a biased division of products into treatment and control groups. Therefore, we apply the Coarsened Exact Matching (CEM) technique (Guo et al. 2023; Nian et al. 2021) to mitigate the concerns about the selection bias. CEM offers advantages over propensity score matching (PSM) by allowing for precise and independent matching of groups on various attributes (Dewan et al. 2023; Mayya et al. 2021). In this process, observations are sorted into strata based on observable covariates, and a matched dataset is constructed, including only those strata that contain observations from both treatment and control groups (Aggarwal and Hsu 2014). Except for control variables in the main analysis (i.e., log(*Price*) and log(*Rank*)), we include additional variables for the matching process, wherein the pretreatment values of time-varying covariates are derived from the period immediately before the introduction of the policy: the number of sellers of the product (*NumSeller*), the accumulated rating to the product (*AccuRating*), the total number of accumulated ratings to the product (*AccuNumRating*), as well as the product tenure (number of days since the product release on Amazon; *ProdTenure*).

We utilize the "MatchIt" R package (Stuart et al. 2011), selecting the "k2k" option for precise one-to-one matching within strata. The quality of matching is assessed by t-tests that compare the pre- and post-matching means of variables. As presented in Table 4, post-matching t-tests reveal no significant differences across all covariates between the treatment and control groups, indicating successful matching and substantial mitigation of covariate imbalance.

**Table 4. Summary Statistics Before and After CEM**

| Variables | Pre-Matching | | | Post-Matching | | |
|---|---|---|---|---|---|---|
| | Mean (Treated) | Mean (Control) | Difference | Mean (Treated) | Mean (Control) | Difference |
| log(Price) | 3.163 | 2.985 | $0.192^{***}$ | 2.981 | 2.962 | 0.020 |
| log(Rank) | 10.452 | 11.067 | $-0.411^{***}$ | 10.953 | 10.964 | -0.007 |
| NumSeller | 3.545 | 3.557 | -0.002 | 1.877 | 2.107 | -0.037 |
| AccuRating | 4.328 | 4.321 | 0.022 | 4.361 | 4.365 | -0.013 |
| AccuNumRating | 2908.934 | 2250.907 | $0.081^{*}$ | 1255.838 | 1039.271 | 0.027 |
| ProdTenure | 1999.548 | 1581.302 | $0.355^{***}$ | 1672.045 | 1596.150 | 0.064 |

Notes: $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

We then re-run the DID regressions from Equation (1) using the matched sample and present the results in Table 5. In line with our primary findings, the coefficients of $AISummary_{it}$ are significantly positive. This analysis further confirms that introducing AIGS to products leads to an increase in the volume of subsequent consumer reviews, providing evidence of the robustness of our main findings.

**Table 5. Impact of AIGS on Consumer Review Volume after CEM**

| Variables | (1)<br>log(RevVolume) | (2)<br>log(RevVolume) |
|---|---|---|
| AISummary | 0.040*** | 0.037*** |
| | (0.012) | (0.011) |
| Control variables | No | Yes |
| Product FE | Yes | Yes |
| Weekly FE | Yes | Yes |
| Observations | 23,276 | 23,276 |

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; Robust standard errors clustered at the product level are in parentheses; FE stands for fixed effect.

### *4.2.3 Goodman-Bacon Decomposition*

Since the AIGS feature has been gradually assigned to products (some units received the treatment earlier, while others received it later), there may be concerns about the negative weights in DID estimates arising from varying treatment times, as highlighted in recent econometrics literature (Goodman-Bacon 2021). This is because the estimated coefficient reflects a composite average from three different pairs of comparisons: (1) units treated earlier as the treatment while units treated later as the control; (2) units treated later as the treatment while units treated earlier as the control; and (3) all treated units as the treatment while units never treated as the control. As demonstrated in previous literature (Goodman-Bacon 2021; De Chaisemartin and d'Haultfoeuille 2020), the second pair of comparisons can introduce bias into the estimates because the units treated earlier are actually treated during both the earlier and later periods. Therefore, the change in the dependent variable caused by the treatment for these units is present in both periods. When these units act as the control, the treatment effect "gets differenced out" in the DID analysis, leading to negative weights.

To mitigate the concern, we follow prior research (Guan et al. 2023; Ozer et al. 2024) to estimate a Goodman-Bacon decomposition. As shown in Table 6, the second pair of comparisons only constitutes a small weight, indicating that the possibility of negative weights is not a big concern in our analysis. The "Overall DID" reflects the DID estimation that includes all three comparisons, whereas "Unbiased DID" considers solely the first and last comparisons. The results confirm the robustness of our main analysis, as the unbiased DID estimate remains significantly positive, indicating that the variation in the timing of the

AIGS introduction does not significantly influence our estimation.

**Table 6. Goodman-Bacon Decomposition**

| | | log(RevVolume) |
|---|---|---|
| DID comparison | Weight | Average DID estimate |
| Earlier treated treatment vs. later treated control | 0.079 | 0.021 |
| Later treated treatment vs. earlier treated control | 0.026 | 0.043 |
| All treated treatment vs. never treated control | 0.895 | 0.076 |
| Overall DID | | 0.071 |
| Unbiased DID | | 0.072 |

### *4.2.4 Poisson Quasi-Maximum Likelihood Estimation*

As highlighted by Chen and Roth (2024) in their work, the use of log transformations presents misspecifications when the variable of interest, $Y$, includes zero values. Since traditional log($Y$) is undefined at $Y$=0, researchers commonly adopt "log-like" transformations such as log($Y+1$). The critical issue of these log-like transformations is their "unit-dependence": the Average Treatment Effect (ATE) estimates derived from the transformations are dependent on the units of the outcome ($Y$) and thus do not reliably approximate percentage effects, which is particularly pronounced when the treatment changes the outcome ($Y$) from zero to a non-zero value. Following prior research (Chen and Roth 2024), we use Poisson quasi-maximum likelihood estimation (QMLE) as an alternative approach to address the issue of log-like transformations. Since the volume of reviews are nonnegative integers, the variable is qualified as the dependent variable in Poisson QMLE. Therefore, we specify the Poisson QMLE to estimate

$$RevVolume_{it} = \exp(\beta_0 + \beta_1 AISummary_{it} + X_{i,\,t-1} + \mu_i + \delta_t + \varepsilon_{it}) \tag{3}$$

The results of Poisson QMLE are presented in Table 7. The coefficients of $AISummary_{it}$ are significantly positive, consistent with the main results. We further calculate $\exp(\beta_1) - 1$ to derive the estimated proportional treatment effects, which are 0.283 ($= e^{0.249} - 1$) and 0.274 ($= e^{0.242} - 1$) for the models excluding and including control variables, respectively. Our analysis using Poisson QMLE indicates that introducing AIGS leads to a 27.4% increase in the subsequent volume of consumer reviews.

**Table 7. Impact of AIGS on Consumer Review Volume Using Poisson QMLE**

| Variables | (1)<br>RevVolume | (2)<br>RevVolume |
|---|---|---|
| AISummary | 0.249*** | 0.242*** |

| | | |
|---|---|---|
| | (0.046) | (0.045) |
| Control variables | No | Yes |
| Product FE | Yes | Yes |
| Weekly FE | Yes | Yes |
| Observations | 69,322 | 69,322 |

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; Robust standard errors clustered at the product level are in parentheses; FE stands for fixed effect.

In addition, we directly use $RevVolume$ without log-transformation as the dependent variable and specify the model as follows:

$$RevVolume_{it} = \beta_0 + \beta_1 AISummary_{it} + X_{i,\,t-1} + \mu_i + \delta_t + \varepsilon_{it} \quad (4)$$

As shown in Table 8, the coefficients of $AISummary_{it}$ are significantly positive. This analysis reinforces the robustness of our main findings by demonstrating results consistent with our main analysis, mitigating concerns related to log transformations.

**Table 8. Impact of AIGS on Consumer Review Volume without Log Transformations**

| Variables | (1) RevVolume | (2) RevVolume |
|---|---|---|
| AISummary | 0.390$^{***}$ | 0.366$^{***}$ |
| | (0.053) | (0.052) |
| Control variables | No | Yes |
| Product FE | Yes | Yes |
| Weekly FE | Yes | Yes |
| Observations | 69,322 | 69,322 |

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; Robust standard errors clustered at the product level are in parentheses; FE stands for fixed effect.

### *4.2.5 Analysis with the US-UK Matched-products Dataset*

For now, we reveal the effect of Amazon's AIGS policy on the volume of subsequent consumer reviews by comparing products that are affected and unaffected within Amazon US. To ensure the robustness of our main findings, we employ an alternative empirical design that leverages a comparative approach between Amazon US and Amazon UK—the latter did not implement the AIGS policy during our observation period. Following prior research (Park et al. 2023), we collect additional data from Amazon UK to construct a US-UK matched-products dataset. This dataset includes products from the treatment group of the main dataset that have identical counterparts available on Amazon UK. The products are matched by the ASIN, the unique identifying number assigned by Amazon to products. The summary statistics of the US-UK matched-products dataset are presented in Online Appendix A. This design allows us to compare the review volumes of identical products sold on both platforms, enabling us to assess the impact of introducing AIGS on subsequent review volume by observing the divergence in review volume trends following the introduction of the AIGS policy on Amazon US. Importantly, this approach mitigates potential selection bias concerns inherent in our primary analysis by facilitating a direct comparison of identical products across the two platforms. Based on the US-UK matched-products dataset, we specify the following regression model:

$$\log\left(RevVolume_{ijt}\right) = \beta_0 + \beta_1 AISummary_{ijt} + X_{ij,\,t-1} + \mu_{ij} + \delta_t + \varepsilon_{ijt} \tag{5}$$

where the dependent variable, $RevVolume_{ijt}$, represents the review volume for product $i$ on platform $j \in \{US, UK\}$ during week $t$. $AISummary_{it}$ is a dummy variable that indicates whether AIGS is displayed on the product page for product $i$ on platform $j$ up to week $t$. $X_{ij,\,t-1}$ represents the same set of control variables in Equation (1). $\mu_{ij}$ represents product–platform specific fixed effects that control for any potential difference in consumers' tendency to write reviews for the same product across the two platforms.

As shown in Table 9, the coefficients of $AISummary_{it}$ are consistently positive across regressions without and with the inclusion of control variables, i.e., Columns (1) and (2) respectively. The results demonstrate that products on Amazon US receive a significant increase in consumer reviews after the introduction of AIGS compared to their identical counterparts on Amazon UK, where AIGS is not implemented. The findings from the US-UK matched-products dataset align with our main results, enhancing the robustness of our primary analysis by addressing potential selection bias concerns related to the selection of products for the analysis.

**Table 9. Impact of AIGS on Consumer Review Volume: Cross-Platform Analysis**

| Variables | (1)<br>log(RevVolume) | (2)<br>log(RevVolume) |
|---|---|---|
| AISummary | 0.148** | 0.154*** |
| | (0.056) | (0.051) |
| Control variables | No | Yes |
| Product–platform FE | Yes | Yes |
| Weekly FE | Yes | Yes |
| Observations | 4,646 | 4,646 |

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Robust standard errors clustered at the product-platform level are in parentheses; FE stands for fixed effect.

### 4.3 Moderation Analysis

In this section, we examine our second research question: Does the introduction of AIGS have heterogeneous effects across different products? In particular, we investigate how a product's accumulated review volume and rating dispersion interact with the introduction of AIGS to influence subsequent consumer review volume.

#### *4.3.1 The moderating role of product's accumulated review volume*

First, we incorporate the product's accumulated review volume as a moderating factor. Specifically, we aim to examine whether the positive effect of introducing AIGS is more pronounced for products with higher (vs. lower) accumulated review volumes. Based on their accumulated number of reviews prior to the policy, we categorize a product as either "well-reviewed" if the number is above the average, or "under-reviewed" if it is below the average. We then formulate the regression models accordingly:

$$\log(RevVolume_{it}) = \beta_0 + \beta_1 AISummary_{it} + \beta_2 AISummary_{it} \times WellReviewed_i$$
$$+ X_{i,\,t-1} + \mu_i + \delta_t + \varepsilon_{it} \quad (6)$$

where $WellReviewed_i$ denotes whether product $i$ is well-reviewed or under-reviewed (1 = well-reviewed, 0 = under-reviewed). Columns (1) and (2) in Table 10 present the main results of the regression analysis. The coefficients of the interaction between $AISummary_{it}$ and $WellReviewed_i$ are consistently significant. This indicates a more pronounced positive effect of introducing AIGS for products with higher accumulated review volumes compared to those with lower volumes. The results align with our proposed explanation of the observed effect. Essentially, AIGS motivates potential contributors to write reviews by enhancing the perceived social influence of an additional review, and the enhancement varies for well-reviewed and under-reviewed products. Specifically, for well-reviewed products, where individual reviews often went unnoticed due to information overload (Jabr and Rahman 2022; Jones et al. 2004; Zhou and Guo 2017), the enhancement is more substantial. In contrast, for under-reviewed products, where each review is already apparently important for potential buyers, the enhancement is less significant.

**Table 10. Moderating Roles of Product's Accumulated Review Volume and Rating Dispersion**

| Variables | (1) log(RevVolume) | (2) log(RevVolume) | (3) log(RevVolume) | (4) log(RevVolume) |
|---|---|---|---|---|
| AISummary | 0.027*** | 0.023*** | 0.048*** | 0.043*** |
| | (0.008) | (0.008) | (0.010) | (0.010) |
| AISummary × WellReviewed | 0.161*** | 0.158*** | | |
| | (0.018) | (0.018) | | |
| AISummary × Polarizing | | | 0.044*** | 0.045*** |
| | | | (0.012) | (0.012) |
| Control variables | No | Yes | No | Yes |
| Product FE | Yes | Yes | Yes | Yes |
| Weekly FE | Yes | Yes | Yes | Yes |
| Observations | 69,322 | 69,322 | 69,322 | 69,322 |

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$; Robust standard errors clustered at the product level are in parentheses; FE stands for fixed effect.

### *4.3.2 The moderating role of product's accumulated rating dispersion*

We then examine whether the impact of introducing AIGS varies with different levels of accumulated rating dispersion for products. Following previous research (Li 2018), we define products as either "polarizing" when their accumulated dispersion of the ratings, calculated as the variance of the ratings, exceeds the median value, or "non-polarizing" otherwise. We then integrate the rating dispersion dummy, $Polarizing_i$, as the moderating factor in our model and specify the regression as follows:

$$log(RevVolume_{it}) = \beta_0 + \beta_1 AISummary_{it} + \beta_2 AISummary_{it} \times Polarizing_i + X_{i,t-1} + \mu_i + \delta_t + \varepsilon_{it} \quad (7)$$

where $Polarizing_i$ denotes whether a product is polarizing or non-polarizing (1 = polarizing, 0 = non-polarizing). Columns (3) and (4) in Table 10 display the main results of the regression analysis. The coefficients of the interaction between $AISummary_{it}$ and $Polarizing_i$ are consistently positive, indicating a more pronounced positive effect of introducing AIGS for products with higher rating dispersion compared to those with lower rating dispersion. This effect can be explained by the fact that compared to lower rating dispersion, higher rating dispersion typically signifies high uncertainty among product evaluations, leading to a greater need for guidance and social validation (Liu and Karahanna 2017). AIGS addresses this need by presenting a summary of prevalent opinions, which enhances the perception that additional reviews will contribute to the social validation process and gain social influence. Consequently, this encourages potential contributors to write reviews (Cheung and Lee 2012; Hennig-Thurau et al. 2004).

The results of the moderation analyses in Section 4.3 address our second research question regarding the heterogeneous effects of introducing AIGS. The findings reveal that the effect is more pronounced among products that are well-reviewed compared to those that are under-reviewed, and among polarizing products compared to non-polarizing ones. These results enrich our understanding of the observed positive effect of AIGS on subsequent review volumes. Notably, these findings are consistent with our hypothesis: The increase in review volume after the introduction of AIGS may stem from an enhanced sense of social influence perceived by potential contributors.

## 4.4 Review Content Analysis

In prior sections, we focus our analysis on the volume of consumer reviews as the dependent variable. Building on this foundation, we proceed to deepen our investigation by analyzing the textual content of the reviews. This section aims to provide a more nuanced understanding of the effects, offering richer theoretical and managerial insights.

### *4.4.1 Textual feature analysis using LIWC*

We analyze consumer reviews using LIWC, a computerized text analysis tool (Pennebaker et al. 2022). LIWC identifies relevant words in given texts and calculates the proportion of words that fit into predefined language and psycholinguistic dimensions. As one of the leading tools for textual analysis in social science, LIWC is extensively utilized in the fields of business and management research (e.g., Blaseg et al. 2020; Kumar et al. 2022; Lei et al. 2021). In our research, we use LIWC to derive textual features indicative of contributors' social impact intentions when writing product reviews. We specifically focus on three relevant LIWC dimensions: *Clout*, *Social*, and *Certitude*.

*Clout*: Following prior research (Aleti et al. 2019), we use *Clout* score to assess the degree to which the text content is externally or internally focused. A higher *Clout* score, indicative of more frequent usage of second-person singular (e.g., "you") and first-person plural (e.g., "we") pronouns, reflects a higher social status and a more externally focused style. Conversely, a lower *Clout* score, marked by more frequent usage of first-person singular pronouns (e.g., "I" and "me"), reflects a lower social status and a more internally focused style. In LIWC, *Clout* is quantified as a standardized composite variable, scaled from 1 to 100.

*Social*: The variable *Social* reflects the extent to which the text content involves social processes. Texts scoring higher in *Social* typically feature more references to social behaviors and social presence, such as interpersonal activities and mentions of friends and family. Marketing and consumer behavior research demonstrates that self-disclosure of social activities (e.g., mentioning friends or family, using social language) in online contexts can enhance interpersonal trust and make content more persuasive (Kim and Song 2016). In LIWC, *Social* is measured as the percentage of words that are relevant to this dimension in the given text.

*Certitude*: The variable *Certitude* indicates the degree to which the text content shows confidence and certainty in statements, with higher scores containing more frequent use of words such as "really, actually, of course, real." Prior research has shown that texts with higher certitude are perceived to be more persuasive and more engaging (Berger et al. 2023; Pezzuti et al. 2021). In LIWC, *Certitude* is measured as the percentage of words that are relevant to this dimension in the given text.

After we generate the variables with LIWC, we specify the following regression to examine the effects of AIGS on review textual features:

$$AveTextFeat_{it} = \beta_0 + \beta_1 AISummary_{it} + X_{i,t-1} + \mu_i + \delta_t + \varepsilon_{it} \quad (8)$$

where the dependent variable, $AveTextFeat_{it}$, includes average scores of relevant LIWC dimensions, i.e., *Clout*, *Social*, and *Certitude,* of reviews for product $i$ in week $t$. We denote three features as $AveClout_{it}$, $AveSocial_{it}$, and $AveCertitude_{it}$, respectively. As displayed in Table 11, the coefficients of $AISummary_{it}$ are significantly positive across three dimensions, suggesting that consumer reviews posted after the AIGS introduction appear to be more externally focused, socially relevant, and assertive in tone. The changes in textual features indicate that AIGS enhances the degree of consumers' external focus, social reference, and expressed assertiveness when writing reviews. Moreover, since increased external focus, social reference, and expressed assertiveness are positively related to the awareness of social presence (Aleti et al. 2019; Berger et al. 2023; Kim and Song 2016), this implies contributors' enhanced intention to exert social influence through reviews after the AIGS introduction.

**Table 11. Impact of AIGS on Review Textual Features**

| Variables | (1)<br>AveClout | (2)<br>AveSocial | (3)<br>AveCertitude |
|---|---|---|---|
| AISummary | 1.428** | 0.490*** | 0.212** |
| | (0.600) | (0.180) | (0.101) |
| Control variables | Yes | Yes | Yes |
| Product FE | Yes | Yes | Yes |
| Weekly FE | Yes | Yes | Yes |
| Observations | 26,026 | 28,707 | 28,707 |

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; Robust standard errors clustered at the product level are in parentheses; FE stands for fixed effect.

### *4.4.2 Review content richness and keyword mentioning*

In addition to textual features, we further explore the impact of introducing AIGS on review content richness and how subsequent reviews relate to AIGS content. For review content richness, we use both the length of reviews (i.e., character count) and the number of sentences as measurements. We first delve into review content richness by applying the following regression:

$$log(AveRevRich_{it}) = \beta_0 + \beta_1 AISummary_{it} + X_{i,\,t-1} + \mu_i + \delta_t + \varepsilon_{it} \tag{9}$$

The dependent variable, $AveRevRich_{it}$, includes two aspects of average review content richness for product $i$ in week $t$: the average length of reviews in terms of character count, denoted as $AveLenRev_{it}$, and the average number of sentences in reviews, denoted as $AveNumSent_{it}$. As displayed in Table 12, the coefficients of $AISummary_{it}$ are significantly positive, indicating that consumer reviews following the AIGS introduction exhibit increases in review length and number of sentences. These results suggest that introducing AIGS enhances the richness of review content.

**Table 12. Impact of AIGS on Review Content Richness**

| Variables | (1)<br>log(AveLenRev) | (2)<br>log(AveLenRev) | (3)<br>log(AveNumSent) | (4)<br>log(AveNumSent) |
|---|---|---|---|---|
| AISummary | 0.068*** | 0.067*** | 0.035*** | 0.034*** |
| | (0.023) | (0.023) | (0.011) | (0.011) |
| Control variables | No | Yes | No | Yes |
| Product FE | Yes | Yes | Yes | Yes |
| Weekly FE | Yes | Yes | Yes | Yes |

| | | | | |
|---|---|---|---|---|
| Observations | 28,789 | 28,789 | 28,789 | 28,789 |

Notes: $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$; Robust standard errors clustered at the product level are in parentheses; FE stands for fixed effect.

Next, in our context, we are particularly interested in whether the enhanced richness of review content primarily arises from the information provided by AIGS or from consumers' own experiences beyond what AIGS describes. Therefore, we utilize a feature of the policy: a set of product attribute keywords listed below the AIGS text, corresponding to the attributes mentioned in the text. To make the treatment and control groups comparable in terms of product attributes, we use the US-UK matched-product dataset for this analysis. For each consumer review, we employ the Natural Language Toolkit (NLTK) in Python (Bird et al. 2009) to identify the presence of keywords associated with the AIGS product attributes and their corresponding sets of cognitive synonyms, as retrieved from NLTK WordNet. Subsequently, we construct an index that captures the number of keywords or their cognitive synonyms are mentioned in each consumer review. The following regression is specified accordingly:

$$\log\left(AveKeyMent_{ijt}\right) = \beta_0 + \beta_1 AISummary_{ijt} + X_{ij,t-1} + \mu_{ij} + \delta_t + \varepsilon_{ijt} \qquad (10)$$

where the dependent variable, denoted as $AveKeyMent_{ijt}$, captures the average number of keywords mentioned in consumer reviews for product $i$ in week $t$ at platform $j$. In addition to weekly fixed effects $\delta_t$, we also include product–platform fixed effects, $\mu_{ij}$, to control for any variations that might arise across the platforms for the same product. Table 13 shows that the coefficients of $AISummary_{ijt}$ are consistently negative, indicating that after the introduction of AIGS, review contributors discuss fewer product attributes that are already provided by AIGS. Together with the observed increase in review content richness, the results suggest that following the introduction of AIGS, contributors are making greater efforts in writing reviews—a phenomenon typically observed in contexts of higher perceived social influence (Hennig-Thurau et al. 2004; Qiao et al. 2020). This also aligns with our hypothesis that the perceived enhanced social influence may drive the observed positive effects of AIGS.

The results of the review content analysis answer our third research question, revealing that reviews following the introduction of AIGS are more externally focused, socially relevant, and assertive in tone, while displaying enhanced content richness and reduced mentioning of AI-generated product attribute keywords. Moreover, these findings consistently indicate that, after the AIGS introduction, review contributors are more likely to write their reviews with the intention of influencing potential buyers.

**Table 13. Impact of AIGS on Attribute Keyword Mentioning**

| Variables | (1)<br>log(AveKeyMent) | (2)<br>log(AveKeyMent) |
|---|---|---|
| AISummary | -0.066$^{***}$<br>(0.024) | -0.066$^{***}$<br>(0.024) |
| Control variables | No | Yes |
| Product–platform FE | Yes | Yes |
| Weekly FE | Yes | Yes |
| Observations | 2,432 | 2,432 |

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; Robust standard errors clustered at the product-platform level are in parentheses; FE stands for fixed effect.

## 4.5 The Effect on Sales: Matthew Effect or Long-tail Effect?

In this section, we probe into the question by examining how the introduction of AIGS interacts with pretreatment baseline sales rank to affect the subsequent sales rank. Products are defined either as "top-ranked" if they rank in the top 20th percentile prior to the policy announcement or as "lower-ranked" otherwise. The 20th percentile cutoff is derived from the classic Pareto principle, commonly known as the 80/20 rule of sales concentration, i.e., the top 20% of products often generate 80% of sales (Brynjolfsson et al. 2010). Accordingly, we specify our regression as follows:

$$\log(Rank_{it}) = \beta_0 + \beta_1 AISummary_{it} + \beta_2 AISummary_{it} \times TopRanked_i + X_{i,\,t-1} + \mu_i + \delta_t + \varepsilon_{it} \quad (11)$$

The dependent variable, $Rank_{it}$, indicates product $i$'s sales rank in Beauty & Personal Care department in week $t$ (a higher value of sales rank indicates worse sales performance). Since Amazon's sales data are not publicly accessible, we use sales rank as a proxy for sales, a well-established approach in prior studies (e.g., Park et al. 2023; Sun 2012). Here in Equation (11), $X_{i,\,t-1}$ includes $\log(Price_{i,\,t-1})$, representing the price of product $i$ during the preceding week $t-1$. As shown in Table 14, the coefficients of the interaction between $AISummary_{it}$ and $TopRanked_i$ are consistently negative. Because we do not invert the sales rank variable, the negative coefficients of $Rank_{it}$ signify increased sales performance.

Therefore, our finding indicates a greater positive effect of introducing AIGS on sales of top-ranked products compared to lower-ranked products. Addressing our fourth research question, these results support a Matthew effect rather than a long-tail effect of introducing AIGS on sales. We also conduct a robustness check using the CEM-matched sample derived in Section 4.2.2, obtaining the same findings. Since the difference in product sales rank between the treatment and control groups is insignificant after matching, this suggests that the observed interaction effect is not due to top-ranked products being more likely to be in the treatment group.

This finding regarding product sales dynamics highlights a potential challenge for e-commerce platforms employing AIGS. Given the essential role small businesses play in innovation and job creation, the observed "the rich get richer and the poor get poorer" Matthew effect of AIGS could threaten the e-commerce ecosystem by jeopardizing small businesses. Additionally, this analysis also adds to the ongoing academic and managerial discussion about fairness issues within AI applications (Brynjolfsson et al. 2010; Elberse 2008; Gu et al. 2013).

**Table 14. The Impact of AIGS on Sales Rank: Moderating Role of Pretreatment Sales Rank**

| Variables | (1)<br>log(Rank) | (2)<br>log(Rank) |
|---|---|---|
| AISummary | $-0.072^{***}$ | $-0.071^{***}$ |
| | (0.019) | (0.019) |
| AISummary × TopRanked | $-0.070^{**}$ | $-0.070^{**}$ |
| | (0.034) | (0.034) |
| Control variables | No | Yes |
| Product FE | Yes | Yes |
| Weekly FE | Yes | Yes |
| Observations | 69,322 | 69,322 |

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; Robust standard errors clustered at the product level are in parentheses; FE stands for fixed effect.

## 5. General Discussion and Conclusions

Recent advancements in generative AI have enabled businesses to revolutionize their interactions with consumers by implementing AIGC-based features such as customer service chatbots and personalized product recommendations (Campbell et al. 2022; De Freitas et al. 2023). This growth in practical applications has significantly fueled academic interest in the commercial applications of generative AI. Our study contributes to this emerging body of knowledge by examining another novel form of generative AI application: AIGS, which utilizes generative AI to summarize existing content and display the summary to users. Utilizing Amazon's policy that introduces generative AI to summarize consumer reviews and display the summary content on product pages, our research explores the effects of AIGS on subsequent consumer review behavior on e-commerce platforms.

Our findings indicate a positive effect of AIGS on subsequent review volume, with the effect being more pronounced among well-reviewed (vs. under-reviewed) and polarizing (vs. non-polarizing) products. To deepen our understanding of the effect and mechanism, we probe into the changes in the review content following the AIGS introduction. Using the LIWC tool to measure linguistic dimensions of *Clout*, *Social*, and *Certitude*, we find that scores increase across all three dimensions after the introduction of AIGS, indicating that reviews are more externally focused, socially relevant, and assertive in tone. We also find that consumer reviews following the introduction of AIGS increase in length and number of sentences, indicating greater review content richness. This increased richness is likely due to more discussion beyond the AIGS content since our further analysis suggests that reviews following the introduction of AIGS discuss fewer product attributes already presented in AIGS. Additionally, our research pays attention to the effect of AIGS on sales dynamics, with a particular focus on policy fairness. Our empirical evidence reveals that top-ranked products benefit more from AIGS than lower-ranked ones, supporting a Matthew effect instead of a long-tail effect.

### 5.1 Theoretical Contribution and Managerial Implications

Our study contributes to the existing body of knowledge from several aspects. First, by providing the first empirical examination of the impact of AIGS introduction in the e-commerce context, we respond to recent academic calls for further research on the integration of generative AI into digital platforms (Wessel et al. 2023). Prior research predominantly concentrates on AIGC-based implementations, such as chatbots and AI-generated commercials, focusing on user perceptions and reactions (Campbell et al. 2022; Luo et al. 2019). Our analysis contributes to a deeper understanding of generative AI applications by exploring a relatively novel practice, AIGS, particularly within the context of consumer review behavior in e-commerce.

Importantly, we demonstrate the positive effect of introducing AIGS on subsequent consumer review behavior, highlighting the benefits this AI tool offers to e-commerce platforms.

Our research advances the knowledge of generative AI tools by differentiating AIGS from AIGC, with a particular focus on their differing source inputs and objectives. These distinctions are vital to understanding how AIGS might influence how platform users perceive the social influence of their contributions. Specifically, we theorize that while AIGC often generates new outputs not directly related to the training data inputs, the AIGS process is tightly related to original inputs as it directly condenses existing information rather than creating new, original content. This close examination of differences between AIGC and AIGS helps to understand how AIGS positively influences subsequent consumer review behavior, providing a nuanced insight into the impact of generative AI on user engagement and decision-making processes.

The existing literature suggests that consumers are often driven by a belief that their reviews help others make more informed purchasing decisions (Cheung and Lee 2012; Hennig-Thurau et al. 2004). Our analysis extends this branch of literature by examining AIGS in the context of consumer reviews. We demonstrate that AIGS acts as an antecedent that amplifies this altruistic motivation by increasing the social relevance and visibility of reviews to potential buyers. Our moderation analysis further shows that this amplification is more pronounced when products have accumulated a large number of reviews and exhibit significant rating dispersion.

Our research adds to the ongoing discourse regarding technology fairness within the context of e-commerce. Our empirical findings reveal a Matthew effect where top-ranked products disproportionately benefit from AIGS than lower-ranked ones. This phenomenon could potentially harm the viability of smaller businesses on digital platforms and challenge the equity of the platform economy. This aspect of our research calls attention to the need for more equitable generative AI integration strategies, particularly within platform environments. It is essential that these strategies are designed to ensure that all market participants, regardless of their sizes or rankings, receive equitable benefits from technological advancements. This discussion also aligns with broader societal concerns about the implications of AI technologies and their influence on existing market inequities (e.g., Rotman 2022; Zhang et al. 2021).

Our research offers several valuable practical implications for the application of AIGS, a generative AI tool that is both relatively new and rapidly expanding in businesses. Major digital platform giants, including Amazon, Yelp, and Microsoft, have already launched policies to utilize AIGS on their platforms (Amazon 2023; Saldanha 2024; Sardo 2023). However, the influence of applying AIGS remains inadequately explored. Therefore, our findings provide essential guidance for managers considering the integration of AIGS into their businesses. Primarily, our results indicate a positive effect of AIGS on consumer review behavior. We further demonstrate that this effect is more pronounced in products with a higher volume of existing consumer reviews and a greater dispersion of ratings. Moreover, we identify a potential risk associated with AIGS: It tends to benefit top-ranked products more than lower-ranked ones, potentially leading to an increased disparity between large and small businesses on the platform, which could harm the overall vitality of the economic ecosystem. These insights offer actionable advice for e-commerce platform managers on how to maximize the benefits and mitigate the potential risks associated with the application of generative AI technologies.

### 5.2 Limitations and Future Research

One limitation of our research is that our empirical results rely on a policy conducted by a single e-commerce platform. However, the platform in our research, i.e., Amazon, is one of the largest e-commerce platforms worldwide. Additionally, the use of AIGS in e-commerce is increasingly popular and has already been adopted in a similar manner by other popular platforms such as the Microsoft Store and Yelp (Saldanha 2024; Sardo 2023). We also recognize limitations posed by the data constraints in our analysis. Future research can incorporate individual reviewer clickstream data, including reviewer purchasing and reviewing history, when such data becomes available.

Our work also opens several directions for future research. First, although our analysis is representative of purchases on e-commerce platforms, it does not encompass all possible scenarios in which AIGS could be applied. Future research could investigate the impact of AIGS on other types of purchases, such as highly experiential ones like travel or highly individualized ones like medical care, to determine if the outcomes differ across these contexts. Moreover, other types of platforms, such as media platforms (e.g., USA Today, Sato 2024) and search platforms (e.g., Google Search, Pierce 2024), have also adopted AIGS. The consequences of AIGS applications on these platforms, however, have not been thoroughly investigated. Scholarly research examining the influence of AIGS on various types of platforms should be encouraged to enhance our understanding of its impacts. Furthermore, given the rapid development of generative AI encompassing various modes of content beyond text (e.g., OpenAI's release of GPT-4o, OpenAI 2024), it would be insightful to explore other modes of AIGS. For instance, platforms such as Bilibili, a popular Chinese video platform similar to YouTube, have also begun to provide AIGS for video content, presenting interesting contexts that could complement the findings of the present research.

## References


Aggarwal, V. A., & Hsu, D. H. (2014). Entrepreneurial exits and innovation. *Management Science*, *60*(4), 867–887.

Agrawal, A., Gans, J. S., & Goldfarb, A. (2023). Do we want less automation?. *Science*, *381*(6654), 155–158.

Aleti, T., Pallant, J. I., Tuan, A., & Van Laer, T. (2019). Tweeting with the stars: Automated text analysis of the effect of celebrity social media communications on consumer word of mouth. *Journal of Interactive Marketing*, *48*(1), 17–32.

Amazon (2024). Amazon and Anthropic deepen their shared commitment to advancing generative AI. Accessed May 26, 2024, https://www.aboutamazon.com/news/company-news/amazon-anthropic-ai-investment.

Ananthakrishnan, U., Proserpio, D., & Sharma, S. (2023). I hear you: Does quality improve with customer voice?. *Marketing Science*, *42*(6), 1143–1161.

Anderson, C. (2004). The long tail. *Wired Magazine*, *12*(10), 170–177.

Angrist, J. D., & Pischke, J. S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Archak, N., Ghose, A., & Ipeirotis, P. G. (2011). Deriving the pricing power of product features by mining consumer reviews. *Management Science*, *57*(8), 1485–1509.

Autor, D. H. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*, *21*(1), 1–42.

Babić Rosario, A., Sotgiu, F., De Valck, K., & Bijmolt, T. H. (2016). The effect of electronic word of mouth on sales: A meta-analytic review of platform, product, and metric factors. *Journal of Marketing Research*, *53*(3), 297–318.

Bail, C. A. (2024). Can generative AI improve social science?. *Proceedings of the National Academy of Sciences*, *121*(21), e2314021121.

Berger, J., Moe, W. W., & Schweidel, D. A. (2023). What holds attention? Linguistic drivers of engagement. *Journal of Marketing*, *87*(5), 793–809.

Bird, S., Klein, E., & Loper, E. (2009). *Natural Language Processing with Python*. O'Reilly Media, Sebastopol, CA.

Blaseg, D., Schulze, C., & Skiera, B. (2020). Consumer protection on Kickstarter. *Marketing Science*, *39*(1), 211–233.
Brandes, L., & Dover, Y. (2022). Offline context affects online reviews: The effect of post-consumption weather. *Journal of Consumer Research*, *49*(4), 595–615.
Brynjolfsson, E., Hu, Y., & Smith, M. D. (2003). Consumer surplus in the digital economy: Estimating the value of increased product variety at online booksellers. *Management Science*, *49*(11), 1580–1596.
Brynjolfsson, E., Hu, Y., & Smith, M. D. (2010). Research commentary—long tails vs. superstars: The effect of information technology on product variety and sales concentration patterns. *Information Systems Research*, *21*(4), 736–747.
Bruce, G. (2021). Most consumers trust review sites. Here's what they use them for most. Accessed May 26, 2024, https://today.yougov.com/technology/articles/35957-most-consumers-trust-review-sites.
Burtch, G., Lee, D., & Chen, Z. (2023). The consequences of generative AI for UGC and online community engagement. *Available at SSRN 4521754*.
Campbell, C., Plangger, K., Sands, S., & Kietzmann, J. (2022). Preparing for an era of deepfakes and AI-generated ads: A framework for understanding responses to manipulated advertising. *Journal of Advertising*, *51*(1), 22–38.
Cao, Y., Li, S., Liu, Y., Yan, Z., Dai, Y., Yu, P. S., & Sun, L. (2023). A comprehensive survey of ai-generated content (aigc): A history of generative ai from gan to ChatGPT. *Available at arXiv:2303.04226*.
Carrefour (2023). Carrefour integrates OpenAI technologies and launches a generative AI-powered shopping experience. Accessed May 26, 2024, https://www.carrefour.com/en/news/2023/carrefour-integrates-openai-technologies-and-launches-generative-ai-powered-shopping.
Chen, J., & Roth, J. (2024). Logs with zeros? Some problems and solutions. *The Quarterly Journal of Economics*, *139*(2), 891–936.
Cheung, C. M., & Lee, M. K. (2012). What drives consumers to spread electronic word of mouth in online consumer-opinion platforms. *Decision Support Systems*, *53*(1), 218–225.
Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, *43*(3), 345–354.
De Chaisemartin, C., & d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, *110*(9), 2964–2996.
De Freitas, J., Uğuralp, A. K., Oğuz-Uğuralp, Z., & Puntoni, S. (2023). Chatbots and mental health: Insights into the safety of generative AI. *Journal of Consumer Psychology*, forthcoming.
Dewan, S., Kim, J., & Nian, T. (2023). Economic impacts of platform-endorsed quality certification: Evidence from Airbnb. *MIS Quarterly*, *47*(3), 1353–1368.
Dholakia, U. M., Bagozzi, R. P., & Pearo, L. K. (2004). A social influence model of consumer participation in network-and small-group-based virtual communities. *International Journal of Research in Marketing*, *21*(3), 241–263.
Elberse, A. (2008). Should you invest in the long tail?. *Harvard Business Review*, *86*(7/8), 88.
Epstein, Z., Hertzmann, A., & Investigators of Human Creativity. (2023). Art and the science of generative AI. *Science*, *380*(6650), 1110–1111.
Forbes Technology Council (2023). AI & fairness metrics: Understanding & eliminating bias. Accessed May 26, 2024, https://councils.forbes.com/blog/ai-and-fairness-metrics#tag=tech.
Furner, C. P., & Zinko, R. A. (2017). The influence of information overload on the development of trust and purchase intention based on online product reviews in a mobile vs. web environment: an empirical investigation. *Electronic Markets*, *27*(3), 211–224.
Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254–277.
Gu, B., Tang, Q., & Whinston, A. B. (2013). The influence of online word-of-mouth on long tail formation. *Decision Support Systems*, *56*, 474–481.
Guan, Y., Tan, Y., Wei, Q., & Chen, G. (2023). When images backfire: The effect of customer-generated images on product rating dynamics. *Information Systems Research*, *34*(4), 1641–1663.

Guo, F., Li, Y., Maruping, L. M., & Masli, A. (2023). Complementarity between investment in information technology (IT) and IT human resources: Implications for different types of firm innovation. *Information Systems Research*, *34*(3), 1259–1275.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet?. *Journal of Interactive Marketing*, *18*(1), 38–52.

Jabr, W., & Rahman, M. S. (2022). Online reviews and information overload: The role of selective, parsimonious, and concordant top reviews. *MIS Quarterly*, *46*(3), 1517–1550.

Jiang, Y., & Guo, H. (2015). Design of consumer review systems and product pricing. *Information Systems Research*, *26*(4), 714–730.

Jones, Q., Ravid, G., & Rafaeli, S. (2004). Information overload and the message dynamics of online interaction spaces: A theoretical model and empirical exploration. *Information Systems Research*, *15*(2), 194–210.

Kim, J., & Song, H. (2016). Celebrity's self-disclosure on Twitter and parasocial relationships: A mediating role of social presence. *Computers in Human Behavior*, *62*, 570–577.

Kumar, M., & Kapoor, A. (2023). Generative AI and personalized video advertisements. *Available at SSRN 4614118*.

Kumar, N., Qiu, L., & Kumar, S. (2022). A hashtag is worth a thousand words: An empirical investigation of social media strategies in trademarking hashtags. *Information Systems Research*, *33*(4), 1403–1427.

Lee, S., Lee, S., & Baek, H. (2021). Does the dispersion of online review ratings affect review helpfulness?. *Computers in Human Behavior*, *117*, 106670.

Lei, Z., Yin, D., & Zhang, H. (2021). Focus within or on others: The impact of reviewers' attentional focus on review helpfulness. *Information Systems Research*, *32*(3), 801–819.

Li, L., Gopinath, S., & Carson, S. J. (2022). History matters: The impact of online customer reviews across product generations. *Management Science*, *68*(5), 3878–3903.

Li, X. (2018). Impact of average rating on social media endorsement: The moderating role of rating dispersion and discount threshold. *Information Systems Research*, *29*(3), 739–754.

Li, Z., Liang, C., Hong, Y., & Zhang, Z. (2022). How do on-demand ridesharing services affect traffic congestion? The moderating role of urban compactness. *Production and Operations Management*, *31*(1), 239–258.

Liu, B., & Karahanna, E. (2017). The dark side of reviews: The swaying effects of online product reviews on attribute preference construction. *MIS Quarterly*, *41*(2), 427–448.

Liu, J., & Cong, Z. (2023). The daily me versus the daily others: How do recommendation algorithms change user interests? Evidence from a knowledge-sharing platform. *Journal of Marketing Research*, *60*(4), 767–791.

Ludwig, S., De Ruyter, K., Friedman, M., Brüggen, E. C., Wetzels, M., & Pfann, G. (2013). More than words: The influence of affective content and linguistic style matches in online reviews on conversion rates. *Journal of Marketing*, *77*(1), 87–103.

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science*, *38*(6), 937–947.

Mayya, R., Ye, S., Viswanathan, S., & Agarwal, R. (2021). Who forgoes screening in online markets and why? Evidence from Airbnb. *MIS Quarterly*, *45*(4), 1745–1776.

Mudambi, S. M., & Schuff, D. (2010). Research note: What makes a helpful online review? A study of customer reviews on Amazon. com. *MIS Quarterly*, *34*(1), 185–200.

Nian, T., Hu, Y., & Chen, C. (2021). Examining the impact of television-program-induced emotions on online word-of-mouth toward television advertising. *Information Systems Research*, *32*(2), 605–632.

Novet, J. (2023). Microsoft's $13 billion bet on OpenAI carries huge potential along with plenty of uncertainty. Accessed May 26, 2024, https://www.cnbc.com/2023/04/08/microsofts-complex-bet-on-openai-brings-potential-and-uncertainty.html.

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, *381*(6654), 187–192.

Oestreicher-Singer, G., & Sundararajan, A. (2012). Recommendation networks and the long tail of electronic commerce. *MIS Quarterly*, *36*(1), 65–83.

OpenAI. (2023). GPT-4 [Large Multimodal Model]. https://platform.openai.com/docs/models/gpt-4.

OpenAI. (2024). Hello GPT-4o. https://openai.com/index/hello-gpt-4o/.

Ozer, G. T., Greenwood, B. N., & Gopal, A. (2024). Noisebnb: An empirical analysis of home-sharing platforms and residential noise complaints. *Information Systems Research*, forthcoming.

Park, J., Pang, M. S., Kim, J., & Lee, B. (2021). The deterrent effect of ride-sharing on sexual assault and investigation of situational contingencies. *Information Systems Research*, *32*(2), 497–516.

Park, S., Shin, W., & Xie, J. (2023). Disclosure in incentivized reviews: Does it protect consumers?. *Management Science*, *69*(11), 7009–7021.

Pennebaker, J. W., Boyd, R. L. Booth, R. J., Ashokkumar, A, & Francis, M. E. (2022). Linguistic Inquiry and Word Count: LIWC-22. Pennebaker Conglomerates.

Pezzuti, T., Leonhardt, J. M., & Warren, C. (2021). Certainty in language increases consumer engagement on social media. *Journal of Interactive Marketing*, *53*(1), 32–46.

Pierce, D. (2024). Google is redesigning its search engine — and it's AI all the way down. Accessed May 26, 2024, https://www.theverge.com/2024/5/14/24155321/google-search-ai-results-page-gemini-overview.

PowerReviews (2022). Ratings & reviews: Av. interactor and impression conversion lift. Accessed May 26, 2024, https://www.powerreviews.com/av-interactor-impression-conversion-lift/.

Pu, J., Kwark, Y., Han, S. P., Ye, Q., & Gu, B. (2023). Uncertainty reduction vs. reciprocity: Understanding the effect of a platform-initiated reviewer incentive program on regular ratings. *Information Systems Research*, forthcoming.

Qiao, D., Lee, S. Y., Whinston, A. B., & Wei, Q. (2020). Financial incentives dampen altruism in online prosocial contributions: A study of online reviews. *Information Systems Research*, *31*(4), 1361–1375.

Qiao, D., & Rui, H. (2023). Text performance on the vine stage? The effect of incentive on product review text quality. *Information Systems Research*, *34*(2), 676–697.

Reddit (2024). Reddit and OpenAI build partnership. Accessed May 26, 2024, https://www.redditinc.com/blog/reddit-and-oai-partner.

Rotman, D. (2022). How to solve AI's inequality problem. Accessed May 26, 2024, https://www.technologyreview.com/2022/04/19/1049378/ai-inequality-problem/.

Saldanha, C. (2024). Yelp releases a series of new discovery, contribution, services and AI-powered features. Accessed May 26, 2024, https://blog.yelp.com/news/winter-product-release-2024/.

Sardo, G. (2023). Welcoming AI to the Microsoft Store on Windows. Accessed May 26, 2024, https://blogs.windows.com/windowsdeveloper/2023/05/23/welcoming-ai-to-the-microsoft-store-on-windows/.

Satell, G. & Abdel-Magied, Y. (2020). AI fairness isn't just an ethical issue. Accessed May 26, 2024, https://hbr.org/2020/10/ai-fairness-isnt-just-an-ethical-issue.

Sato, M. (2024). Newspaper conglomerate Gannett is adding AI-generated summaries to the top of its articles. Accessed May 26, 2024, https://www.theverge.com/2024/5/16/24158531/gannett-ai-generated-overviews-usa-today-memo.

Schermerhorn, V. (2023). How Amazon continues to improve the customer reviews experience with generative AI. Accessed May 26, 2024, https://www.aboutamazon.com/news/amazon-ai/amazon-improves-customer-reviews-with-generative-ai.

Schoenmueller, V., Netzer, O., & Stahl, F. (2020). The polarity of online reviews: Prevalence, drivers and implications. *Journal of Marketing Research*, *57*(5), 853–877.

Shan, G., & Qiu, L. (2023). Examining the impact of generative AI on users' voluntary knowledge contribution: Evidence from a natural experiment on Stack Overflow. *Available at SSRN 4462976.*

Staiirs (2023). Chinese E-commerce Innovation: The AI Shopping Experience Introduced by Taobao Wenwen. Accessed May 26, 2024, https://staiirs.com/taobao-ai-shopping-china-ecommerce/.

Stack Overflow (2024). Stack Overflow and OpenAI partner to strengthen the world's most popular large language models. Accessed May 26, 2024, https://stackoverflow.co/company/press/archive/openai-partnership.

Stuart, E. A., King, G., Imai, K., & Ho, D. (2011). MatchIt: Nonparametric preprocessing for parametric causal inference. *Journal of Statistical Software*, *42*, 1–28.

Sun, M. (2012). How does the variance of product ratings matter?. *Management Science*, *58*(4), 696–707.

Susarla, A., Gopal, R., Thatcher, J. B., & Sarker, S. (2023). The Janus effect of generative AI: Charting the path for responsible conduct of scholarly activities in information systems. *Information Systems Research*, *34*(2), 399–408.

Warren, T. (2024). Microsoft's OpenAI investment was triggered by Google fears, emails reveal Microsoft was 'very worried' it was years behind Google's AI efforts. Accessed May 26, 2024, https://www.theverge.com/2024/5/1/24146302/microsoft-openai-investment-google-worries-internal-emails.

Wessel, M., Adam, M., Benlian, A., Majchrzak, A., & Thies, F. (2023). Call for papers to the special issue: Generative AI and its transformative value for digital platforms. *Journal of Management Information Systems*.

Westmoreland, M. B. (2024). Amazon selling partners can now access even more generative AI features to create high-quality product listings. Accessed May 26, 2024, https://www.aboutamazon.com/news/innovation-at-amazon/amazon-generative-ai-powered-product-listings.

Yazdani, E., Gopinath, S., & Carson, S. (2018). Preaching to the choir: The chasm between top-ranked reviewers, mainstream customers, and product sales. *Marketing Science*, *37*(5), 838–851.

Zhang, S., Srinivasan, K., Singh, P. V., & Mehta, N. (2021). AI can help address inequity–if companies earn users' trust. Accessed May 26, 2024, https://hbr.org/2021/09/ai-can-help-address-inequity-if-companies-earn-users-trust.

Zhou, S., & Guo, B. (2017). The order effect on online review helpfulness: A social influence perspective. *Decision Support Systems*, *93*, 77–87.

Zhu, F., & Zhang, X. (2010). Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of Marketing*, *74*(2), 133–148.

# Online Appendix A

**Table A.1. Summary Statistics of US-UK Matched-products Dataset**

| Variable | Definition | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| RevVolume | the number of reviews for a product in a week | 2.05 | 4.64 | 0 | 72 |
| AISummary | whether a product has AIGS (1: Yes; 0: No) in a week | 0.23 | 0.42 | 0 | 1 |
| Rank | the sales rank of a product at the end of a week | 23,918.00 | 47,973.89 | 2 | 800,706 |
| Price | the price of a product, averaged through a week | 29.60 | 32.32 | 1.28 | 256.00 |
| AveKeyMent | the average number of sentences of reviews for a product in a week the average number of keywords mentioned in each review for a product in a week | 0.59 | 0.66 | 0.00 | 5.00 |

Notes: SD is for standard deviation; Min is for minimum; Max is for maximum.