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Augmented Reality and Online Ratings: The Usage and Effects of Alternative Information Sources

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Abstract

Online retailers increasingly integrate augmented reality (AR) into product pages to provide additional information on how the item fits consumers' physical context. However, the click-through rates for AR suggest sometimes consumers bypass these tools, relying instead on other available information. Through modeling consumers' information acquisition and purchase decisions, we derived propositions that are further supported by real-world observations. Our findings reveal the key relationships that a higher click rate to AR tools is associated with (i) lower volume of other information; (ii) higher valence of product ratings; and (iii) higher relative importance of contextual fit. With a quasi-experiment setting, we further find that online rating characteristics moderate the effect of AR on product sales, and the average rating score increases after the introduction of AR. In conclusion, this study highlights the boundary conditions of AR adoption effects, delivering both theoretical contributions and managerial implications to online business operators.

Keywords: augmented reality, online reviews, consumer decisions, contextual fit

Introduction

Augmented reality (AR) is a digital technology that enhances the real-world environment by adding interactive visual elements, sounds, and other sensory stimuli through holographic technology. AR has already been applied to online shopping platforms such as Sephora and IKEA, allowing consumers to virtually try on makeup or place furniture in their homes. According to Tracxn, a research platform for investment decisions, there are 1,033 AR startups in the US as of 2022, and the AR software market is projected to reach a value of $137.14 billion by 2028. However, according to the survey, 52% of retailers have not yet integrated AR into their retail strategy, indicating a lack of preparedness in this area. As the adoption of AR features in product information displays continues to increase, it is important to understand how this technology will change the online shopping environment and what effects it will have on consumer behavior (Tan et al., 2021).

AR introduces unique factors that are different from conventional information displayed in online shopping platforms. Fidelity is an essential factor, as creating 3D models with lighting, shadows, and textures can make users believe that virtual objects exist in the physical world (Louis et al., 2020). Spatial presence, which is achieved through surface detection and depth-sensing technology, enables virtual objects to be integrated into the physical environment at an appropriate scale, thereby creating a sense of realism for the user (Hilken et al., 2017). Users can control virtual objects through AR to have a view from different angles and place them in different locations, evaluating the product as it appears in their real physical context. It addresses uncertainty that cannot be resolved through product descriptions or online reviews - how the item will fit into the environment. Therefore, the AR interface adds additional information to the existing information displayed on product pages, allowing consumers to make more informed purchasing decisions.

In the context of online shopping, consumers often face uncertainty about product attributes and rely on available information to update their product knowledge (Bettman et al., 1998). Established theories of consumer information acquisition activities suggest that in the purchase decision process, search behavior is motivated in part by perceived risk (i.e., product uncertainty in this scenario) and the consumer's ability to acquire relevant information (Murray, 1991). It has been long argued that consumers seek information from a variety of sources when faced with risk or uncertainty, including personal communications such as word-of-mouth and direct experience information sources (Cox, 1967). A principle of information integration also suggests that a person combines the valuation of different stimuli and the associated weights to form a response of attitude change (Anderson, 1971).

Augmented reality, as an emerging technology that provides consumers a new approach to immersively and interactively view the product, has the potential to reduce product uncertainty as alternative information sources. Therefore, this study takes a perspective of information integration to discuss the relationships between AR and traditional information sources, predicting consumer responses to the integration. Traditional information sources, such as product descriptions and reviews, may not fully address experiential attributes, leading to consumer uncertainty. Some uncertainties are addressed by reading product descriptions, such as color and size; some can be addressed by learning prior consumers' post-purchase experience (i.e., online reviews). However, there are idiosyncratic uncertainties that can only be addressed by evaluating the contextual use case, which we define as contextual experience. For example, consumers can hardly know how lipstick make-up looks on one's own face. Through AR, consumers can experience products more realistically and interactively, allowing them to evaluate product attributes more effectively.

This paper aims to analytically and empirically investigate how the introduction of a new information source to an online shopping platform, to reveal product uncertainty, will interplay with the information displayed or generated in the platform. More specifically, as consumers universally rely on online rating systems nowadays, it is important to understand the information acquisition and consequences when consumers are provided with a new information tool such as AR. Thus, we form our first question:

RQ1: As two different information sources, how do existing online reviews and AR affect product sales synergistically? Specifically, do existing online ratings and what characteristics of the ratings affect the usage of AR? How could product ratings moderate the effect of AR on product sales?

The answer to this question is not obvious, as there could be several ways AR interplays with online reviews. First, the searching process is sequential, consumers are motivated to seek new information depending on other factors. Second, the impact of existing online reviews on sales performance might change because of the new information source. By diving into the mechanism of their interplay, we will develop a deeper understanding of the usage and the effect of AR interfaces under different conditions.

Besides, online reviews reflect post-purchase satisfaction. As the purchase decisions are changed, consumers' post-purchase satisfaction also changes, and it will affect the afterward WOM building for products. Therefore, the pattern of newly generated online reviews might change because of the new information source. Formally, our second question is,

RQ2: How does the adoption of the AR interface affect the new online reviews? Does it help to increase the average product ratings?

We highlight both theoretical contributions and managerial implications in this paper. The analytical model we built contributes to the stream of literature on consumer search behavior. In particular, our model provides a perspective of information acquisition and insights into the intertwined relationship between existing information, product categories, and the effect of the adoption of a new information tool. The endogenized usage of AR explains the low click-rate observed in practice. We empirically tested the hypotheses made from the model propositions and the empirical evidence shows that the volume of alternative information sources significantly decreases the usage of AR interface, and the valence of online ratings affects usage of AR together with the relative importance of contextual fit and negatively moderates the effect of AR adoption on subsequent outcomes. These findings, from modeling and testing, indicate boundary conditions of AR adoption effect on online business operators.

The rest of the paper will first review the related literature on augmented reality, product uncertainty, and online rating systems. Then we analytically investigate the impact of the introduction of AR and discuss the propositions we derived from the model. The later section introduces the empirical setting and the analysis results. Finally, we discuss the contribution and limitations in the last section.

Related Work

Augmented Reality in E-Commerce

Previous literature used lab or field experiments to show that VR/AR interfaces enhance brand equity (Nah et al., 2011) and consumers' perceptions of online experience (Hilken et al., 2017), lowering price sensitivity (Meißner et al., 2020), leading to higher purchase intention (Yim et al., 2017; Brengman et al., 2019; Heller et al., 2019). Tan et al. (2022) is the earliest study that empirically tested the effect of AR on sales performance in an online retailing platform of cosmetic products. They proposed that AR increases sales by reducing uncertainty and instilling purchase confidence, and thus product characteristics regarding uncertainty moderate the effect of AR on sales.

Although many studies highlight the positive effects of AR in online retail, some have identified specific boundary conditions that some constructs can moderate AR's impact or even result in backfire. For example, AR's perceived usefulness is influenced by user characteristics, such as their approach to information processing (Hilken et al., 2017) and their need for self-referencing (Yim and Park, 2019). Additionally, AR's effectiveness is linked to product characteristics, including material properties (Brengman et al., 2019) and the perceived completeness of the product information displayed (Hoffmann et al., 2022). Therefore, this work aims to investigate the effects when AR interplays with other information such as online ratings.

Uncertainty in Online Marketplace

Compared to the offline shopping environment, online shopping presents consumers with more ex-ante uncertainty, sourced from the retailers, service, and the product itself. As products are differentiated vertically and horizontally (Garvin 1984), consumers could be uncertain about the vertical attributes such as quality (i.e., common utility), and the horizontal attributes such as taste or fit (i.e., idiosyncratic utility) (Gu and Chen, 2020; Chen et al., 2021). Particularly, fit uncertainty can refer to a wide range of uncertainty on horizontal attributes, and firms can disclose certain information to mitigate it. For example, Lahiri and Dey (2018) consider versioning to disclose product fit information in the context of information goods. The version information described by the firm is easy to search and benefits all consumers. Wang et al. (2021) specified ordinal-fit uncertainty and differentiated the fit information types – fit valence and fit reference and showed that the combination of the two types is more helpful in reducing product returns. The fit valence and fit reference come from online reviews, which are widely adopted to help consumers address not only fit uncertainty but also quality uncertainty (Gu and Chen, 2020). In general, the aforementioned strategies and tools for coping with fit uncertainty in the online shopping environment are to offer information from the sellers or other consumers' experiences. Immersive technologies such as AR and VR, however, break the spatial constraint to provide the chance to indirectly experience the product by oneself when shopping online (Suh and Lee, 2005).

Online Rating Systems

While augmented reality is a relatively emerging technology in business studies, the online reviews system has been a well-established research stream in the field of E-commerce and digital marketing. A lot of previous work studied the relationship between online sales, as a dependent variable being influenced, and the online reviews characteristic, including volume, valence, and variance (Zablocki et al., 2019). However, there are mixed results in the literature on the impact of each characteristic. For example, Amblee and Biu (2011) found that it was high volume but not high valence of reviews that is associated with better sales rank of e-books on Amazon, while Xie et al. (2014) showed both volume and valence are positively associated with the future performance of hotels. It is agreed that the effect of online review characteristics is contingent on other factors. Zhu and Zhang (2010) found that all three characteristics of online reviews influence the sales of less popular online games, implying an increased share of niche products in online markets. Cui et al. (2012) studied the effect of online reviews on new product sales on Amazon and showed that the effects of online reviews on new product sales were dependent on different product categories. In recent years, practitioners and researchers have paid more attention to different dimensions of online reviews. Chen et al. (2018) showed the value of multidimensional rating systems implemented in a website on restaurant ratings for consumers. Overall, these works all suggest that online ratings or reviews provide product information from prior purchasers, which is impactful on consumers' choices, especially for experiential goods and niche products.

Previous studies also interpret the nature of online reviews as consumers' post-purchase satisfaction. Consumers make purchase decisions after evaluating the product information including existing online reviews written by prior consumers, and generate new online reviews after experiencing the product, forming the circulative process of online review dynamics (Li and Hitt, 2008; Chen et al., 2021). We propose that with the introduction of augmented reality, the pattern of online reviews generated by new consumers might change. If an augmented reality interface is helpful to mitigate ex-ante uncertainty, more consumers would be informed, and the product would receive fewer low ratings.

Theoretical Model

We build our model by extending the model of product ratings (Chen and Xie, 2008; Sun, 2012; Chen et al., 2021), which models the demands and ratings for a product that has both horizontal and vertical attributes. Our model demonstrates innovation from two perspectives. First, given the existing product ratings, we consider how the adoption of the AR interface affects the product demands and newly generated ratings. Second, we consider the usage of AR as a decision of consumers, following the decision rules of sequential attribute search for product information (Branco et al., 2012). For better readability, we provide a table of nomenclature that summarizes the key notations used in the model (see Table 1). Detailed proof of the propositions in this section is provided as an online appendix[1].

Table 1: Notation and Definitions

[1] We provide this online appendix due to page limits. Reading only the main text should suffice for understanding the theoretical model and its underlying intuition.

Notation	Definition
v	The common utility shared by all consumers (e.g., the product quality)
x_i^N	The non-contextual fit that consumers can discover through online reviews.
x_i^C	The contextual fit that consumers can discover only through AR.
ω	The relative importance of contextual fit in product utility (intrinsic to product category).
L	Click-through rate to the AR page.
D	Demand of the product (i.e., sales quantity).
R_0, R_1	The average product rating with AR (R_1) or without AR (R_0).

Model Setup

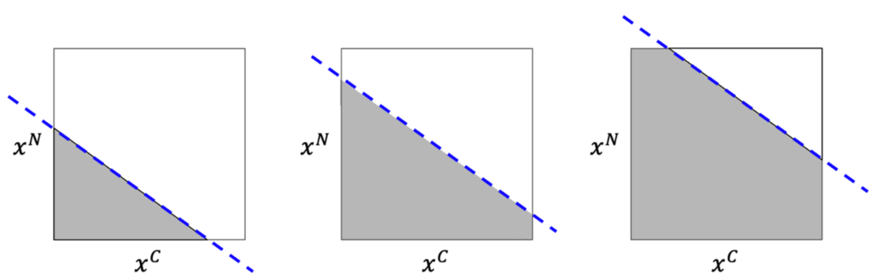
In a marketplace where exists ex-ante uncertainty, rational consumers formulate expected utility and make choices based on the product information available to them (Sun and Tyagi, 2020; Chen et al., 2021). Consider a market of one unit mass of consumers and one product that has both vertical and horizontal attributes. All vertical attributes are into a single objective quality index (q) of which the value is equally perceived by each consumer in the utility model. The horizontal attributes, capture the product fit and are idiosyncratic to each consumer. To demonstrate the function of AR in product valuation, we separate the horizontal attributes into contextual (x_i^C) and non-contextual attributes (x_i^N). The values of x_i^C and x_i^N indicate the distance between the actual product and the ideal product of consumer i, associated with a misfit cost t per unit of distance to the ideal product. Accordingly, the utility of a product with quality q and price p for a consumer i with a taste of (x_i^N, x_i^C) is

$$U(x_i^N, x_i^C, q) = q - t \times (\omega^N x_i^N + \omega^C x_i^C) - p \tag{1}$$

where ω^N and ω^C are both positive and intrinsic to the product category (Chen et al., 2021), indicating the weights of non-contextual and contextual horizontal attributes in consumer's utility. The higher the values of x_i^C or x_i^N, the more misfit consumer i perceive on the product, and per unit increase in total misfit lowers the utility level by t. For simplicity, we rewrite the utility function as

$$U(x_i^N, x_i^C, v) = v - x_i^N - \omega x_i^C \tag{2}$$

where $v = \frac{q-p}{t\omega^N}$ is a normalized net value of vertical attributes, and the coefficient $\omega = \frac{\omega^C}{\omega^N}$ represents the relative importance of x_i^C in horizontal attributes. Consider a market with a one-unit mass of consumers uniformly distributed (Hotelling, 1929), both x_i^N and x_i^C are uniformly distributed between [0, 1]. Figure 1 shows the distribution of consumers as squares with a width and height of one. The blue dotted lines located differently depending on the value of v and ω, depict the product utility level of zero. Consumers located in the gray area with relatively smaller values of x_i^N and x_i^C have positive utility levels if owning the product, while those located in the white area have negative utility. We assume that $0 < v < 1 + \omega$ to ensure that the two types of consumers both exist in this market. Note that within the same product category, v is the common utility for every consumer, and it indicates the highest value a consumer can obtain from purchasing the product. For a consumer i with misfit $x_i^N = 0$ and $x_i^C = 0$, the product perfectly fits her tastes or needs, and her utility will be v if purchasing the product.



(i) $0 < v < \omega$ (ii) $\omega < v < 1$ (iii) $1 < v < 1 + \omega$

Figure 1: The distribution of consumers in terms of x_i^N and x_i^C

However, with ex-ante uncertainty, the actual utility one can obtain from the product is not clear to the consumers. Instead, they assess expected utility $E[U(x_i^N, x_i^C, v)]$ and make the decisions whether to make a purchase. Without enough information, consumer i know the distributions $\widetilde{x_i^N}, \widetilde{x_i^C}, \tilde{v}$ from product description provided by the seller and other signals, while the exact values of common utility v and misfit x_i^N and x_i^C are uncertain. However, one can be inferred from other information sources. For example, the vertical part in the utility that common to every consumer, can be inferred from the average rating scores which indicates the product quality; the non-contextual fit to one's taste can be inferred from online reviews that describe the product experience; and the contextual fit, as we defined, can be inferred using the AR interface. We assume that the inference from information sources can perfectly reveal related utility or misfit; that is, through the provided online ratings system, consumers know the exact value of v and x_i^N, and via using the AR interface, consumers uncover the contextual misfit and know the exact value of x_i^C.

The consumers shape expected utility conditional on the common utility and misfit revealed in information investigation. If there is no available information about the product, it means the product is completely uncertain and consumers use an unconditional expected utility of the product to decide whether to purchase. If consumers have access to all information provided, they are fully informed on the common utility (v) and the misfit (x^N and x^C), and their expected utility would be equal to the realized utility. Consumers will purchase the product if and only if the expected utility meets or exceeds the reservation utility (U_0). For notational simplicity, we normalize reservation utility to zero ($U_0 = 0$).

Decision Rule 1 (purchase): *The consumers purchase the product if* $E[U_i] \geq 0$.

- *Without other information,* $E[U_i] = E[U(x_i^N, x_i^C, v)] = \bar{v} - \frac{1+\omega}{2}$.
- *With the online rating system,* $E[U_i] = E[U(x_i^N, x_i^C, v)|x_i^N, v] = v - (\frac{\omega}{2} + x_i^N)$.
- *With only the AR interface,* $E[U_i] = E[U(x_i^N, x_i^C, v)|x_i^C] = \bar{v} - (\omega x_i^C + \frac{1}{2})$.
- *With the online rating system and the AR interface,* $E[U_i] = U(x_i^N, x_i^C, v) = v - x_i^N - \omega x_i^C$.

Consumer Decision of AR Usage

The usage of an AR interface is a voluntary decision. Consumers can sequentially acquire the information to uncover the product attributes, and the stop of acquisition is decided by comparing the expected gain and the search cost (Branco et al., 2012). We model the usage of augmented reality as consumer decisions in the search process, by following the stopping rule in consumer search literature (Greminger, 2022). To be specific, consumers use AR if and only if they expect to benefit from using it. As we consider the case that search cost is homogenous to every consumer, we normalize it to zero to simply the model.

If using AR, consumers can uncover contextual misfits and decide whether to purchase based on revealed x_i^C. The expected increase in the expected utility gain comes from the flip of consumer decision-making. Due to the additional information provided by the AR interface, their expected utility changes from $E[U(x_i^N, x_i^C, v)|\cdot]$ to $E[U(x_i^N, x_i^C, v)|\cdot, x_i^C]$, where $\cdot$ can be the case where consumers are fully informed on v and x^N when other available information is informative enough, or the case where other information is inadequate. Based on the new expected utility, the purchase decision a consumer makes change from $I(purchase|\cdot)$ to $I(purchase|\cdot, x_i^C)$. Since consumers purchase the product only if the product has a positive expected utility, the change of expected utility gain with decision-making is formulated as follows:

$$\Delta EU = E[U(x_i^N, x_i^C, v)\big|\cdot, x_i^C]I(purchase\big|\cdot, x_i^C) - E[U(x_i^N, x_i^C, v)\big|\cdot]I(purchase\big|\cdot) \tag{4}$$

Before the actual usage of AR, consumers haven't yet uncovered the contextual fit information x_i^C to know the gain of AR usage, ΔEU. Therefore, they decide whether to use AR by taking the expectation of ΔEU over the distribution of x_i^C.

$$E_{x_i^C}[\Delta EU] = E_{x_i^C}[E[U(x_i^N, x_i^C, v)\big|\cdot, x_i^C]I(purchase\big|\cdot, x_i^C)] - E[U(x_i^N, x_i^C, v)\big|\cdot]I(purchase\big|\cdot) \tag{5}$$

Decision Rule 2 (AR usage): *The consumers use the AR interface when they expect to have a positive gain in expected utility* ($E_{x^C}[\Delta EU] > 0$).

Note that if the consumers expect that they won't have a decision flip after using AR interface, which means $I(purchase|\cdot, x^C) = I(purchase|\cdot)$ for any x^C, then $E_{x^C}[\Delta EU] = 0$ and the consumers expect no benefit from using AR interface. The formulation carries the intuition that, when not much uncertainty left to decide purchase or not before using the AR interface, consumers do not expect a lot from using it and there is no motivation to use it, which leads to an ending search. Therefore, it is necessary to discuss the different conditions of how much consumers are informed before using AR. We consider two cases in each one the information set is different.

Case I: Informative Online Rating System

With an informative online rating system, a consumer i located at (x_i^N, x_i^C) can know the exact value of x_i^N and v and make decisions based on the inferred information. Based on Equation (5) and *Decision Rule 1*, we derived the condition of $E_{x^C}[\Delta EU] > 0$ for *Proposition 1*. The proof of *Proposition 1* is included in the online appendix.

Proposition 1: *With informative online ratings, consumers fully informed on* v *and* x^N *have incentives to use the AR interface iff the consumer is located with* $x_i^N \in [0,\ 1] \cap (v - \omega, v)$.

Figure 2 illustrates the intuition of Proposition 1. On one hand, when consumers perceive high non-contextual misfit and relatively low value ($x_i^N > v$), they expect no benefit from using AR because they don't purchase it even if the revealed contextual attributes perfectly fit ($x_i^C = 0$). On the other hand, when the perceived non-contextual misfit is low and the relative value is high enough ($x_i^N < v - \omega$), they will make a purchase even if the revealed contextual misfit is at the maximum ($x_i^C = 1$). Thus, only consumers who infer that $v - \omega < x_i^N < v$ may change their decision after AR usage and expect to benefit from that.

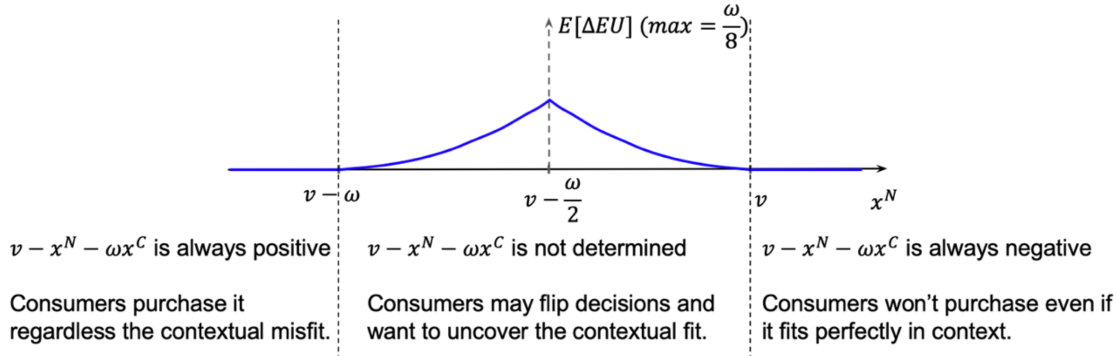


Figure 2: Expected increase in ΔEU varying in x^N

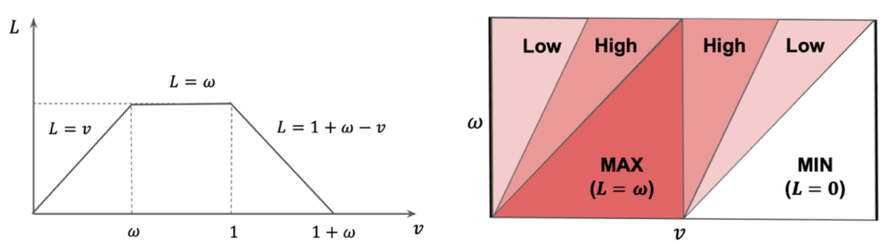


Figure 3: The usage rate of AR varying in v and ω

Note that the length of $\{x_i^N | x_i^N \in [0,\ 1] \cap (v - \omega, v)\}$ (denote as L) indicates the proportion of consumers who are predicted to use AR interface, because x_i^N is uniformly distributed between 0 and 1. Therefore, the usage rate among the population depends on the values of v and ω, and their relationship is entangled and non-monotonic. Figure 3 shows how L, the usage rate of AR, varies in different values of the category-intrinsic ω and the normalized verticle product value v.

For different products within the same category, the relative importance of contextual fit (ω) is fixed, and the common utility shared by all consumers (v) varies by product. When v is very low or high, fewer consumers will be motivated to use the AR interface, so the usage rate of AR is relatively low. When v is moderate, more consumers will realize the chance to flip their decisions with the assistance of AR, so the usage rate of AR is relatively high. For different product categories, the higher the value of ω, the more motivation consumers have to use AR. We found that the usage rate of AR is non-decreasing in ω, and positively associated with ω when v is relatively high. Thus, we have *Observation 1* as follows.

Observation 1: *With informative online ratings, the usage rate of the AR interface is related to the common utility consumers can infer from online ratings and the product category.*

- *Usage rate of AR is negatively associated with high and low vertical values inferred from the online ratings.*
- *Usage rate of AR is positively associated with product categories that demonstrate the high importance of contextual fit.*

Case II: No Information Extracted from Online Ratings

Consider an extreme case where before the usage of AR, a consumer can infer no information about the value of x_i^N and v, let alone x_i^C. In this case, the consumer remains totally uncertain about the product, and thus they always have the motivation to acquire some product information through the AR interface. In the online appendix, we provide a simple derivation to prove *Proposition 2*.

Proposition 2: *When no information is extracted from the online rating system, consumers expect to have an increase in expected utility* ($E_{x^C}[\Delta EU] > 0$) *and choose to use the AR interface almost everywhere.*

In real situations, usually, the available information is between the two extreme cases where the consumers are either fully informed or totally blind. The more available information there is, the more likely the consumers are to be informed and the usage rate will be closer to the case of informative other information ($L < 0$) and more distant from the case of no available information ($L = 1$). Based on the two propositions, we have *Observation 2* as follows.

Observation 2: *A higher volume of other information makes consumers more informed before using AR, which is associated with a lower usage rate of AR interface.*

Demand Estimation

After building the link between characteristics of existing ratings and AR usage, we take a step back to estimate the demand before and after AR adoption according to decision rules of AR usage and purchase. *Proposition 3* describes the change in product demand after the AR interface is provided to consumers.

Proposition 3*: With other information available and informative to reveal* v *and* x^N*, the change of product demand after AR depends on the value of* v *and* ω*. To be specific,*

$$\Delta D(v,t) = \begin{cases} \dfrac{v^2}{2\omega}, & 0 < v \le \dfrac{\omega}{2} \\ \dfrac{(v-\omega)^2}{2\omega}, & \dfrac{\omega}{2} < v \le \omega \\ 0, & \omega < v \le 1 \\ -\dfrac{(v-1)^2}{2\omega}, & 1 < v \le 1 + \dfrac{\omega}{2} \\ -\dfrac{(v-1-\omega)^2}{2\omega}, & 1 + \dfrac{\omega}{2} < v \le 1 + \omega \end{cases}$$

From *Proposition* 3, we find that for fixed product type, product demand after AR adoption may decrease for products with high common utility (in vertical attributes). Intuitively, some consumers who purchase with uncertain contextual misfit will stop purchasing after using AR and revealing a high misfit, while others switch from no purchase to purchase after realizing a good contextual fit. For products with high perceived common utility, the former population is larger than the latter population, and vice versa for products with low perceived common utility. Based on the demand change and the intuition shown in Figure 4, we further have *Observation 3*.

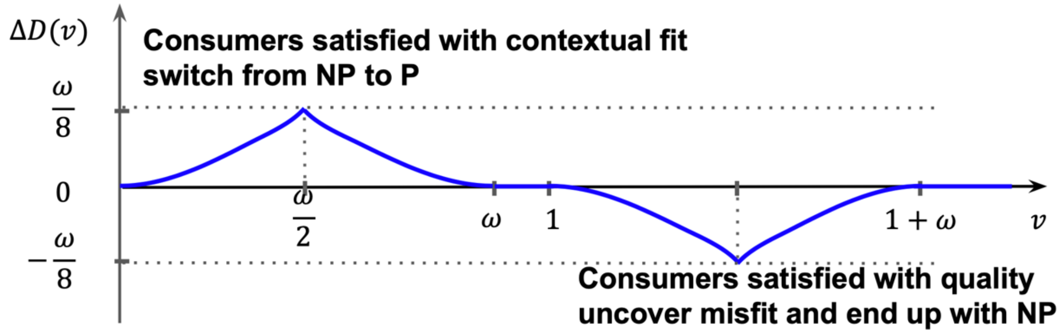


Figure 4: Demand change varying in *v* with a fixed value of *t*

Observation 3*: For products with adequate information, the product sales after AR adoption will*

- *increase if the product vertical value inferred from ratings is low.*
- *do not change if the product vertical value inferred from ratings is in a medium range.*
- *decrease if the product vertical value inferred from ratings is high.*

Post-Purchase Product Rating

After the purchase the uncertainty is revealed, consumers know the realized utility $U(x_i^N, x_i^C, v)$, and they can rate the product accordingly. We make the *Decision Rule 3* for product rating as follows.

Decision Rule 3 (rating): *The purchasers give the product rating scores that are proportional to their realized utility* $U(x_i^N, x_i^C, v)$.

Although the AR interface does not affect the realized utility, it changes the population of purchasers and thereby changes the post-purchase product ratings. In the case where informative prior online ratings exist, the consumers who used the AR interface are fully informed, so their expected utility is exactly the realized utility. Therefore, the consumers with negative realized utility won't make a purchase and rate the product with low scores. Assuming that the probability of rating the product is independent of their realized utility, which means a random set of purchasers provide ratings, we derive the average product rating score with and without an AR interface.

Proposition 4: *The average rating score with an AR interface, denoted as* R_1, *is proportional to the expected realized utility* $E_{U(x_i^N, x_i^C, v)>0}[U(x_i^N, x_i^C, v)]$, *while that without an AR interface, denoted as* R_0, *is proportional to* $E_{E[U(x_i^N, x_i^C, v)|x_i^N, v]>0}[U(x_i^N, x_i^C, v)]$. *For any* v *and* ω *such that* $v \le 1+\omega$, $R_1 - R_0 > 0$.

The proof of *Proposition 4* is included in the online appendix. Hence, we have *Observation 4* as follows.

Observation 4*: After the adoption of AR, the average rating towards the focal item increases.*

Empirical Analysis

Research Context and Data

We assembled a dataset of online retailing markets from September 2020 to September 2021. Our data combines two sources. First, we collaborated with a leading online shopping platform, which launched the

AR feature in 2017, to obtain sales statistics at the item-daily level. The sellers are encouraged to adopt the feature by uploading 3-D models of selected items and displaying the AR interface entrance on the product page. During the 13-month observation period, there are 654 items adopted the AR interface. The control group consists of 436 items that did not adopt the AR interface during the whole observation period. Second, we used a web scripting tool to collect online reviews and ratings at the review level. For each item in the dataset, we collected all reviews if the total amount is no more than one thousand; otherwise, we collected the most recent 1000 pieces. However, some items turned invalid before we scripted the online reviews (December 2022). We first merged the two datasets by item id and found the online reviews for 806 items were collected; then censored items that adopted the AR interface but no information for either pre-adoption or post-adoption periods, to ensure we could compare the online review changes. Finally, 414 items with AR adoption and 255 items without AR adoption remain in our dataset.

We aggregated the data at the item-week level and used all online ratings received at least one week before the week of usage to compute the characteristics of online ratings including average rating ($AvgRating$) and volume of rating ($logRatingVol$) observable to the consumers. We also created two variables, the logged counts of product dimensions ($logDescription$) and logged length of title ($logTitle$), as proxies to control the volume of other information. We used the click rate of the AR interface ($ARClickRate$) to measure the usage of AR, and a dummy variable ($ARAdoption$) indicates that the item has AR interface adopted.

To understand whether our empirical results support the observations from the model, we connect the model setup and propositions to the empirical setting. First, we use the average rating scores ($AvgRating$) as the common utility one can perceive from information alternatives because the average rating is a purely vertical attribute – the higher the average rating is, the higher utility one can expect without evaluating misfit. Considering the common utility (v) is normalized by the non-contextual fit misfit cost. Second, we extract the relative importance of contextual fit ($Contextual$) from online reviews by topics extraction and counts. Within the range of all items offered in the platform, there exist mainly three large product categories - appliance, furniture, and home improvements. These categories encompass seven classes: refrigerators, air conditioners, beds, sofas, shower heads, cabinets, and toilets. Sellers often choose to adopt the AR interface for their products within these classes. To support our arguments about the relative importance of contextual fit, we count the product tags generated from consumers' online reviews. For each product category, we classified all product tags into either contextual-related ones or non-contextual-related ones. Then we count the frequencies and total number of contextual-related versus non-contextual-related tags. It was observed that function-related tags received significantly more votes than appearance-related tags in certain categories, with air conditioners and refrigerators displaying ratios of 2.72:1 and 3.08:1 as examples (see Table 2).

Table 2: Relative Importance of Contextual Fit for Different Product Categories

	NonContextual- v.s. Contextual-Related	Salience of Contextual Experience
Bathroom Cabinets	250:400	0.75
Sofa	97:58	1.67
Shower heads	1280:723	1.77
Toilets	866:961	0.9
Refrigerators	3785:1228	3.08
Air Conditioners	1536:565	2.72

The Characteristics of Online Ratings Affect the Usage of AR

We use beta regression to model the click rate to the AR interface due to its nature of proportional values (Ferrari and Cribari-Neto, 2004; Lappas et al., 2016; Atasoy et al., 2021). Since we use the cumulative online ratings received at least one week before the week of usage as observable online ratings, and the other features such as product description and title are not expected to change due to clicks to AR, there should exist no reverse causality. The model includes two fixed effects: (i) store dummies as each store operates only one brand and one product category, and (ii) month dummies for platform-level time-specific variance. We further control the lag of sales ($logSalesLag$) and the prices ($logPrice$) as these are also key information that drives consumers expected utility. For each of the regressions, we estimate the results with either logit or probit as the link function. We also perform fractional regression and linear regression to check robustness, and the empirical results are consistent.

Table 3 shows the results of testing the relationship between the volume of information alternatives and the click rate to AR. Columns (1) and (3) show that the volume of information alternatives is negatively associated with the click rate to the AR interface. Columns (2) and (4) show that for cold-start items that start with few online reviews, the click rate to the AR interface is significantly and substantially high. The coefficients of the logged counts of product dimensions ($logDescription$) and logged length of title ($logTitle$) are also negative. The results demonstrate that the more information consumers can learn from the other sources, the less chance they need to use the AR interface to acquire additional information, supporting the observation from our analytical model.

Table 3: Volume of Information Alternatives and AR Click Rate

	(1) BetaReg: Logit	(2) BetaReg: Logit	(3) BetaReg: Probit	(4) BetaReg: Probit
	$ARClickRate$	$ARClickRate$	$ARClickRate$	$ARClickRate$
logRatingVol	-0.029*		-0.016**	
	(0.016)		(0.007)	
ColdStartItem		0.782***		0.358***
		(0.142)		(0.065)
ExcessiveItem		-0.040		-0.022
		(0.034)		(0.014)
logDscp	-1.114***	-1.089***	-0.423***	-0.411***
	(0.121)	(0.120)	(0.051)	(0.050)
logTitle	-0.023	-0.235*	-0.003	-0.087*
	(0.120)	(0.123)	(0.051)	(0.052)
logPrice	-0.097***	-0.090***	-0.040***	-0.038***
	(0.013)	(0.014)	(0.006)	(0.006)
logSalesLag	0.149***	0.060	0.060***	0.028
	(0.042)	(0.042)	(0.018)	(0.018)
Month	yes	yes	yes	yes
Store	yes	yes	yes	yes
Constant	3.902***	3.909***	6.936***	6.961***
	(0.024)	(0.024)	(0.082)	(0.082)
Observations	4348	4354	4348	4354
Chi-squared	1348.1	1378.4	1283.9	1315.1

Note. Robust standard errors are shown in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table 4 shows the results of testing the relationship between the vertical value inferred from online ratings and the click rate to AR. Note that the cold-start items are excluded from the analysis to calculate the average rating scores (i.e., the valence of online ratings), which is considered as the vertical value of the products. Within each product category, we sort the items by average online rating scores and create two dummy variables, indicating whether the item is among the group with the highest average ratings (*AvgRatingHeadGroup*) and lowest average ratings (*AvgRatingTailGroup*), respectively. Columns (1) (2) and (3) show the results of different cutoff of head (tail) groups, using top (bottom) 30%, 25%, or 20% as the threshold. We found that in general AR click rate is lower for the two groups with the highest and lowest average ratings, which means consumers are more likely to click AR when exploring items in the group with moderate average ratings (i.e., the baseline group). This finding is consistent with our observation on AR usage when the online rating system is informative.

Table 4: Valence of Online Rating and AR Click Rate (Cold-Start Items Excluded)

	(1)	(2)	(3)

	BetaReg: Logit	BetaReg: Logit	BetaReg: Logit
	ARClickRate *Head/Tail Percentage: 30%*	*ARClickRate* *Head/Tail Percentage: 25%*	*ARClickRate* *Head/Tail Percentage: 20%*
AvgRatingHeadGroup	-0.079	-0.094	-0.304***
	(0.062)	(0.069)	(0.064)
AvgRatingTailGroup	-0.016	-0.120***	-0.092**
	(0.059)	(0.043)	(0.042)
logDscp	-1.633***	-1.586***	-1.523***
	(0.181)	(0.185)	(0.177)
logTitle	-0.399**	-0.377**	-0.405**
	(0.165)	(0.162)	(0.160)
logPrice	0.129*	0.124*	0.152**
	(0.067)	(0.067)	(0.066)
logSalesLag	-0.028	-0.031	-0.022
	(0.022)	(0.022)	(0.022)
Month	yes	yes	yes
Store	yes	yes	yes
Constant	2.237*	2.083*	2.026*
	(1.148)	(1.124)	(1.113)
Observations	4203	4203	4203
Chi-squared	23705.4	23812.1	21901.4

Note. Robust standard errors are shown in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table 5 shows the results of testing the relationship between the relative importance of contextual fit and the click rate of AR interfaces. Our model suggests that the AR click rate is non-decreasing in the relative importance of contextual fit for any level of product ratings, so overall they are positively associated. This observation is supported by the coefficients of $Contextual$ in Columns (1) and (3). Besides, our model also suggests that the AR click rate is increasing in the relative importance of contextual fit when average product ratings are relatively high. Using the threshold of the top 20%, we add the interaction term between the group of high average ratings and the relative importance of contextual fit in the regression. In Columns (2) and (4), we found that the coefficient of the interaction term is significantly positive, as we expected, and the coefficients of $Contextual$ and $AvgRatingHeadGroup$ keeps consistent with previous regression results. Therefore, a consumer is more likely to use the AR interface if the contextual fit is relatively important, especially when the average rating of the item is high among the items in the same product category.

Table 5: Relative Importance of Contextual Fit and AR Click Rate

	(1) BetaReg: Logit	(2) BetaReg: Logit	(3) BetaReg: Probit	(4) BetaReg: Probit
	$ARClickRate$	$ARClickRate$	$ARClickRate$	$ARClickRate$
$Contextual$	0.153*	0.180*	0.061*	0.069
	(0.086)	(0.105)	(0.036)	(0.045)
$Contextual \times$		0.319***		0.122**
$AvgRatingHeadGroup$		(0.114)		(0.049)
$AvgRatingHeadGroup$		-0.327***		-0.119***
		(0.104)		(0.045)
logDscp	-0.049***	-0.052***	-0.023***	-0.024***
	(0.015)	(0.015)	(0.006)	(0.006)
logDscp	-1.176***	-1.189***	-0.451***	-0.458***
	(0.120)	(0.120)	(0.050)	(0.050)
logTitle	-0.041	-0.044	-0.014	-0.018

	(0.122)	(0.122)	(0.052)	(0.052)
logSalesLag	-0.097***	-0.092***	-0.040***	-0.039***
	(0.014)	(0.014)	(0.006)	(0.006)
Month	Yes	Yes	Yes	Yes
Store	Yes	Yes	Yes	Yes
Constant	3.899***	3.901***	6.927***	6.932***
	(0.024)	(0.024)	(0.082)	(0.082)
Observations	4348	4348	4348	4348
Chi-squared	11862.0	11865.2	11830.6	11833.4
Month	1338.4	1344.9	1275.5	1281.1

Note. Robust standard errors are shown in parentheses.
*p<0.1; **p<0.05; ***p<0.01

AR Adoption Effect on Subsequent Outcomes

Matching and DID

We matched the items have AR adopted (i.e., treated group) and the items without AR (i.e., control group) to estimate the adoption effect. We first match the items exactly on product categories because it is unreasonable to compare one category with another due to unobservable category-specific confounders. Additionally, we perform exact matches on stores because the store operation strategy could potentially confound the effect of AR adoption. Then we use PSM to match multiple variables to make control and treated groups comparable. Table 6 reports some statistics of the two groups before and after the matching. The standard differences in the variables between the two groups are considerably decreased. We then use the difference-in-difference (DID) method to identify the effect of AR adoption on product sales ($logSaleQtty$) and the change of average ratings ($\Delta AverageRating$). We use TWFE to control the item-level idiosyncratic unobservable factors and the weekly variance to the whole platform.

Table 6: Matching Covariates in PSM with Exact Matching

	Unmatched			Matched		
Means	Treated	Untreated	Std. Diff	Treated	Untreated	Std. Diff
LogPrice	7.809965	7.706158	.1092415	7.957594	7.882757	.078755
LogOnShelveWeeks	4.348958	3.170267	1.265566	3.76536	3.383682	.4098098
BrandPopularity	.0814895	.0884121	-.0704772	.0987319	.1006633	-.019663
StorePopularity	.1398977	.2610309	-.3060838	.1573816	.1530718	.0108902

AR Adoption and the Synergistic Effect with Online Ratings on Sales

Table 7 reports the results of the estimation. In columns (1)-(3) we controlled both item fixed effect and week fixed effect. Column (1) shows the overall effect of AR adoption that on average AR increases the sales quantity by about 32.5%. Column (2) reports the results of the heterogenous effect on different groups of online rating valence (vif = 3.76). For the group of low ratings and medium ratings, the increases resulting from AR adoption are relatively high (by around 50%). However, for the group of high ratings, the effect of AR adoption is negatively moderated, and the coefficients cancel out to be about an 11% increase. We further add the interaction with the relative importance of contextual fit in column (3) (vif = 4.73) and found that it positively moderates the effect of AR adoption. Column (4)-(6) relax the time fixed effect, using month dummies and controlling the special weeks of promotion events and holidays, and the results are consistent.

Table 7: AR Adoption Effect on Product Sales

	(1) DID: full sample	(2) DID: cold-start excluded	(3) DID: cold-start excluded	(4) DID: full sample	(5) DID: cold-start excluded	(6) DID: cold-start excluded
	$logSaleQtty$	$logSaleQtty$	$logSaleQtty$	$logSaleQtty$	$logSaleQtty$	$logSaleQtty$
$ARAdoption$	0.325***	0.494***	-0.028	0.323***	0.476***	-0.032
	(0.088)	(0.120)	(0.220)	(0.095)	(0.131)	(0.241)

$ARAdoption$		-0.381**	-0.376**		-0.335*	-0.332*
$\times AvgRatingHeadGroup$		(0.179)	(0.177)		(0.202)	(0.200)
$ARAdoption$		0.201	0.369*		0.112	0.274
$\times AvgRatingTailGroup$		(0.210)	(0.215)		(0.236)	(0.243)
$ARAdoption$			0.615***			0.597**
$\times Contextual$			(0.220)			(0.241)
$AvgRatingHeadGroup$		0.339**	0.334**		0.333**	0.329**
		(0.147)	(0.146)		(0.159)	(0.159)
$AvgRatingTailGroup$		-0.405**	-0.520***		-0.439**	-0.548***
		(0.181)	(0.181)		(0.196)	(0.199)
$logPrice$	-0.074	-0.065	-0.159	-0.180	-0.159	-0.247
	(0.149)	(0.170)	(0.171)	(0.151)	(0.174)	(0.176)
$SpecialWeeks$				0.257***	0.317***	0.318***
				(0.040)	(0.046)	(0.046)
$Constant$	3.156***	3.016**	3.774***	3.907***	3.660***	4.363***
	(1.173)	(1.316)	(1.329)	(1.192)	(1.347)	(1.363)
$Item\ FE$	yes	yes	yes	yes	yes	yes
$Store$	no	no	no	yes	yes	yes
$Week$	yes	yes	yes	no	no	no
$Observations$	3605	2687	2687	3605	2687	2687
adj. R^2	0.710	0.714	0.715	0.675	0.677	0.677

Note. Robust standard errors are shown in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Although there is no evidence supporting that the adoption of AR decreases product sales when the vertical value is considerately high, we do find that the group with high average ratings negatively moderates the adoption effects of AR. Compared to the groups of medium and low ratings, the increase in product sales for the group of high ratings is significantly lower, while the change in product sales after AR adoption is still positive. There could be several reasons to explain this empirical finding. First, the average rating is bounded in online shopping platforms. Consumers might not perceive such a vertical value that is high enough to reach the threshold of decreasing demand. Second, the stores may strategically and selectively adopt an AR interface, so there is barely an observation of product sales decrease. Third, consumers are not always making rational decisions based on the expected product utility. The novel and unique experience of AR may attract consumers and trigger their purchase decisions, which leads to an additional boost in product sales. Therefore, the empirical findings do not contradict the observations from our model.

AR Adoption Effect on the Characteristics of Online Ratings Change

We expect an increase in average rating scores, as suggested by the model. However, the average rating scores are trending data which are highly dependent on the lags. A Dickey-Fuller test result shows that the time series of average rating scores are non-stationary, which can cause the problem of spurious regression (Dickey and Fuller, 1979; Stock and Watson, 1988). Alternatively, we calculate the change of average rating in the following four weeks as the dependent variable ($\Delta AverageRating$). The coefficient of the dummy variable $ARAdoption$ captures the difference of rating change of the treated group compared to the control group. The results reported in Table 8 show that the change in average rating score is significantly increased, which is consistent with our model proposition.

Table 8: AR Adoption Effect on Average Rating Change

	(1)	(2)	(3)	(4)
	$\Delta AverageRating$	$\Delta AverageRating$	$\Delta AverageRating$	$\Delta AverageRating$
$ARAdoption$	0.004**	0.005**	0.004**	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
	-0.002	-0.001	-0.002	-0.001

$logPrice$	(0.002)	(0.003)	(0.002)	(0.003)
$SpecialWeeks$			0.001	0.001
			(0.002)	(0.002)
$Constant$	0.014	0.009	0.014	0.008
	(0.013)	(0.021)	(0.013)	(0.021)
$Month$	yes	yes	yes	yes
$Store$	no	yes	no	yes
$Observations$	2910	2910	2910	2910
adj. R^2	0.000	0.007	0.010	0.017

Note. Robust standard errors are shown in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Discussion

This study aims to investigate how the adoption of AR interface as an alternative information source synergistically works with online review systems to influence online sales and how the pattern of online reviews as a proxy of post-purchase satisfaction changes due to the AR interface. We answer the question first through prediction with an analytical model and then empirically test it using item-weekly level data from a leading online shopping platform. Although lacking consumer-level impacts and actions, this study provides valuable insights for online retailers and business operators to take effective strategies with AR adoption. It makes a contribution to both theory and practice in the domain of augmented reality (AR) adoption within the context of online shopping.

Theoretical Contribution

This study focuses on understanding the intricate mechanism of how the introduction of a new information tool (i.e., AR), which can alleviate uncertainty on some unique horizontal attributes, can influence the demands and the consumer post-purchase satisfaction (i.e., online reviews). Taking a perspective of information integration to discuss the relationships between AR and traditional information sources, our analytical model predicts how a consumer will responses to the integration of AR. Notably, by considering the consumers' decisions about AR usage, we add depth and realism to the model investigation. Our findings reveal that the click rate to the AR interface reflects not just consumer interest but also their perception of the cost associated with potential misfit between the product and their needs, as well as the perceived value of the product. This nuanced understanding of AR's impact on consumer decision-making fills a critical gap in the existing literature.

Managerial Implication

From a managerial perspective, our findings offer actionable insights that can guide marketers and retailers in formulating effective strategies for AR adoption. We provide valuable information on how consumers decide to leverage this emerging source of information, thereby aiding businesses in optimizing their AR implementation. Our analysis also highlights the factors contributing to the relatively low usage rates of AR, helping practitioners identify potential barriers and devise strategies to overcome them. Furthermore, our research explores the potential of AR to benefit products in various stages of their lifecycle. We investigate its capacity to assist in the discovery and evaluation of cold-start products, providing retailers with insights into how AR can mitigate the influence of limited online reviews. Additionally, we examine how AR can impact products with fit uncertainty by enhancing consumer confidence and reducing the weight of online reviews in their purchase decisions. This practical dimension of our study has direct relevance for retailers seeking to leverage AR as a tool for product differentiation and customer engagement in the highly competitive online marketplace.

In conclusion, this study offers a comprehensive and multi-faceted examination of the effects of AR adoption on consumer behavior and product evaluations in the context of online shopping. By addressing the theoretical and practical aspects of AR utilization, we provide a holistic perspective that can inform both academic research and industry practices, ultimately contributing to the advancement of knowledge and the enhancement of online shopping experiences.

Limitations

While our study provides valuable insights into consumer information acquisition behavior and its subsequent outcomes, it's important to acknowledge certain limitations. First, this work analyzes from the online retailer's perspective. We neglected the individual traits such as the inclination of technology adoption and learning curves due to the data limitation. Because of privacy concerns, it is hard to retrieve consumer click and purchase history and personal information. Future research could solve this issue by laboratory or field experiments.

Secondly, our study's scope was also constrained by data limitations, restricting us to testing a limited number of product categories and validating only a subset of the propositions and corollaries derived from our model. Future studies should encompass a wider array of AR applications across various product categories, including search goods and highly contextual-related products, in order to extend the empirical validation of the hypotheses presented in this study.

Third, our paper does not consider the issue of fake reviews, as the review generation process is hidden and unobservable. Although fake reviews should be included in characteristics of existing ratings, we should have excluded them when studying the effect of AR on new ratings. To mitigate the concerns, we will include text mining methods to detect potential fake reviews and provide the results after removing fake reviews as a robustness check.

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