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Unraveling the impacts of review content features on consumer perceptions considering initial and appended reviews

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Benjiang Lu
School of Management, Lanzhou University, Lanzhou, China, and
Baojun Ma
Key Laboratory of Brain-Machine Intelligence for Information Behavior (Ministry of Education and Shanghai), School of Business and Management, Shanghai International Studies University, Shanghai, China

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Abstract

Purpose – An appended review serves as an additional evaluation provided by the buyers after a period of product usage that complements their initial reviews. Consumers usually rely on online reviews to make their purchase decisions, with the content of these reviews playing a crucial role. However, the impact of different review content features on consumers' perceptions in relation to initial and appended reviews remains unclear. This study aims to address this gap by categorizing review contents into surface- and deep-level features and constructing a model for analyzing the effects of these features on consumers' trust and perceived review helpfulness while considering initial and appended review forms.

Design/methodology/approach – After collecting online reviews related to clothing products from a leading Chinese e-commerce platform (i.e. Taobao), we constructed a thematic feature corpus that includes surface- and deep-level features and then refined this corpus using theoretical sampling. Afterward, we invited consumer participants to rate the perceived trust and review helpfulness of the collected reviews. We eventually applied multiple regression models to validate our hypotheses.

Findings – Experiment results indicate that surface- and deep-level review features positively affect consumers' perceived trust toward reviews. However, the surface-level features appearing in initial reviews are perceived as more trustworthy than those appearing in appended reviews and the deep-level features in appended reviews are perceived as more trustworthy than those in initial reviews. Furthermore, consumers' trust toward online reviews subsequently affects the perceived helpfulness of these reviews.

Originality/value – This study is among the first to uncover the joint impact of review content features (i.e. surface- vs deep-level features) and review forms (i.e. initial vs appended reviews) on consumers' perceived review helpfulness while considering consumers' trust as the mediating variable. The results offer viable guidance for managing online reviews on e-commerce platforms.

Keywords Initial review, Appended review, Surface-level features, Deep-level features, Trust, Review helpfulness

Paper type Research paper

1. Introduction

Online reviews play an important role on e-commerce platforms as they serve as the primary reference for consumers when making online purchasing decisions (Chen and Xie, 2008;

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Ethical approval: We confirm that all procedures performed in this study were in accordance with the ethical standards.

Informed consent: Informed consent was obtained from all individual participants before they could participate in the rating experiments.

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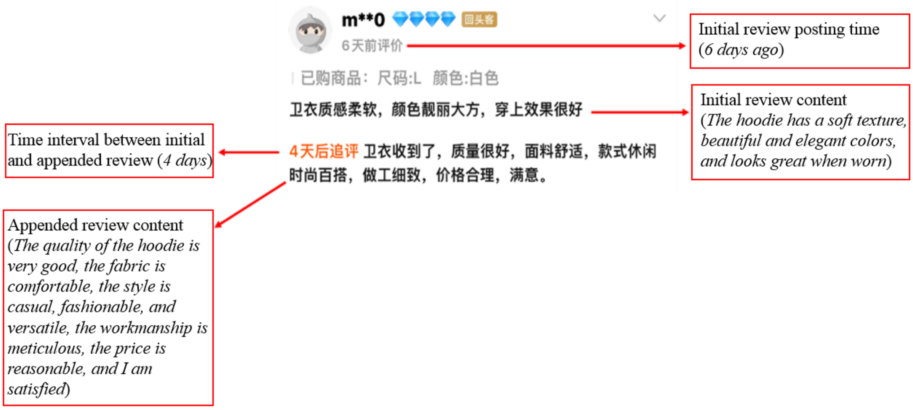
Ma *et al.*, 2024; Mudambi and Schuff, 2010). Statistics show that more than 90% of consumers read online reviews pertaining to relevant products before making a purchase (Tang *et al.*, 2014). With the evolution of eWOM, new forms of online reviews have emerged. For example, in recent years, prominent e-commerce platforms (e.g. Taobao and Pinduoduo) have implemented an appended review function to enhance their online evaluation systems. This function allows the buyers to supplement their initial reviews with additional comments, thus providing additional information regarding the products without impacting the sellers' ratings on the platform (i.e. the buyers cannot rate sellers in the appended reviews). Furthermore, when a buyer posts an appended review, the platform permits the seller to respond. However, buyers are unable to delete or modify their appended reviews at a later stage. Figure 1 presents examples of initial and appended reviews on Taobao.

While numerous studies have examined initial reviews (Cao *et al.*, 2011; Chen and Lurie, 2013; Huang *et al.*, 2018; Wu *et al.*, 2021), appended reviews have received relatively limited research attention. Most studies on appended reviews have primarily focused on the sentiment consistency between initial and appended reviews (Chen *et al.*, 2019; Wang *et al.*, 2021; Zhou and Li, 2017) and failed to comprehensively explore the content features within appended reviews. The content of a review conveys the most valuable information for consumers, while its features provide an effective means for classifying the information contained within the review, thus significantly influencing consumers (Wu *et al.*, 2021; Zhu *et al.*, 2024). Taking clothing as an example, some reviews on e-commerce platforms mainly focus on the superficial attributes of clothing products, such as their color, style, and texture, while other reviews primarily revolve around their deeper attributes, such as their durability and resistance to wrinkles and stains. These content features offer a significant reference value for potential consumers when making purchasing decisions. However, how these content features affect consumers' evaluations of review helpfulness and whether they have different impacts on consumers' perceived helpfulness of different review forms (i.e. initial and appended reviews) remain unclear. Given that consumers' perceived review helpfulness has significant practical implications, many studies have explored those factors influencing review helpfulness (Li and Huang, 2020; Wu *et al.*, 2021; Zhu *et al.*, 2022). However, the vast majority of these studies have mainly focused on the helpfulness of initial reviews, and only a few have explored this issue in consideration of different content features and review forms.

To fill this gap, we regard trust as a potential mechanism when investigating the combined effects of review content features and review forms on consumers' trust and perceived review



Source(s): Taobao.com

Figure 1. An example of initial review and appended review

helpfulness. Trust plays a vital role in virtual network environments by establishing connections among unknown entities (Cheng *et al.*, 2019; McKnight *et al.*, 2002). We categorize review content features into surface- and deep-level features based on these reviews' portrayal of product attributes, and we categorize review form into initial and appended reviews. We consequently obtain four scenarios that combine these review content features and forms, namely, surface-level features in initial reviews, deep-level features in initial reviews, surface-level features in appended reviews, and deep-level features in appended reviews. We then explore the impacts of these combinations on consumers' trust and perceived review helpfulness. This research significantly contributes to the literature on online reviews, especially appended reviews, and review helpfulness by simultaneously considering review content features and forms. Our findings also provide viable guidance for e-commerce platforms to further leverage initial and appended reviews.

The rest of this paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the hypotheses. Section 4 elaborates on our research method. Section 5 presents the statistical analyses and discusses the results. Section 6 concludes the paper with a summary of our research contributions, limitations, and potential future directions.

2. Literature review

To explore the joint impacts of review content features and review forms on consumers' trust and perceived review helpfulness, we review two streams of literature relevant to our research, namely, research on appended reviews and research on review helpfulness.

2.1 Appended reviews

As a new form of online review, appended review functions have been widely integrated into various leading e-commerce platforms to allow consumers to provide further evaluations and opinions regarding their product usage experiences. Scholars usually compare appended reviews with initial reviews and consider them as supplementary evaluations of products. Previous research has established that consumers perceive higher value in appended reviews than in initial reviews (Shen *et al.*, 2015; Wang *et al.*, 2021) due to the fact that consumers who provide appended reviews have had a longer experience with the product, thus having a more comprehensive understanding of its quality or performance (Wang *et al.*, 2021).

Some studies have treated appended reviews as outcomes of an external stimulus. For example, Zhao *et al.* (2020) investigated the impact of managerial response on consumers' appended review valence and revealed a significant positive influence. Further explorations show that these positive impacts are mainly due to the positive effects of managerial responses on non-positive initial reviews, thereby suggesting that managerial responses to non-positive reviews are effective tools for managing customer complaints. Ma *et al.* (2024) explored the effects of performance-contingent incentivized reviews (PIRs) on subsequent supplementary reviews (SRs) and demonstrated that the emergence of PIRs in an online review system has a positive spillover effect on subsequent SRs. Such positive impact is further magnified for products with non-video descriptions (vs video display) and experiential (vs search) products [1].

Another stream of research has investigated the influence of appended reviews on various outcomes. For example, Wang *et al.* (2021) explored how the interplay between initial and appended reviews influences consumers' decision making by proposing an ambivalence–confidence framework based on the heuristic–systematic model. They found that the truthfulness of online reviews and seller responses act as additional heuristics that bias systematic processing to mitigate the detrimental effects of inconsistent reviews. Zhou and Li (2017) investigated the impact of appended reviews on consumers' information adoption across different review combinations and found that when the initial review is positive, consumers tend to adopt inconsistent reviews (positive initial reviews and negative appended reviews) than consistent ones (positive initial reviews and positive appended reviews). By contrast, when the initial review is negative, consumers tend to adopt consistent reviews (negative initial reviews and negative appended reviews). Chen *et al.* (2019) explored the influence of appended reviews on consumers' purchase intention and uncovered that the sequence of positive or negative appended reviews affects the consumers' purchase intention while the degree of product involvement adjusts the relationship between them. Shen *et al.* (2015) investigated the differential impacts of appended and initial reviews and found that appended reviews have a greater influence on consumers' purchase intention and attitude certainty compared with initial reviews.

Despite these advances in the literature, only a few studies have explored the joint impacts of review content features and review forms on consumers' perceptions. Given that review contents directly convey information about the buyers' product usage experience, opinions, and attitudes toward the purchased products, unraveling the effects of review content features on the helpfulness of reviews becomes meaningful, especially when considering different review forms.

2.2 Review helpfulness

Consumers rely on online reviews to assess product features, determine whether a product meets their purchasing needs, and guide their subsequent decision-making behaviors (Chen and Lurie, 2013; Mudambi and Schuff, 2010). The perceived helpfulness of online reviews indicates the extent to which consumers perceive review information as valuable in evaluating those products they are interested in (Huang *et al.*, 2013). Online reviews are typically generated after consumers have made their purchases and are commonly consulted prior to making future purchasing decisions, thus completing a cycle in the consumer decision-making process (Chen and Lurie, 2013; Huang *et al.*, 2018).

An increasing number of studies have explored those factors that influence online review helpfulness, which include a relatively standard set of review attributes, such as review length (Li and Huang, 2020), readability (Korfiatis *et al.*, 2012), content depth (Wu *et al.*, 2021), sentiment (Banerjee and Chua, 2016), images in review content (Chen *et al.*, 2019), and emotions (Xu *et al.*, 2023; Yin *et al.*, 2016); and a diverse range of reviewer attributes, such as reviewer information disclosure (Forman *et al.*, 2008), expert label (Zhu *et al.*, 2014), profile image (Karimi and Wang, 2017), reviewer expertise and reputation (Racherla and Friske, 2012), reviewer innovativeness (Pan and Zhang, 2011), and reviewer online attractiveness (Zhu *et al.*, 2014).

Despite the extensive literature on online reviews, there remains a significant research gap concerning review content features. Previous studies have primarily focused on extracting features from a technical standpoint, thereby leaving a large room for a qualitative analysis of review content features grounded in theoretical foundations. Furthermore, the interaction between review content features and review forms has not been adequately explored, making it a key focus of this study.

3. Theoretical lens and research hypotheses

Trust is widely deemed as a key factor in addressing uncertainty issues on e-commerce platforms (Cheng *et al.*, 2019; Lam *et al.*, 2023; McKnight *et al.*, 2002; Pavlou *et al.*, 2007). Trust is a multifaceted concept that encompasses benevolence, integrity, and ability (Al-Natour *et al.*, 2010; McKnight *et al.*, 2002). Benevolence is an altruistic behavior where sellers prioritize consumers' interests, thereby fostering trust. Integrity involves adhering to moral principles and commitments, which is crucial in online transactions where consumers rely on sellers' honesty to assess product quality. Ability refers to sellers' proficiency in delivering tailored products and services, thus mitigating consumers' confusion and strengthening trust. These dimensions collectively shape consumers' trust perception toward sellers on e-commerce platforms. Previous research indicates that trust has a significant impact on consumers' willingness to make online purchases and assists them in making decisions in the presence of information asymmetry (Pavlou *et al.*, 2007). In this study, given the information asymmetry between online review posters and potential consumers (i.e. review posters have experiences regarding product usage, while potential consumers have no prior product knowledge), we regard trust as a potential theoretical mechanism when evaluating the impacts of review content features and review forms on consumers' perceived review helpfulness.

3.1 The impact of surface- and deep-level features of review content on consumers' trust

Consumers often encounter product uncertainty issues during online transactions and rely on various informative cues to make judgments (Dimoka *et al.*, 2012; Hong and Pavlou, 2014). One established informative cue is an online review. Product buyers post reviews on e-commerce platforms to share their shopping experiences, thereby assisting potential consumers in making informed purchasing decisions (Huang *et al.*, 2018). By reading these reviews, potential consumers can gain insights into buyers' recognitions and opinions on specific products. They can perceive that posting online reviews is a behavior motivated by one's desire to share and help others (Qiao *et al.*, 2020), thus further cultivating these consumers' trust toward reviews.

Prior studies have directed research attention to explore the trustworthiness or credibility of online reviews, and the factors such as source credibility (Cheung *et al.*, 2009; Filieri, 2016), expertise of review posters (Thomas *et al.*, 2019), review argument quality (Cheung *et al.*, 2012; Thomas *et al.*, 2019), review consistency (Cheung *et al.*, 2012), review valence (Filieri, 2016) and product/service rating (Thomas *et al.*, 2019) have been identified as influential antecedents of trustworthiness or credibility of reviews. However, it's still unclear whether the different content features may affect consumers' perceived trust toward online reviews, especially considering initial and appended review forms.

In this study, we categorized review content features into surface- and deep-level features following previous studies on traditional management (Bell, 2007; Harrison *et al.*, 1998). Specifically, the surface-level features in online reviews refer to direct descriptions of observable attributes related to the reviewed product. A higher occurrence of such descriptions indicates a more comprehensive observation of the product's explicit attributes and a greater willingness of the buyer to share his/her observations through reviews. Potential consumers perceive a stronger sense of benevolence from a buyer that demonstrates such sharing behavior (Qiao *et al.*, 2020), thus increasing their level of trust toward this buyer's online reviews. For instance, when a consumer intends to purchase a jacket on an e-commerce platform, some of its features, such as thickness and size, can be directly observed and categorized as surface-level features. If reviews contain a higher number of descriptions regarding these features, then potential consumers are more likely to perceive the buyer's intention to provide comprehensive information about the product's explicit attributes, thereby assisting other consumers in making informed decisions. Similarly, deep-level features in online reviews can shape consumers' perception of the buyer's motivation for sharing. A greater occurrence of these descriptions enhances consumers' perception of the goodwill conveyed by the buyer's sharing behaviors (Cheng *et al.*, 2019). Therefore, we propose hypothesis H1:

H1. Surface- and deep-level features in online reviews have positive impacts on consumers' trust perception.

However, deep-level features differ from surface-level features in the sense that they are not directly observable and require a period of experience to be discerned, thus necessitating buyers to invest more effort and demonstrate stronger observational skills. A higher number of deep-level features in online reviews signifies the buyer's heightened observational ability regarding the reviewed product. Certain attributes of a jacket, such as its durability, dirt resistance, and popularity, may necessitate a certain period of experience before they can be accurately evaluated. Identifying these features also requires buyers to possess a certain level of product knowledge accumulation and judgment capability. In this case, the presence of deep-level features in online reviews can enhance consumers' trust perception by influencing their perception of the buyer's benevolence and ability. Compared with surface-level features, consumers cultivate a higher level of trust toward deep-level features. Based on these arguments, we propose the following:

H2. Deep-level features in online reviews have a stronger impact on consumers' trust perception compared with surface-level features.

3.2 The impact of surface- and deep-level features of review content on consumers' trust under different review forms

Initial and appended reviews are subject to different posting time restrictions, with appended reviews enjoying more relaxed constraints. For instance, on Taobao website, consumers are allowed to post initial reviews within 15 days after completing a transaction, while the time restriction for posting appended reviews extends to 180 days after the transaction.

Compared with initial reviews, appended reviews generally convey higher perceived value to other consumers (Shen *et al.*, 2015; Wang *et al.*, 2021). Given the extended observation period for posting appended reviews, buyers are more likely to uncover the product's deep features in these reviews. Buyers who describe the deep features of a product in their appended reviews can enhance consumers' awareness of content reliability. Conversely, when buyers release their initial reviews shortly after experiencing a product, they cannot gain a profound understanding of this product's deep features within such a limited timeframe. Therefore, when buyers include deep features in their initial reviews, consumers may feel skeptical. Building upon this premise, we hypothesize the following:

H3. Compared with deep-level features in initial reviews, deep-level features in appended reviews have a greater positive impact on consumers' trust perception.

Consumers tend to describe surface-level features in their initial reviews. When they initially encounter a product, they primarily focus on its observable attributes and develop a strong recollection of the specific details related to these attributes. According to construal level theory (Trope and Liberman, 2010), consumers' attention toward these specific attributes diminishes over time, leading to a time discount effect (Kirshner and Moritz, 2022; Trope and Liberman, 2010). Therefore, when creating appended reviews, consumers no longer devote sufficient attention to the specifics of surface features, which prevents them from accurately evaluating the true product attributes. For instance, when consumers initially receive a product, such as a jacket, they have a clear understanding of its explicit features, such as color and size. However, as time passes and individual usage habits differ, this jacket may undergo wear and deviate from its original state to some extent. At this point, consumers evaluate its surface-level features based on their recollection of the old product, resulting in the poor reliability of their evaluation. By contrast, the initial review, which is written shortly after completing the transaction, exhibits a high level of attention to the explicit attributes of the product before undergoing significant changes. Therefore, the initial review provides an accurate understanding of the surface-level features of the original product, which contributes to a relatively truthful evaluation. In this case, the inclusion of surface-level features in initial reviews can enhance consumers' trust perception in online reviews by imparting a strong sense of authenticity. We then propose the following:

H4. Compared with surface-level features in appended reviews, surface-level features in initial reviews have a greater positive impact on consumers' trust perception.

3.3 The impact of consumers' trust on perceived review helpfulness

Perceived trust reflects a belief in the integrity, benevolence, and competence of exchange partners (Al-Natour *et al.*, 2010; McKnight *et al.*, 2002). In e-commerce transactions, trust serves as a fundamental consumer perception belief that can positively influence the transaction process due to the high level of risk, uncertainty and interdependence that characterizes online interactions (Jarvenpaa *et al.*, 2000; Moloi *et al.*, 2022). Prior studies have found that the more trust consumers have for online reviews or the source, the more likely they will perceive the reviews to be helpful (Filieri *et al.*, 2018; Moloi *et al.*, 2022).

In our research context, when potential consumers trust the content of online reviews, the presence of surface- and deep-level features within these reviews helps reduce their uncertainty regarding the product and assist them in making judgments about its quality and whether this product fits their needs. Therefore, the higher the level of consumer trust in an online review, the greater the perceived value of this review. In other words, when potential consumers engage with online reviews, their trust in the content of these reviews significantly affects their perception of review helpfulness. Based on these arguments, we propose the following:

H5. Consumers' perception of trust in reviews has a positive impact on their perceived review helpfulness.

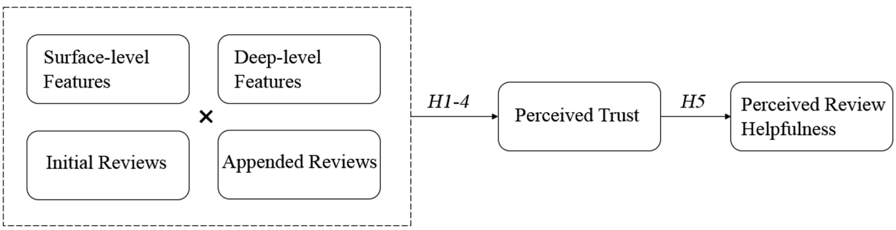
Based on the above hypothesis elaboration, the research model is depicted in Figure 2.

4. Research data and measurements

4.1 Data collection

We collected our data from Taobao, a subsidiary of the Alibaba Group (http://www.taobao.com/). We specifically focused on clothing products for two primary reasons. First, clothing is one of the most prevalent products being sold on e-commerce platforms, and a vast majority of consumers have experienced purchasing clothes online. Second, clothing represents a typical experience product. Compared with search products, evaluating the quality and fit of clothes before their purchase can be challenging for consumers, and this decision-making process is significantly influenced by the content of online reviews (Senecal and Nantel, 2004).

In the data collection process, we selected 40 clothing products with similar sales volumes (approximately 10,000 monthly sales) by entering the keyword "clothing" in the Taobao search bar. We controlled the number of followers in the respective product stores to be equivalent (with a follower base of approximately 1 million) to mitigate the interference of store promotions, product sales, and other factors on consumers' online reviews. We used a crawler program to randomly retrieve 1,137 online review data. Given that our study focuses on the influence of initial and appended review content on consumers' perceptions, we firstly excluded those reviews without appended ones and the reviews accompanied by images. Secondly, we excluded the negative reviews because the percentage of negative reviews is quite small (around 6%) and even fewer consumers made appended reviews for these initial negative reviews. Thirdly, we manually screened and removed some perfunctory reviews that



Source(s): Authors' own work

Figure 2. Research model

do not involve an evaluation of product attributes (e.g. “I like it,” “I will purchase again,” etc.). Ultimately, we retrieved 599 positive online review data with appended reviews for the subsequent experimental analysis.

4.2 Review content analysis

We categorized the content in online reviews into surface- and deep-level features based on Cheng *et al.*’s (2019) methodological approach for analyzing thematic content in online reviews. We also adopted a manual coding approach to process the appended online reviews. The steps are described as follows.

We constructed and refined a thematic feature corpus using theoretical sampling methods (Eisenhardt and Graebner, 2007). We randomly divided the sample data into 6 groups, with each group comprising 100 reviews (with the last group having 99 reviews). We sequentially labeled these groups as A, B, C, D, E, and F. We invited four research assistants with various backgrounds to conduct the manual coding. First, we provided these research assistants with the definitions of surface- and deep-level features of review contents. Second, these research assistants separately performed word segmentation and classification coding on the sample data of group A. The average Kappa value among them reached 0.78, which exceeded the threshold of 0.65 (Moore and Benbasat, 1991), indicating a high level of consistency in their classification of the sample data. These research assistants discussed and resolved any inconsistencies in the classified word segmentation results to reach a consensus. The results from group A served as the initial corpus for the surface- and deep-level features of review content. We then applied a pre-coding method to continue the manual coding process for groups B to F. After each round of coding, if any new words or phrases appeared that were not identified in the existing surface- or deep-level feature corpus, then we would continue the coding process until no new words or phrases appeared. During the formal coding process, the research assistants coded all the six sample groups, and we observed no new words or phrases in the corpus after the research assistants completed the coding for group D, indicating that the coding of group E and F generates no new words. The convergence of the coding process indicates that the review content feature corpus was completed. Table 1 presents some typical examples of thematic features.

After constructing the corpus of diverse features in online reviews, we used Python programming to quantitatively process the sample data containing the appended reviews. First, we divided the content of each sample data containing appended reviews into sub-sentences based on punctuation marks (e.g. “.”, “!”, and “?”). Second, we applied keyword matching for each sentence derived from the split of the appended reviews. If a word from the corpus of diverse features in online reviews appears in a sentence, then we would assign a score of 1 to the corresponding category feature of that word in the corpus. Lastly, we accumulated the scores at the review level. By summarizing the scores for each sentence according to the corresponding online review, we can obtain the cumulative quantified score for each review in terms of surface- and deep-level features. Table 2 shows an example regarding the measure of surface- and deep-level features.

Table 1. Examples of reviews’ content features

Review content features	Definition	Examples
Surface-level features	Surface-level features refer to direct description of observable attributes related to the product	Thickness, size, color, etc.
Deep-level features	Deep-level features are not directly observable and require a period of experience to be discerned	Popularity, dirt resistance, durability, etc.

Source(s): Authors’ own work

Table 2. Measure of review content features

Reviews	Features	Feature values
Initial review: this shirt is the same color as shown on the website, the panel shape is nice and fitted, and the quality is good	Surface-level features: color, panel shape Deep-level features: quality	Surface-level feature value: 2 Deep-level feature value: 1
Appended review: this shirt is very durable and dirt resistant, and the panel shape does not change easily	Surface-level features: panel shape Deep-level features: durability, dirt resistance	Surface-level feature value: 1 Deep-level feature value: 2

Source(s): Authors' own work

4.3 Measurement of consumers' trust and perceived review helpfulness

To measure consumers' trust and perceived review helpfulness, we employed a questionnaire survey with items derived from previous studies. Our measurement of trust utilized the following items adopted from Lu and Chen (2021): (1) This review is relevant to my interests; (2) This review is written honestly; and (3) This review provides professional descriptions of the product. Meanwhile, our measurement of perceived review helpfulness utilized the following items adopted from Huang *et al.* (2018): (1) This review helps me determine whether I should purchase the product; (2) This review helps me understand whether I would like the product; and (3) This review contains useful information about the product.

To evaluate trust and perceived review helpfulness, we invited 34 college students with online shopping experience and familiarity with online reviews via Credamo [2] to rate the 599 review samples. To mitigate the interference of poster characteristics on the rating outcomes, we withheld specific information about the review posters. We provided the raters with visible information about the reviews, including the initial and appended reviews and their corresponding posting times.

Prior to rating, we provided all the raters with a simple training, informed them of the specific rating process, and explained the specific meanings of surface- and deep-level review content features. After reading each review, we asked these raters to rate the six measurement items for trust and perceived helpfulness on a seven-point Likert scale. As each rater was asked to rate all the 599 review data, we reminded the raters not to exceed 100 ratings per day and to spend at least 1 min rating each review to ensure relative stability in rating quality. We gave each rater 100 RMB as a reward for their participation.

5. Results

5.1 Descriptive analysis

We conducted a descriptive statistical analysis and present the results in Table 3. The mean value of surface-level features is approximately twice that of deep-level features, indicating that the content of surface-level features significantly outweighs that of deep-level features in online reviews. Different types of reviews exhibit variations in their numerical representation of surface- and deep-level features. Specifically, the content in initial reviews describing deep-level features is more prevalent than that describing surface-level features. However, in appended reviews, we observe a significant increase in the content describing surface-level features. Each review comprises approximately 92 words on average, indicating that the overall review content is rich and readable.

5.2 Measurement model

We then tested our measurement model, including the reliability and validity for trust and perceived review helpfulness (Table 4). Results of the SPSS analysis indicate that the

Table 3. Descriptive statistics (N = 599)

Variables	N	Min	Max	Mean	SD
Perceived review helpfulness *(1–7)*	599	3.33	6.00	4.55	0.47
Trust *(1–7)*	599	2.67	6.33	4.98	0.51
Surface-level features *(number)*	599	0	39	20.12	9.35
Deep-level features *(number)*	599	0	59	11.18	10.36
Surface-level features in initial review *(number)*	599	0	37	4.81	7.23
Deep-level features in initial review *(number)*	599	0	37	7.41	7.78
Surface-level features in appended review *(number)*	599	0	38	15.32	10.71
Deep-level features in appended review *(number)*	599	0	37	3.77	6.76
Time interval between initial and appended review *(day)*	599	0	29	12.51	8.13
Posting time of initial review *(day)*	599	2	61	5.32	5.23
Review length *(number of words)*	599	8	492	92.78	74.144

Source(s): Authors' own work

Table 4. Results of reliability test and validity test (N = 599)

Variables	Items	Cronbach's α	Loadings	AVE	CR	Correlation	Sqrt (AVE)
Trust	Item 1		0.759				
	Item 2	0.818	0.715	0.607	0.822	0.680	0.779
	Item 3		0.857				
Perceived review	Item 1		0.801				
helpfulness	Item 2	0.834	0.786	0.642	0.843	0.680	0.801
	Item 3		0.816				

Source(s): Authors' own work

Cronbach's α values for each construct are all above 0.65, indicating high reliability. To examine whether the sample data for these two constructs were suitable for factor analysis, we conducted the Kaiser–Meyer–Olkin (KMO) test and Bartlett's sphericity test. A KMO value above 0.7 and a significant result in Bartlett's sphericity test confirm that the sample is suitable for factor analysis. After the SPSS analysis, we obtained a KMO value of 0.808, which is greater than 0.7, and a significance level (sig) of 0.000, altogether confirming the suitability of our sample for factor analysis.

Given that we derived our measurement items from the literature, we directly performed confirmatory factor analysis to assess the convergent and discriminant validities of the scales. Convergent validity refers to the correlation between the common factors and their corresponding individual items. This measure is typically evaluated through average variance extracted (AVE), composite reliability (CR), and standardized factor loadings. A good convergent validity is achieved when AVE > 0.5, CR > 0.7, and standardized factor loadings >0.7. Discriminant validity, which refers to the differences among the latent variables, is evaluated by testing whether the correlation between common factors is less than the square root of the AVE. A good discriminant validity is achieved when the correlation among common factors is less than the square root of the AVE. The results in Table 4 demonstrate good convergent and discriminant validities for the constructs involved in this study.

5.3 Hypothesis testing

5.3.1 Validation of H1 and H2. To validate H1 and H2, we utilized consumers' trust as the dependent variable and incorporated the time interval between the appended and initial reviews, the initial review posting time, and the review length as control variables to establish a regression model for consumers' trust as shown in Equation (1), where α is a constant, and ε_n is an error term representing the impact of any possible factors (other than the independent variables) on the dependent variable. Table 5 presents the variable symbols used in the model and their corresponding definitions, and Table 6 presents the results.

$$\begin{aligned} Trust_n &= \alpha + \beta_1 (Surface_{level})_n + \beta_2 (Deep\_level)_n + \beta_3 (Appended\_time)_n \\ &\quad + \beta_4 (\mathrm{Initial\_time})_n + \beta_5 (Length)_n + \varepsilon_n \end{aligned} \tag{1}$$

When the dependent variable is consumers' trust, as shown in Table 6, the adjusted R-square of regression Model 1 is 0.157 with a significance level of $p < 0.01$, thereby confirming the acceptability of the model's results. The tolerances for each variable are within an appropriate range (tolerance > 0.1), and the variance inflation factors (VIF) are all less than 3, thereby suggesting the absence of multicollinearity among the variables (Midi *et al.*, 2010). The Durbin–Watson test value of 2.109 indicates the absence of significant autocorrelation among the independent variables (Durbin and Watson, 1951). The regression coefficients of surface- and deep-level features are significant, thereby confirming the significant positive impacts of these features on consumers' trust and supporting H1. The standardized coefficient of deep-level features is also greater than that of surface-level features. When using the Stata17 "test" command to construct the Wald statistic, the statistical results demonstrate a significant difference between the coefficients of the two variables ($F = 8.21, p < 0.05$), indicating that the impact of deep-level features on trust is significantly greater than that of surface-level features, thus supporting H2.

Table 5. Variables and descriptions (Model 1)

Variables	Description
$(\mathrm{Trust})_n$	Consumers' perceived trust towards the nth review with appended one
$(Surface\_level)_n$	Surface-level features embedded in nth review with appended one
$(Deep\_level)_n$	Deep-level features embedded in nth review with appended one
$(Appended\_time)_n$	Time interval between nth review and its appended review
$(\mathrm{Initial\_time})_n$	Posting time of nth review
$(Length)_n$	Length of nth review

Source(s): Authors' own work

Table 6. Regression results of Model 1 (dependent variable: trust)

Variables	Coefficient	Tolerance	VIF	t-value	p-value
Constant				69.916	0.000**
$(Surface\_level)_n$	0.133	0.966	1.035	3.468	0.001**
$(Deep\_level)_n$	0.185	0.970	1.031	4.852	0.000**
$(Appended\_time)_n$	0.103	0.993	1.007	2.741	0.006**
$(\mathrm{Initial\_time})_n$	−0.249	0.865	1.156	−6.157	0.000**
$(Length)_n$	0.247	0.867	1.153	6.120	0.000**
R^2	0.164				
Adj. R^2	0.157				
F-value	23.248**				
Durbin-Watson value	2.109				

Note(s): $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$
Source(s): Authors' own work

5.3.2 Validation of H3 and H4. To verify H3 and H4, we further categorized the surface- and deep-level features in online reviews into surface-level features in initial reviews, deep-level features in initial reviews, surface-level features in appended reviews, and deep-level features in appended reviews. We incorporated these four variables into the regression model for analysis, and the established regression Model 2 is shown in Equation (2). Table 7 presents the new variables and their definitions, and Table 8 presents the results of Model 2.

$$\begin{aligned} Trust_n = \mathrm{a} &+ b_1(Initial\ surface\_level)_n + b_2(Initial\ deep\_level)_n \\ &+ b_3(Appended\ surface\_level)_n + b_4(\mathrm{Appended}\ deep\_level)_n \\ &+ b_5(Appended\_time)_n + b_6(\mathrm{Initial\_time})_n + b_5(Length)_n + e_n \end{aligned} \tag{2}$$

The regression results of Model 2 are also acceptable (adjusted R-square = 0.161, $sig < 0.01$), with the tolerances and VIF values of the variables falling within acceptable ranges (tolerance < 0.1, VIF < 3). The Durbin–Watson test value is around 2, indicating the independence of residuals. The standardized coefficient of deep-level features in appended reviews is significant, and its absolute value exceeds that of the standardized coefficient of deep-level features in initial reviews. The Wald test is significant (0.167 > 0.146; $F = 4.43$, $p < 0.05$), thereby suggesting that the presence of deep-level features in appended reviews has a greater impact on consumers' trust than that in initial reviews, hence supporting H3. The absolute value of the standardized coefficient of surface-level features in initial reviews is higher than that in appended reviews, and the difference between these two is significant

Table 7. New variables and descriptions (Model 2)

Variables	Description
$(Initial\ surface\_level)_n$	Surface-level features in initial reviews
$(Initial\ deep\_level)_n$	Deep-level features in initial reviews
$(\mathrm{Appended}\ surface\_level)_n$	Surface-level features in appended reviews
$(\mathrm{Appended}\ deep\_level)_n$	Deep-level features in appended reviews

Source(s): Authors' own work

Table 8. Regression results of Model 2 (dependent variable: trust)

Variables	Coefficient	Tolerance	VIF	t-value	p-value
Constant				67.461	0.000**
$(Initial\ surface\_level)_n$	0.169	0.653	1.532	3.650	0.000**
$(Initial\ deep\_level)_n$	0.146	0.853	1.172	3.595	0.000**
$(\mathrm{Appended}\ surface\_level)_n$	0.128	0.691	1.448	2.837	0.005**
$(\mathrm{Appended}\ deep\_level)_n$	0.167	0.903	1.107	4.239	0.000**
$(Appended\_time)_n$	0.108	0.989	1.011	2.875	0.004**
$(\mathrm{Initial\_time})_n$	−0.247	0.864	1.157	−6.140	0.000**
$(Length)_n$	0.239	0.859	1.164	5.905	0.000**
R^2	0.170				
Adj. R^2	0.161				
F-value	17.346**				
Durbin-Watson value	2.092				

Note(s): ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$
Source(s): Authors' own work

(0.169 > 0.128; Wald test $F = 6.82$, $p < 0.05$). In other words, surface-level features in initial reviews have a greater impact on consumers' trust, thus supporting H4.

5.3.3 Validation of H5. To verify the impact of trust on consumers' perceived review helpfulness, we constructed multiple regression Model 3 as shown in Equation (3). Table 9 presents the regression results of Model 3.

$$Helpfulness_n = \mathrm{h} + g_0(Trust)_n + g_1(Surface\_level)_n + g_2(Deep\_level)_n + g_3(Appended\_time)_n + g_4(\mathrm{Initial\_time})_n + g_5(Length)_n + k_n \quad (3)$$

The regression results indicate that when the dependent variable is perceived review helpfulness, the regression coefficient of trust is significant and positive, thereby confirming that consumers' trust has a positive impact on perceived helpfulness of reviews and supporting H5. We verified our examination of the mediating effect by adopting a stepwise regression method (Hayes, 2017). First, the results in Model 3 already demonstrate that the surface- and deep-level features of online reviews have positive impacts on consumers' perceived review helpfulness with significant and positive regression coefficients, thereby validating the first step of the stepwise regression. Second, Model 1 shows that the surface- and deep-level features have positive impacts on consumers' trust, and the analysis results in Model 3 indicate that trust has a positive and significant impact on perceived review helpfulness. These results confirm the second step of the stepwise regression and demonstrate the significant mediating effect of trust. Third, given that the regression coefficients of surface- and deep-level features are significant in Model 3, trust plays a partial mediating role in the impact of these features on perceived review helpfulness.

6. Discussion

6.1 Results summary

This study investigates the joint impacts of different review content features (i.e. surface- vs deep-level features) and review forms (i.e. initial vs appended reviews) on consumers' trust toward reviews, which in turn affects perceived review helpfulness. The results are summarized as follows: (1) Surface- and deep-level features have significant positive impacts on consumers' trust perception. Given that the surface- and deep-level features of products shared in online reviews reflect the review posters' efforts in evaluating the products and their

Table 9. Regression results of Model 4 (dependent variable: perceived review helpfulness)

Variables	Coefficient	Tolerance	VIF	*t*-value	*p*-value
Constant				35.303	0.000**
Trust	0.053	0.836	1.196	2.402	0.017*
$(Surface\_level)_n$	0.170	0.947	1.056	8.175	0.000**
$(Deep\_level)_n$	0.134	0.933	1.072	6.382	0.000**
$(Appended\_time)_n$	0.063	0.980	1.020	3.073	0.002**
$(\mathrm{Initial\_time})_n$	0.064	0.813	1.230	2.860	0.004**
$(Length)_n$	0.799	0.816	1.226	35.578	0.000**
R^2	0.757				
Adj. R^2	0.754				
F-value	306.583**				
Durbin-Watson value	1.952				

Note(s): ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$
Source(s): Authors' own work

benevolence to other potential consumers, this sharing behavior significantly contributes to cultivating consumers' trust perception toward these reviews. (2) The impact of surface- and deep-level features of review content on consumers' trust varies between the two review forms. Specifically, surface-level features in initial reviews lead to a higher perceived trust among consumers compared with those in appended reviews, while deep-level features in appended reviews have a stronger impact on consumers' trust compared with those in initial reviews. (3) Consumers' trust positively affects perceived review helpfulness, and surface- and deep-level features have direct positive impacts on consumers' perceived review helpfulness, with trust partially mediating this process. These results further underscore the vital role of trust in an e-commerce context facing information asymmetry and product uncertainty issues.

6.2 Theoretical contributions

The theoretical contributions of our work can be summarized in several key aspects. First, this study further expands the research on the antecedents of review helpfulness. Previous studies on this topic have predominantly focused on the helpfulness of initial reviews and mainly concentrated on certain review characteristics, such as review length (Li and Huang, 2020), readability (Korfiatis *et al.*, 2012), content depth (Wu *et al.*, 2021), sentiment (Banerjee and Chua, 2016), and emotions (Xu *et al.*, 2023; Yin *et al.*, 2016). As a significant departure from these studies, we simultaneously consider the joint impact of review content features (i.e. surface- vs deep-level features) and review forms (i.e. initial vs appended reviews) and reveal the different impacts of each content feature between the two review forms.

Second, we link review characteristics to helpfulness by considering the mediating role of consumers' trust. By constructing four combinations of review content types and review forms (i.e. surface-level features in initial reviews, deep-level features in initial reviews, surface-level features in appended reviews, and deep-level features in appended reviews), we adopt trust as a theoretical lens to reveal how these combinations affect consumers' perceived review helpfulness. Though prior studies have identified source credibility (Cheung *et al.*, 2009; Filieri, 2016), expertise of review posters (Thomas *et al.*, 2019), review argument quality (Cheung *et al.*, 2012; Thomas *et al.*, 2019), review consistency (Cheung *et al.*, 2012), review valence (Filieri, 2016) and product/service rating (Thomas *et al.*, 2019) as influential antecedents of trustworthiness or credibility of reviews. To the best of our knowledge, this study is among the few to uncover how specific review features affect consumers' perceived trust toward reviews, which further affect perceived review helpfulness in a virtual environment.

Third, this study provides a new angle for analyzing appended online reviews. Previous studies regarding initial and appended reviews have mainly focused on the sentiment polarity of these reviews (Chen *et al.*, 2019; Wang *et al.*, 2021; Zhou and Li, 2017), while our study unravels the differential impacts of online reviews by comparatively analyzing the differences between initial and appended reviews in consideration of review content features, thus offering an open avenue for future research in this area.

6.3 Practical implications

We enumerate the practical implications of our study as follows. First, our findings uncover what kind of reviews are perceived as more trustworthy and helpful. Specifically, the surface-level features in initial reviews and deep-level features in appended reviews are perceived to be more trustworthy. Therefore, online sellers can manage the online reviews of their products by employing some strategies, such as guiding consumers to further describe the surface-level features of their products when posting initial reviews and further describe deep-level features when posting appended reviews, under the ethical principles of authenticity and objectivity. In practice, this can be achieved by automatically prompting some potential product feature labels for consumers when they write specific type of reviews (i.e. initial review or appended review). These practices can further enhance the trust perception of other potential consumers toward these product reviews.

Second, our findings may guide e-commerce platforms in optimizing the display and arrangement of their online reviews. E-commerce platforms often have thousands of product reviews, leading to information overload for consumers. Therefore, they need to select the most helpful reviews and recommend them to users to reduce their information search costs. They can refer to our proposed online review content analysis method to improve their algorithms for sorting and recommending online reviews. By adhering to the ethical principles of objectivity and authenticity, these platforms can prioritize displaying those reviews with high perceived trustworthiness and helpfulness to enhance the reference value of these reviews for consumers.

7. Conclusion

This study has several limitations that may offer potential directions for future research. First, we quantitatively processed the content features via corpus construction and keyword matching. However, these text processing methods are based on the assumption of word independence and neglect the semantic relationships among texts, which may lead to certain errors in the quantitative analysis. Future research may consider other text semantic analysis techniques to provide a highly sophisticated quantitative treatment of content features in reviews. Second, we conducted experiments with a sample of college students to validate our hypotheses. Although college students are familiar with our research context, the limited representativeness of our sample may cause potential bias in our findings. Future research may include a larger sample to enhance the external validity of our findings. Third, we only analyzed the positive reviews with appended ones in this study, which overlooks the potential impact of negative reviews. Though the negative reviews, especially negative reviews with appended ones, occupied a very small percentage of all the review samples, the generalizability of our findings needs to be interpreted with caution. Future research could compare and analyze reviews with different valence to further understand the impact of review valence in our research model. Fourth, although in the experimental setting we have managed to rule out potential external influencing factors, there is still an ambiguity regarding whether the review posters in this study were motivated by certain incentives. These incentives could include coupons offered by either the sellers or the platforms. To tackle this issue, future research could attempt to directly obtain internal platform data. By doing so, it would be possible to effectively eliminate this potential confounding impact and gain a more accurate and unbiased understanding of the review-related phenomena.

Notes

1. Experiential products are the products that consumers evaluate mainly through direct experience during or after consumption rather than through pre-purchase inspection and standardized attribute information gathering like search products.
2. Credamo is an online research platform that enables researchers to efficiently design surveys, recruit a diverse pool of participants, and collect high-quality data, while also offering tools for data analysis, thus streamlining the entire research process from start to finish.

References

Al-Natour, S., Benbasat, I. and Cenfetelli, R. (2010), “The adoption of online shopping assistants: perceived similarity as an antecedent to evaluative beliefs”, *Journal of the Association for Information Systems*, Vol. 12 No. 5, pp. 347-374, doi: 10.17705/1jais.00267.

Banerjee, S. and Chua, A.Y. (2016), “In search of patterns among travellers’ hotel ratings in TripAdvisor”, *Tourism Management*, Vol. 53, pp. 125-131, doi: 10.1016/j.tourman.2015.09.020.

Bell, S.T. (2007), "Deep-level composition variables as predictors of team performance: a meta-analysis", *Journal of Applied Psychology*, Vol. 92 No. 3, pp. 595-615, doi: 10.1037/0021-9010.92.3.595.

Cao, Q., Duan, W. and Gan, Q. (2011), "Exploring determinants of voting for the 'helpfulness' of online user reviews: a text mining approach", *Decision Support Systems*, Vol. 50 No. 2, pp. 511-521, doi: 10.1016/j.dss.2010.11.009.

Chen, Z. and Lurie, N.H. (2013), "Temporal contiguity and negativity bias in the impact of online word of mouth", *Journal of Marketing Research*, Vol. 50 No. 4, pp. 463-476, doi: 10.1509/jmr.12.0063.

Chen, Y. and Xie, J. (2008), "Online consumer review: word-of-mouth as a new element of marketing communication mix", *Management Science*, Vol. 54 No. 3, pp. 477-491, doi: 10.1287/mnsc.1070.0810.

Chen, H., Yan, Q., Xie, M., Zhang, D. and Chen, Y. (2019), "The sequence effect of supplementary online comments in book sales", *IEEE Access*, Vol. 7, pp. 155650-155658, doi: 10.1109/access.2019.2948190.

Cheng, X., Fu, S., Sun, J., Bilgihan, A. and Okumus, F. (2019), "An investigation on online reviews in sharing economy driven hospitality platforms: a viewpoint of trust", *Tourism Management*, Vol. 71 No. 1, pp. 366-377, doi: 10.1016/j.tourman.2018.10.020.

Cheung, C.M.Y., Luo, C., Sia, C.L. and Chen, H. (2009), "Credibility of electronic word-of-mouth: informational and normative determinants of on-line consumer recommendations", *International Journal of Electronic Commerce*, Vol. 13 No. 4, pp. 9-38, doi: 10.2753/jec1086-4415130402.

Cheung, C.M.Y., Sia, C.L. and Kuan, K.K.Y. (2012), "Is this review believable? A study of factors affecting the credibility of online consumer reviews from an ELM perspective", *Journal of the Association for Information Systems*, Vol. 13 No. 8, pp. 618-635, doi: 10.17705/1jais.00305.

Dimoka, A., Hong, Y. and Pavlou, P.A. (2012), "On product uncertainty in online markets: theory and evidence", *MIS Quarterly*, Vol. 36 No. 2, pp. 395-426, doi: 10.2307/41703461.

Durbin, J. and Watson, G.S. (1951), "Testing for serial correlation in least squares regression. II", *Biometrika*, Vol. 38 Nos 1-2, pp. 159-178, doi: 10.1093/biomet/38.1-2.159.

Eisenhardt, K.M. and Graebner, M.E. (2007), "Theory building from cases: opportunities and challenges", *Academy of Management Journal*, Vol. 50 No. 1, pp. 25-32, doi: 10.5465/amj.2007.24160888.

Filieri, R. (2016), "What makes an online consumer review trustworthy?", *Annals of Tourism Research*, Vol. 58, pp. 46-64, doi: 10.1016/j.annals.2015.12.019.

Filieri, R., McLeay, F., Tsui, B. and Lin, Z. (2018), "Consumer perceptions of information helpfulness and determinants of purchase intention in online consumer reviews of services", *Information and Management*, Vol. 55 No. 8, pp. 956-970, doi: 10.1016/j.im.2018.04.010.

Forman, C., Ghose, A. and Wiesenfeld, B. (2008), "Examining the relationship between reviews and sales: the role of reviewer identity disclosure in electronic markets", *Information Systems Research*, Vol. 19 No. 3, pp. 291-313, doi: 10.1287/isre.1080.0193.

Harrison, D.A., Price, K.H. and Bell, M.P. (1998), "Beyond relational demography: time and the effects of surface- and deep-level diversity on work group cohesion", *Academy of Management Journal*, Vol. 41 No. 1, pp. 96-107, doi: 10.2307/256901.

Hayes, A.F. (2017), *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*, Guilford Publications, New York.

Hong, Y. and Pavlou, P.A. (2014), "Product fit uncertainty in online markets: nature, effects, and antecedents", *Information Systems Research*, Vol. 25 No. 2, pp. 328-344, doi: 10.1287/isre.2014.0520.

Huang, L., Tan, C.-H., Ke, W. and Wei, K.K. (2013), "Comprehension and assessment of product reviews: a review-product congruity proposition", *Journal of Management Information Systems*, Vol. 30 No. 3, pp. 311-343, doi: 10.2753/mis0742-1222300311.

Huang, L., Tan, C.-H., Ke, W. and Wei, K. (2018), "Helpfulness of online review content: the moderating effects of temporal and social cues", *Journal of the Association for Information Systems*, Vol. 19 No. 6, pp. 503-522, doi: 10.17705/1jais.00499.

Jarvenpaa, S.L., Tractinsky, N. and Vitale, M. (2000), "Consumer trust in an internet store", *Information Technology and Management*, Vol. 1 No. 1, pp. 45-71.

Karimi, S. and Wang, F. (2017), "Online review helpfulness: impact of reviewer profile image", *Decision Support Systems*, Vol. 96, pp. 39-48, doi: 10.1016/j.dss.2017.02.001.

Kirshner, S.N. and Moritz, B.B. (2022), "For the future and from Afar: psychological distance and inventory decision-making", *Production and Operations Management*, Vol. 32 No. 1, pp. 170-188, doi: 10.1111/poms.13829.

Korfiatis, N., García-Bariocanal, E. and Sánchez-Alonso, S. (2012), "Evaluating content quality and helpfulness of online product reviews: the interplay of review helpfulness vs review content", *Electronic Commerce Research and Applications*, Vol. 11 No. 3, pp. 205-217, doi: 10.1016/j.elerap.2011.10.003.

Lam, T., Heales, T. and Hartley, N. (2023), "The role of positive online reviews in risk-based consumer behaviours: an information processing perspective", *Aslib Journal of Information Management*, Vol. 77 No. 2, pp. 282-305, doi: 10.1108/ajim-03-2023-0102.

Li, M. and Huang, P. (2020), "Assessing the product review helpfulness: affective-cognitive evaluation and the moderating effect of feedback mechanism", *Information and Management*, Vol. 57 No. 7, 103359, doi: 10.1016/j.im.2020.103359.

Lu, B. and Chen, Z. (2021), "Live streaming commerce and consumers' purchase intention: an uncertainty reduction perspective", *Information and Management*, Vol. 58 No. 7, 103509, doi: 10.1016/j.im.2021.103509.

Ma, Y., Yao, Z., Zhang, J. and Tang, P. (2024), "Unveiling the impacts of performance-contingent incentivized reviews on subsequent supplementary reviews", *Information Processing and Management*, Vol. 61 No. 3, 103692, doi: 10.1016/j.ipm.2024.103692.

McKnight, D.H., Choudhury, V. and Kacmar, C. (2002), "Developing and validating trust measures for e-commerce: an integrative typology", *Information Systems Research*, Vol. 13 No. 3, pp. 334-359, doi: 10.1287/isre.13.3.334.81.

Midi, H., Sarkar, S.K. and Rana, S. (2010), "Collinearity diagnostics of binary logistic regression model", *Journal of Interdisciplinary Mathematics*, Vol. 13 No. 3, pp. 253-267, doi: 10.1080/09720502.2010.10700699.

Moloi, M., Quaye, E.S. and Saini, Y.K. (2022), "Evaluating key antecedents and consequences of the perceived helpfulness of online consumer reviews: a South African study", *Electronic Commerce Research and Applications*, Vol. 54, 101172, doi: 10.1016/j.elerap.2022.101172.

Moore, G.C. and Benbasat, I. (1991), "Development of an instrument to measure the perceptions of adopting an information technology innovation", *Information Systems Research*, Vol. 2 No. 3, pp. 192-222, doi: 10.1287/isre.2.3.192.

Mudambi, S.M. and Schuff, D. (2010), "What makes a helpful review? A study of customer reviews on Amazon.com", *MIS Quarterly*, Vol. 34 No. 1, pp. 185-200, doi: 10.2307/20721420.

Pan, Y. and Zhang, J.Q. (2011), "Born unequal: a study of the helpfulness of user-generated product reviews", *Journal of Retailing*, Vol. 87 No. 4, pp. 598-612, doi: 10.1016/j.jretai.2011.05.002.

Pavlou, P.A., Liang, H. and Xue, Y. (2007), "Understanding and mitigating uncertainty in online exchange relationships: a principal-agent perspective", *MIS Quarterly*, Vol. 31 No. 1, pp. 105-136, doi: 10.2307/25148783.

Qiao, D., Lee, S.Y., Whinston, A.B. and Wei, Q. (2020), "Financial incentives dampen altruism in online prosocial contributions: a study of online reviews", *Information Systems Research*, Vol. 31 No. 4, pp. 1361-1375, doi: 10.1287/isre.2020.0949.

Racherla, P. and Friske, W. (2012), "Perceived 'usefulness' of online consumer reviews: an exploratory investigation across three services categories", *Electronic Commerce Research and Applications*, Vol. 11 No. 6, pp. 548-559, doi: 10.1016/j.elerap.2012.06.003.

Senecal, S. and Nantel, J. (2004), “The influence of online product recommendations on consumers’ online choices”, *Journal of Retailing*, Vol. 80 No. 2, pp. 159-169, doi: 10.1016/j.jretai.2004.04.001.

Shen, T., Dai, Q., Wang, R. and Gou, Q. (2015), “The impact of online additional reviews on consumer’s purchase process”, *International Journal of Information Systems and Social Change*, Vol. 6 No. 1, pp. 24-40, doi: 10.4018/ijissc.2015010102.

Tang, T., Fang, E. and Wang, F. (2014), “Is neutral really neutral? The effects of neutral user-generated content on product sales”, *Journal of Marketing*, Vol. 78 No. 4, pp. 41-58, doi: 10.1509/jm.13.0301.

Thomas, M.J., Wirtz, B.W. and Weyerer, J.C. (2019), “Determinants of online review credibility and its impact on consumers’ purchase intention”, *Journal of Electronic Commerce Research*, Vol. 20 No. 1, pp. 1-20.

Trope, Y. and Liberman, N. (2010), “Construal-level theory of psychological distance”, *Psychological Review*, Vol. 117 No. 2, pp. 440-463, doi: 10.1037/a0018963.

Wang, Y., Tariq, S. and Alvi, T.H. (2021), “How primary and supplementary reviews affect consumer decision making? Roles of psychological and managerial mechanisms”, *Electronic Commerce Research and Applications*, Vol. 46, 101032, doi: 10.1016/j.elerap.2021.101032.

Wu, C., Mai, F. and Li, X. (2021), “The effect of content depth and deviation on online review helpfulness: evidence from double-hurdle model”, *Information and Management*, Vol. 58 No. 2, 103408, doi: 10.1016/j.im.2020.103408.

Xu, W., Yao, Z., He, D. and Cao, L. (2023), “Understanding online review helpfulness: a pleasure-arousal-dominance (PAD) model perspective”, *Aslib Journal of Information Management*, Vol. 77 No. 2, pp. 391-412, doi: 10.1108/ajim-04-2023-0121.

Yin, D., Mitra, S. and Zhang, H. (2016), “When do consumers value positive vs negative reviews? An empirical investigation of confirmation bias in online word of mouth”, *Information Systems Research*, Vol. 27 No. 1, pp. 131-144, doi: 10.1287/isre.2015.0617.

Zhao, Y., Wen, L., Feng, X., Li, R. and Lin, X. (2020), “How managerial responses to online reviews affect customer satisfaction: an empirical study based on additional reviews”, *Journal of Retailing and Consumer Services*, Vol. 57, 102205, doi: 10.1016/j.jretconser.2020.102205.

Zhou, H. and Li, S.J. (2017), “The impact of online additional comments on consumers’ information adoption”, *Sociology Mind*, Vol. 7 No. 2, pp. 60-71, doi: 10.4236/sm.2017.72005.

Zhu, L., Yin, G. and He, W. (2014), “Is this opinion leader’s review useful? Peripheral cues for online review helpfulness”, *Journal of Electronic Commerce Research*, Vol. 15 No. 4, pp. 267-280.

Zhu, Z., Liu, J. and Dong, W. (2022), “Factors correlated with the perceived usefulness of online reviews for consumers: a meta-analysis of the moderating effects of product type”, *Aslib Journal of Information Management*, Vol. 74 No. 2, pp. 265-288, doi: 10.1108/ajim-02-2021-0054.

Zhu, Z., Zhao, Y. and Wang, J. (2024), “The impact of destination online review content characteristics on travel intention: experiments based on psychological distance perspectives”, *Aslib Journal of Information Management*, Vol. 76 No. 1, pp. 42-64, doi: 10.1108/ajim-06-2022-0293.

About the authors

Benjiang Lu is an Associate professor in the School of Management, Lanzhou University. He received his Ph.D. in Management Science and Engineering from Tsinghua University. His recent research interests include live streaming, online community and consumer behavior. He has published papers in ranked journals such as *Journal of Management Information Systems, Information and Management, Decision Support Systems, International Journal of Electronic Commerce, Electronic Commerce Research, Computers in Human Behaviors, Journal of Systems Science and Systems Engineering*, and others.

Baojun Ma is a professor at School of Business and Management, Shanghai International Studies University, who has received his Ph.D. degree and the bachelor degree both from Tsinghua University. He is also the Deputy Director and Principal Investigator of Key Laboratory of Brain-Machine Intelligence for Information Behavior (Ministry of Education and Shanghai). His research interests focus on brain-machine intelligence for information behavior, mobile big data analytics and financial technology. His work has been published in journals such as *INFORMS Journal on Computing, Information and Management, Information Sciences, Information Processing and Management, Electronic Commerce Research and Applications, Computers in Human Behavior*, and others. Baojun Ma is the corresponding author and can be contacted at: mabaojun@shisu.edu.cn