Journal of Retailing and Consumer Services 81 (2024) 103980

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: www.elsevier.com/locate/jretconser

Impact of heuristic–systematic cues on the purchase intention of the electronic commerce consumer through the perception of product quality

Elena Rosillo-Díaz [a], Juan Francisco Muñoz-Rosas [b], Francisco Javier Blanco-Encomienda [a,*]

[a] Faculty of Education, Economy and Technology, University of Granada, c/ Cortadura del Valle, s.n., 51001, Ceuta, Spain
[b] Faculty of Economics and Business Administration, University of Granada, Campus Universitario de Cartuja, s.n., 18071, Granada, Spain

ARTICLE INFO

Keywords:
Perceived product quality
Heuristic–systematic model
Dual-process theory
Purchase intention
e-commerce

ABSTRACT

For electronic commerce (e-commerce) consumers, it is impossible to evaluate the quality of the products on offer as they are unable to physically test them before purchase. Therefore, sellers must convey quality cues that are readily identifiable to such consumers. However, thanks to major technological advances and the development of social interaction systems on e-commerce platforms, individuals can now access large volumes of information (reviews, opinions, ratings) posted directly by fellow consumers, which can also provide cues by which to judge product quality, pre-purchase. Based on dual-process theory and signaling theory, the objective of this study is to analyze the impact of the heuristic or systematic cues related to electronic word-of-mouth on consumer perceived product quality, to determine how this quality affects perceived product performance risk and consumer purchase intention. A quantitative approach was taken using a structured online questionnaire. Data were collected from 835 consumers of e-commerce platforms and analyzed using maximum likelihood structural equation modeling and LISREL software. The results show that the quantity of reviews, source credibility, review usefulness, and brand experience all exert a positive and significant effect on perceived product quality, which, in turn, positively and significantly influences purchase intention. A negative and significant relationship between product performance risk and purchase intention is also found. The findings contribute to the literature by improving our understanding of those determinants of perceived product quality in e-commerce that motivate consumers to make a purchase and can help sellers improve their use of integrated social interaction tools to adequately reflect the quality of their products.

1. Introduction

The popularity of e-commerce is such that it is now ubiquitous, largely thanks to the wide range of benefits it offers to both consumers and sellers (Rahayu and Day, 2017). By 2021, 77% of internet users globally were making purchases via e-commerce platforms (Kemp, 2021). Yet, despite the unquestionable advantages it offers to both sellers and consumers, the latter are faced with the drawback of not being able to physically test products while shopping. For sellers, this creates the complex challenge of how to convey the right cues that do justice to the products on offer by accurately reflecting their quality (Mavlanova et al., 2016; Miyazaki et al., 2005). However, it is far from straightforward to adequately convey information about the quality of their products using cues (Xiao et al., 2016). Thus, in recent decades, research into consumer perceptions of quality has increasingly focused on the e-commerce context (Lee and Lin, 2005; Rosillo-Díaz et al., 2022; Sullivan and Kim, 2018).

In light of the evolution of new technologies, signaling theory has been used in the context of e-commerce to analyze quality cues such as website quality (Mavlanova et al., 2012; Wells et al., 2011), website reputation and pricing (Sullivan and Kim, 2018), the effectiveness of market popularity (Yu et al., 2018a), quality/certification marks (Yu et al., 2018b), and website characteristics (Lee et al., 2019a). But the clearest and most important cue on an e-commerce platform is the information that is provided to consumers about the product (Lee et al., 2019a). And, to compensate for the fact that they cannot interact with products on such platforms, consumers not only turn to the firm's product description for that information but also show even greater trust in the feedback provided by other consumers who have made previous purchases (Moro et al., 2017). For this reason, online reviews are considered one of the main sources of information that enable consumers to gauge the quality of the products or services offered on

* Corresponding author. University of Granada, Faculty of Education, Economy and Technology, 51001, Ceuta, Spain.
E-mail addresses: erosillo@ugr.es (E. Rosillo-Díaz), jfmunoz@ugr.e (J.F. Muñoz-Rosas), jble@ugr.es (F.J. Blanco-Encomienda).

https://doi.org/10.1016/j.jretconser.2024.103980
Received 21 January 2024; Received in revised form 19 May 2024; Accepted 28 June 2024
Available online 2 July 2024

e-commerce platforms (Cai et al., 2023; Yang et al., 2016).

Therefore, in contrast to the past, when the buying public relied on the ads produced by the firms themselves and the information disseminated by reference groups or individuals, today's consumers can also consult information shared online by their fellow consumers (Li and Hitt, 2008). However, the fact that the product information shared by other consumers across different digital media is now so abundant and widely dispersed means that people have to use simplifying heuristics in order to process it meaningfully (King et al., 2014). Here, dual-process theories come into play in attempting to comprehend how individuals process information and, more specifically, the influence that online reviews exert on users (Yeon et al., 2019; Zhang et al., 2014).

Multiple studies have analyzed the effect of certain heuristic and systematic cues on different variables in the digital environment. For example, Vijay et al. (2017) examined the effect of quantity of reviews and source credibility on perceived value in online shopping. Ruiz-Mafe et al. (2020) analyzed the impact of TripAdvisor review usefulness on emotions. And Cheong et al. (2020) studied the impact of review quantity on online purchase intention. However, while many studies suggest that these cues or signals may reflect product quality (Kordrostami and Rahmani, 2020; Xu et al., 2020), they do not analyze the actual impact of these cues on perceived product quality. Thus, there is an important gap in the literature regarding certain cues that derive from electronic word-of-mouth (eWOM) that can be processed heuristically or systematically, bearing in mind that, thanks to technological advances in recent decades, consumers can now access an immense amount of product information easily and instantly (Gursoy, 2019).

Thus, more research is called-for to analyze how product-quality cues related to online review tools influence consumer purchase behavior, addressing any type of product and any age group (Flanagin et al., 2014; Kim, 2021). Such research is needed as a starting point for future studies into the determinants of perceived quality in e-commerce. The present study therefore seeks to better understand how certain forms of eWOM reflect product quality and how this perceived quality, in turn, affects consumer purchase behavior.

A further gap in the literature is concerned with the possible determinants and consequences of different types of risks in e-commerce, which requires deeper investigation by marketers (Guru et al., 2020). Specifically, greater research insights are needed on the impact of certain types of risks—particularly, product performance risk—on purchase intention, due to a lack of conclusive evidence and the existence of intense debate in certain contexts (Dai et al., 2014; Paluch and Wünderlich, 2017).

In the context of e-commerce, although we were able to identify some relevant studies, none examines the specific question of how perceived product performance risk—a perception that the consumer picks up from certain eWOM cues that signal product quality—influences purchase intention. Therefore, the objective of the present study is to analyze the effect of perceived product quality—which the consumer derives from specific eWOM cues available on e-commerce platforms (quantity of reviews, source credibility, review usefulness, and brand experience)—on perceived product risk and purchase intention. The study also seeks to determine which of these cues results in greater perceived quality. Given the research gaps identified here, the following research questions are addressed.

RQ1: What is the effect of social interaction (eWOM) cues available on e-commerce platforms (quantity of reviews, source credibility, review usefulness, and brand experience) on perceived product quality?
RQ2: What is the influence of perceived product quality on perceived product performance risk and purchase intention on e-commerce platforms?
RQ3: What is the impact of product performance risk on purchase intention in e-commerce?

The paper is organized as follows. Section 2 presents a comprehensive review of the relevant research in the field. Section 3 explains the methodology employed in this study. Section 4 presents the results and analysis. Finally, Section 5 presents a discussion of the findings and their implications, and outlines potential directions for future research.

2. Literature review and hypotheses

2.1. Dual-process theory applied to the analysis of product quality

Thanks to the major advances in information and communication technologies and the Internet, it is now easier than ever before, for sellers and consumers alike, to offer and access vast volumes of information (Gursoy, 2019; Zhang et al., 2014). The two most widely used dual-process models in the literature are the elaboration likelihood model or ELM (Petty and Cacioppo, 1986) and the heuristic–systematic model or HSM (Chaiken, 1980), with the two approaches sharing certain core premises.

On the one hand, the central processing route in the ELM and systematic information-processing in the HSM both hold that individuals exert a high degree of cognitive effort to process information. On the other hand, the peripheral processing route in the ELM and heuristic information-processing in the HSM are both premised on the idea that individuals use simple rules to make judgments quickly and easily. The two models, then, reflect equivalent mechanisms for understanding and explaining how individuals process information (Zhang et al., 2014).

The HSM model has been applied in fewer studies than the ELM. However, it is attracting growing interest from information systems researchers. Among the authors who favor studies dealing with HSM theory in information systems are Zhang et al. (2014), who concluded that source credibility and the quantity of reviews, perceived as heuristic factors, influence the quality of the argument conveyed by the review, as a systematic factor, and that the latter impacts on consumer intention. From that study onward, many researchers have begun to apply the HSM model as a dual-process theory to analyze information-processing. For example, Xu and Yao (2015) found that the argument quality of online reviews positively influences the adoption of those reviews and their perceived value, and that the credibility of the information and the desirable amount of information contained in a review both positively influence argument quality. Thus, in the absence of literature on the effect of the aforementioned cues interpreted through heuristic–systematic processing, in the present study we consider "quantity of reviews" as a heuristic cue, and review usefulness, source credibility, and brand experience as systematic cues.

2.1.1. The impact of the quantity of reviews on perceived product quality

The mere quantity of consumer reviews that a product receives is considered a useful decision rule for consumers making purchasing judgments (Todorov et al., 2002). This is a heuristic factor that gives rise to perceptions originating from heuristic processing (Zhang et al., 2014), with reviews constituting relevant information-processing cues. Consumers who take into account the number of online reviews tend to take the heuristic information-processing route. This means that they are more likely to be drawn to products with multiple customer reviews than those with few or none. Similarly, when considering those products that have received a high number of reviews, investing minimal effort in reading only a handful of positive comments will often suffice for these consumers to make a purchasing decision (Vijay et al., 2017).

Cues that hint at the popularity of a product positively affect perceptions of product quality (Dean, 1999). For instance, the quantity of reviews that consumers share about a given product may act as a sign of its popularity and the strength of WOM it has attracted (Cui et al., 2012; Park and Kim, 2008). Zhang et al. (2014) observe that the perceived number of reviews acts as an indicator of the popularity of products on websites that feature integrated social interaction tools. This is because a larger number of comments equates to a higher volume of previous sales of the product, which can suggest to potential consumers that it is widely accepted (Duan et al., 2008) and thus prompt greater confidence in making a purchase. In essence, users who perceive a significant quantity of reviews are likely to imitate the behavior of the consumers of the product in question (Zhang et al., 2014).

Over the last several decades, various studies have examined how the quantity of customer reviews received by a product influences purchasing behaviors. These studies have analyzed such effects on the sales of products and/or services in different fields and products such as books on Amazon (Chevalier and Mayzlin, 2006), coffee shops (Huyen and Costello, 2017), movies (Duan et al., 2008), or video games (Zhu and Zhang, 2010). In addition, the existence of a large number of reviews has been shown to exert a significant effect on consumer purchase intention (Huyen and Costello, 2017). In all these studies, it was found that the presence of a large number of reviews made a positive impact on product sales.

It has been demonstrated that consumers tend to leave online reviews for a product they have purchased and used when that product is of high quality (Chen et al., 2004). In so far as this is true, it suggests that a high number of online reviews for a given product may indicate to potential consumers that it is of a relatively high quality. In this regard, users' product reviews and ratings now occupy an important place in consumer decision-making as a result of their ability to provide information about product quality in the market (Xie et al., 2016). Jeong and Kwon (2012) also found that perceptions of product quality can be affected by the experiences and opinions that consumers share about their purchases on online platforms. The number of online reviews, then, may act as a heuristic cue for consumers who are making purchase decisions (Zhang et al., 2014).

Indeed, since the earliest days of e-commerce, studies have been showing that the number of reviews can be understood as a quality cue (Hellofs and Jacobson, 1999). For example, Chen et al. (2004) found that the quantity of reviews on electronic platforms increases perceived product quality, and Metzger et al. (2010) concluded through focus groups that the quantity of reviews is relevant for judging products. However, more recent studies were not able to confirm this positive relationship. For example, Flanagin et al. (2014) claim that the quantity of reviews is a necessary but insufficient cue to perceive product quality. Likewise, Filieri (2015) confirms that the quantity of reviews is not perceived by consumers to be an indicator of product performance or quality.

Therefore, the need for further research on the study of the number of reviews as a determinant of perceived product quality in the e-commerce environment is highlighted (Flanagin et al., 2014; Sigurdsson et al., 2020). Thus, to respond to the described controversy and to extend the research in this context, based on the presented results, it is suggested that product quality can be perceived by the popularity of a product quantified, for example, by the number of reviews. We therefore hypothesize that:

H1. The quantity of reviews increases perceived product quality among consumers on e-commerce platforms.

2.1.2. *The impact of source credibility on perceived product quality*

The credibility of the information source is one of the fundamental heuristic cues in information-processing (Sussman and Siegal, 2003; Zhang et al., 2014). On websites with social interaction tools, any consumer can share their experience of products and/or services, brands, companies, or sellers (Vijay et al., 2017). If individuals choose to consult the information (opinions, evaluations, feedback) shared online by other consumers, there is a greater need for them to judge the credibility of those sources than when considering information shared by people known to them, such as friends or family, in offline settings (Flanagin et al., 2014).

Thus, the credibility of the source is a primary factor used by consumers when evaluating the information disseminated on websites (Wathen and Burkell, 2002; Zhang and Watts, 2008). When individuals consider the product information to have been written by a credible consumer, they will perceive that information to be useful and valuable, which increases the likelihood of purchasing the product (Hussain et al., 2017; Ismagilova et al., 2020; Kaushik et al., 2018; Vijay et al., 2017). It can be said, then, that consumers' judgment and choices will depend on the source—that is, on whoever transmitted the information about the product in an e-commerce setting (Brown et al., 2007).

As noted earlier, when the source of the product information disseminated online (in this case, product reviews) is perceived to be credible, this increases consumer perceived quality in e-commerce (Duarte and e Silva, 2020). However, what remains unclear is whether consumers would automatically go to the trouble of scrutinizing the online profile of the source to judge its trustworthiness in evaluating product performance and quality (Filieri, 2015). Some recent research, such as the study by Loureiro et al. (2018), concludes that consumers with e-commerce experience do not care about reviewer credibility because they are more independent and self-confident when it comes to making purchasing decisions.

Therefore, although there are several studies dealing with source credibility, there is a discernible gap in the literature in the field of signaling theory, in which the effect of such credibility is analyzed as a cue indicating product quality on e-commerce platforms. If we assume that the greater the credibility of the source, the greater the perceived utility and value of the information, it follows that source credibility can help inform perceptions of whether a product is of quality or not. Thus, we hypothesize that:

H2. Information-source credibility increases perceived product quality among consumers on e-commerce platforms.

2.1.3. *The impact of review usefulness on perceived product quality*

More and more consumers are sharing their reviews on various online platforms via interaction tools—a phenomenon that is causing certain complexities in identifying useful and relevant information about goods or services, due to the information overload it can create for consumers (Cao et al., 2011). To address this challenge, various e-commerce platforms have implemented a system that prioritizes customer product reviews according to the usefulness of the review itself, as rated by platform users (Siering et al., 2018). The thinking behind this move is that inviting users to vote on the usefulness of the reviews published on the platform will make it easier to attract consumers who are looking for information about products (Malik and Hussain, 2017).

Review usefulness has been defined as the measure of perceived value that helps the consumer during the decision-making process (Kaushik et al., 2018; Mudambi and Schuff, 2010). A useful review is one that describes aspects and characteristics of the product, such that it enables consumers to evaluate its quality (Zheng et al., 2013). However, some segments of the academic literature suggest that the usefulness scoring system can be too easily manipulated (Pan and Zhang, 2011) and that this mechanism is vulnerable to certain biases as a result of the tendency for reviews that have been online for longer to obtain a greater number of votes and, as a consequence, receive greater attention (Li et al., 2013).

Baek et al. (2012) analyze the usefulness variable and find that it is influenced by the credibility of the review and the rating given to it by users. The positive effect of review quality on review usefulness on the Amazon platform has also been studied and affirmed (Chua and Banerjee, 2016). According to Jiang and Benbasat (2004, 2007), the usefulness of the information disseminated by consumers on the platform enables potential consumers to gauge the quality of the product in question. Going a stage further, Siering et al. (2018) examine the relationship between the nature of the review and consumer decision-making. They find that, in an information-heavy environment, the review must present quality cues and product sentiment to be useful to someone making purchase decisions. Filieri (2015) also shows that a useful review enables people to evaluate the quality and performance of the product before purchasing it.

On this basis, we propose the following hypothesis:

H3. Review usefulness increases perceived product quality among consumers on e-commerce platforms.

2.1.4. The impact of brand experience on perceived product quality

Brand experience is a concept that began to enjoy popularity among marketing researchers in the 1990s, when scholars began to focus on the consumer experience surrounding products or services (Chang, 2018). Since then, this concept has been gaining more and more relevance across a range of research areas as it is an essential element in maintaining relationships with consumers in the post-purchase phase (Nayeem et al., 2019; Park et al., 2023).

The brand experience construct is measured using different dimensions of consumer response: the sensory experience, which includes the visual aspects of the brand that are perceived by consumers through the senses; the affective experience, which refers to the subjective experiences derived from the consumer's internal emotions and feelings; the cognitive experience, which is concerned with aspects that stimulate analytical or imaginative thinking; and the behavioral experience, which is about the actions, day-to-day habits, and experiences generated through interacting with the brand (Brakus et al., 2009; Hwang and Hyun, 2012).

Importantly, consumers do not experience the brand only in traditional commerce but also in e-commerce, since they can now share their experiences and feelings about the brand with each other whenever they want, thanks to the vast possibilities offered by the Internet (Wang et al., 2015). Thus, the consumer can experience a brand when interacting either directly (physically) with the product or indirectly (through online content) (Schmitt et al., 2015). For example, in offline and online settings alike, visual stimuli come into play when the consumer analyzes the product to assess its quality and make a purchase decision (Atulkar, 2020). In the online context, such stimuli may include photographs shared by customers of the product in use, as well as the images provided by the seller as part of the product description (Vazquez et al., 2023).

Despite suggestions that a satisfactory brand experience may indicate that the firm cares about its consumers and thus offers quality products (Khan and Rahman, 2016), few studies have analyzed the brand experience as a cue that consumers use to identify the quality of products in the context of e-commerce. Duarte and e Silva (2020) confirmed that brand experience acts as a determinant of perceived product quality in the online sale of products. More recently, Beig and Nika (2022) found that the four dimensions of brand experience (sensory, affective, behavioral, and intellectual) positively influence the four dimensions of brand equity (brand awareness, brand association, brand loyalty, and perceived quality) in online shopping. Similarly, Tran et al. (2023) found that brand experience is positively related to perceived product quality when consumers are exposed to brands advertised online.

In light of these findings, it may be the case that, when consumers have previously enjoyed a good experience with the product of a given brand, this will positively influence their perceptions of the quality of products sold by that brand on the e-commerce platform. On this basis, we hypothesize that:

H4. Brand experience increases perceived product quality among consumers on e-commerce platforms.

2.2. Perceived product quality and performance risk in e-commerce

Perceived risk can be defined as the extent of uncertainty a consumer perceives when making a purchase decision about a specific product (Uhm et al., 2022). Forsythe and Shi (2003) defined perceived risk as the consumer's subjective expectation of potential loss at the point of making a transaction on a shopping website. In the online context generally, the literature examines performance, financial, privacy, time, psychological, social, and delivery risk (Chiu et al., 2014; Forsythe and Shi, 2003; Lee and Moon, 2015).

Several researchers have found that perceived product quality negatively influences consumer perceived risk in traditional commerce (Beneke et al., 2015; Snoj et al., 2004). With regard to e-commerce transactions, it has also been concluded in the literature that the higher the perceived quality of the product, the lower the consumer perceived risk (Chen and Dubinsky, 2003; Snoj et al., 2004). Perceived performance risk is arguably the type of risk that is inherently most closely related to perceived product quality being based on the fear that the product will actually not meet an expectation or given standard. For this reason, in traditional commerce, the effect of perceived performance risk on perceived product quality has been analyzed extensively, with researchers verifying that the former negatively impacts the latter (Vo and Nguyen, 2015).

Likewise, due to the impossibility of physically verifying the quality of a product before making an online purchase, the consumer is uncertain as to whether it will meet the standard specified on the shopping platform and match the performance and/or appearance (color, shape, size) in the product description (Garbarino and Strahilevitz, 2004). It is this uncertainty regarding the standard—quality—of the purchased product that causes the consumer to perceive performance risk, which implies a loss to them if the purchased product fails to meet their quality expectations (Ariffin et al., 2018). In fact, it is known that when consumers have less information about the product they wish to purchase on the platform, they perceive a higher performance risk (Nepomuceno et al., 2014). Moreover, in e-commerce, when the effect of perceived product quality on performance risk has been analyzed, studies have confirmed that, when the consumer perceives high product quality, their perception of product risk is lessened (Eryiğit and Fan, 2021).

Therefore, it appears that, in e-commerce, perceived product quality is essential to minimize certain risk perceptions, such as that relating to product performance. However, more research is needed to further investigate this relationship, as studies on this question are limited. Thus, we propose that:

H5. Perceived product quality reduces perceived product performance risk among consumers on e-commerce platforms.

2.3. Online purchase intention

2.3.1. Impact of perceived product quality on purchase intention in e-commerce

The perceived quality of a product offered on e-commerce platforms is one of the primary determinants in encouraging consumers to make the purchase. This is especially so if it is the first time they are acquiring that particular product (Wang et al., 2010), given the information asymmetry that exists regarding quality, which prompts consumers to seek relevant information before making a purchase decision (Tang et al., 2023; Xiao et al., 2023; Zhao et al., 2022).

As Sullivan and Kim (2018) observe, the relationship between perceived quality and purchase decision-making or behavior has been widely tested and analyzed in the literature, especially in traditional commerce (Chong et al., 2022; Lee et al., 2019b) but also in the e-commerce context (Colamatteo et al., 2021; Konuk, 2018; Mavlanova et al., 2016; Wells et al., 2011). In this online context, perceived product quality has been shown to positively influence consumers' purchase intention (Boon et al., 2018; Flanagin et al., 2014; Mavlanova et al., 2016; Wells et al., 2011). For instance, Konuk (2018) finds that the perceived quality of private-label organic products increases consumers' purchase intention. Similarly, Nofrizal et al. (2023) show that perceived product quality positively influences purchase intention for fashion products in e-commerce. Conversely, product-quality uncertainty has been shown to reduce consumer purchase intention (Chen et al., 2023;

Lu and Chen, 2021), which supports the positive relationship between quality perceptions and purchase intention: if there were no uncertainty about quality, the predisposition to buy would be greater.

In this sense, a positive relationship has been demonstrated between the perceived quality of different types of products and purchase intention in e-commerce. However, little is known about the impact of perceived quality when this is derived from product information provided via different social interactions or eWOM cues on such platforms. Thus, given the smaller number of studies identified in the context of e-commerce, it is of interest to continue expanding the field of research on perceived quality in e-commerce, particularly regarding the effects of the different cues available on the different platforms. In addition, the impossibility of physically testing the products in the online context renders perceived product quality even more interesting. Thus, based on the literature review, we propose the following hypothesis:

H6. Perceived product quality increases purchase intention among consumers on e-commerce platforms.

2.3.2. Impact of perceived product performance risk on purchase intention in e-commerce

Risk perception is a key element in an individual's purchasing behavior (Hussain et al., 2017). This is because all purchases generate a feeling that one can either stand to gain or lose from the transaction, which causes a certain level of risk and uncertainty (Chen et al., 2023). The perception of risk is even greater in e-commerce than in traditional settings (Ariffin et al., 2018). For several decades, researchers have analyzed the impact of perceived risk on purchase/repurchase intention, especially in the online context, concluding that the risk perceived by the consumer can reduce their purchase intention (Baek and King, 2011; Chang and Chen, 2008).

However, according to Dai et al. (2014), there is a marked lack of consensus regarding the effect of risk on purchase intention. Some scholars find a negative impact on purchase intention (Chang and Chen, 2008; Sullivan and Kim, 2018), while others identify no significant effect between some types of risk and purchasing behavior (Forsythe and Shi, 2003; Liu and Wei, 2003).

Hong and Cha (2013) analyzed the effect of performance, psychological, social, financial, online payment, and delivery risks on the purchase intention of consumers of Korea's first e-commerce platform (Interpark.com). They concluded that these types of risk negatively influence purchase intention, with the exception of social and delivery risk. Elsewhere, Dai et al. (2014) analyzed the impact of product, financial, and privacy risks on online purchase intention and confirmed the negative effect of product and financial risk on such intention. Likewise, Ariffin et al. (2018) found that financial, performance, security, time, and psychological risks negatively influence purchase intention among consumers on Malaysian e-commerce platforms.

Ahmad et al. (2020) concluded that price and product risk dampen consumers' purchase intention on e-commerce platforms. Similarly, Lakchan and Samaraweera (2022) analyzed the effect of different types of risks—financial, product, security, time, psychological, and delivery risk—on purchase intention moderated by eWOM, finding that financial, psychological, delivery, security, and product risk negatively and significantly influence purchase intention toward online fashion products. Likewise, Yuniarti et al. (2022) confirmed a negative and significant effect of product risk on online retail consumer repurchase intention. However, Munikrishnan et al. (2023) could not confirm a significant relationship between food product performance risk and online purchase intention.

Despite the large body of existing research examining the impact of perceived risk on consumer behavior, it is necessary to take risk into account in the proposed model as it is a strong predictor of e-commerce consumer purchase intention. Furthermore, more research is required on the effects of certain types of risk on purchase intention due to the lack of conclusive evidence in certain contexts, especially perceived product performance risk (Dai et al., 2014; Paluch and Wünderlich, 2017). On this basis, we hypothesize that:

H7. Perceived product performance risk reduces purchase intention among consumers on e-commerce platforms.

3. Method

3.1. Measurement

Using a structured online questionnaire, a web survey was conducted to study the impact of heuristic–systematic cues on the purchase intention of e-commerce consumers, via perceived product quality. The questionnaire was administered in the United States and Spain, and, accordingly, two versions were produced, one in English and one in Spanish. For both versions of the questionnaire, the back-translation technique proposed by Brislin (1970) and used in recent research (Elshaer et al., 2024) was employed.

To generate the constructs of the variables under study and design the measurement instrument, the literature was rigorously reviewed, to ensure the concurrent validity of each of the constructs (Berger et al., 2020). The measurement items used here were drawn from previous research that has shown them to offer good reliability and validity, which has supported the formulation of our research hypotheses and the approach we adopted in creating the proposed structural model. Seven-point Likert scales were used in the questionnaire (where 1 = "strongly disagree" and 7 = "strongly agree"). Quantity of reviews was measured using a 3-item scale adapted from Zhang et al. (2014). Source credibility was measured using four items adapted from the scale used by Cheung et al. (2008). Review usefulness was measured using three items adapted from the scales proposed by Sen and Lerman (2007) and Yin et al. (2014). Brand experience was measured using 12 items adapted from the scales developed by Brakus et al. (2009) and Beig and Nika (2022).

To measure perceived product quality, a 4-item scale adapted from the work of Buil et al. (2013) was used. Performance risk was measured using a 3-item scale adapted from Hong and Cha (2013). Lastly, purchase intention was measured using four items adapted from the scale used by Sullivan and Kim (2018).

Prior to its dissemination, the questionnaire was submitted for review to a group of experts in marketing and market research for their feedback. This step was included to ensure that the scale items were correctly adapted to our study, were worded correctly, and achieved the intended understanding. Based on the comments and suggestions made by these experts, some changes were made to the wording and format.

3.2. Data collection and sample

The data used in this study derive from the aforementioned web survey disseminated in the United States and Spain by a multinational panel provider during July 2022, which was required to fulfill certain quotas in terms of age, gender, and country of origin. This company digitally disseminated the link to the online questionnaire to the users of the panels in both countries.

As recommended and performed in previous research in the context of e-commerce (Cheah et al., 2022; Lim et al., 2022), non-probabilistic sampling was conducted to collect the data, using a purposive approach. All the individuals selected to be part of the research were consumers of e-commerce platforms. To select the respondents, potential participants were first asked if they made purchases through any e-commerce platform, and only those who answered "yes" were invited to continue the questionnaire. In addition, to check that respondents definitely had experience of making purchases through e-commerce, an open-ended and compulsory question was included, asking them to indicate which platform they most frequently used. They were then requested to answer the entire questionnaire in the context of this preferred platform. A control question was also added to rule-out those individuals who did not pay close enough attention to the questions.

After applying the selected inclusion criteria and eliminating cases in which subjects did not correctly complete the questionnaire, the final sample comprised 835 consumers who use e-commerce platforms—415 from the United States and 420 from Spain. Table 1 summarizes the sample description.

Non-response bias was tested using a *t*-test. For this purpose, the mean response times of two groups of respondents were compared: late-response respondents and early-response respondents (Elshaer et al., 2024). The results of the *t*-test pointed to significant relationships between the two groups, which indicates that the results of this study were not affected by non-response bias (Bryman and Cramer, 2012). Likewise, the Shapiro–Wilk and Kolmogorov-Smirnov tests were performed, the values of which highlighted the significance of all the variables under study. For even greater precision, a skewness and kurtosis analysis was performed. It showed that the values of the statistic were within the values recommended by the literature (−3 and +3), thus confirming that there were no problems in the assumption of normality of the data distribution (Hair et al., 2021; Sadiq et al., 2021).

Note that, once the data were collected, descriptive analyses were performed using IBM SPSS software. Likewise, the measurement model was evaluated to check the psychometric properties of the measurement scales used, as well as the proposed structural model by means of a structural equation model using LISREL software, which allows estimation by robust maximum likelihood.

3.3. Common method bias

Taking into account the methodology used by Chen et al. (2021) and Kock et al. (2021), since the present study was based on a self-administered questionnaire for data collection and the data came from a single panel provider, it was necessary to carry out Harman's single-factor test to test for the existence of possible common method bias (Mackenzie et al., 2005; Podsakoff et al., 2003). This test indicates that if the unrotated solution with all the items to be measured accounts for more than 50% of the variance, the scale and observations obtained present common method bias (Fuller et al., 2016). After performing the aforementioned test on the seven variables under study that constitute the conceptual model, it was observed that the total variance extracted by one factor was 48.34%, which is below the recommended threshold of 50%. Thus, it can be affirmed that the results of the present study are not influenced by common method bias.

3.4. Measurement invariance

Since the sample comprised consumers from the United States and Spain, the measurement invariance was analyzed using multiple-sample confirmatory factor analysis (CFA) to assess whether the study constructs had the same meaning across the two groups of respondents (Byrne, 2016). The model for each group surpassed the model fit-indices thresholds (Alrawad et al., 2023), thus confirming measurement invariance.

4. Results and analysis

4.1. Analysis of measurement model

The quality of a measurement instrument is based on, and measured by, reliability and validity. To analyze the convergent validity and the discriminant validity of the constructs, a CFA was performed using maximum likelihood estimation (MLE) (Hair et al., 2010). For convergent validity, we calculated individual reliability, standardized coefficients, composite reliability (CR), and average variance extracted (AVE). These values are considered acceptable if they are greater than 0.50, 0.70, 0.70, and 0.50, respectively (Fornell and Larcker, 1981). The results reflected values in line with the thresholds recommended in the literature. The measurement model reflected good indicators for overall

Table 1
Sample description.

Variable	Frequency	Percentage
Gender		
Male	386	46.20
Female	438	52.50
Other	11	1.30
Age		
18–24	98	11.70
25–34	195	23.40
35–44	197	23.60
45–54	155	18.60
>54	190	22.80
Educational level		
Primary/Secondary education	297	35.60
Higher education	538	64.40
Employment status		
Student	53	6.30
Employed	501	60.00
Self-employed	95	11.40
Unemployed	85	10.20
Retired	86	10.30
Other	15	1.80
Monthly income (USD/EUR)		
<600	70	8.40
600–1200	127	15.20
1201–1800	154	18.40
1801–2400	146	17.50
2401–3000	93	11.10
3001–4000	86	10.30
>4000	159	19.00

Table 2
Confirmatory Factorial Analysis results.

Factor	Observed variable	Coefficient (t-value)	R^2	CR	AVE
Quantity of Reviews	QR1	0.83*	0.69	0.86	0.67
	QR2	0.80 (24.53)	0.63		
	QR3	0.82 (25.96)	0.67		
Source Credibility	SC1	0.77*	0.60	0.91	0.71
	SC2	0.76 (24.94)	0.58		
	SC3	0.90 (29.22)	0.81		
	SC4	0.92 (29.31)	0.84		
Review Usefulness	RU1	0.80*	0.64	0.88	0.70
	RU2	0.82 (26.08)	0.68		
	RU3	0.89 (32.93)	0.79		
Brand Experience	BE1	0.82*	0.67	0.97	0.72
	BE2	0.83 (34.05)	0.69		
	BE3	0.85 (31.08)	0.71		
	BE4	0.88 (30.33)	0.77		
	BE5	0.89 (30.84)	0.79		
	BE6	0.89 (30.31)	0.78		
	BE7	0.87 (27.56)	0.76		
	BE8	0.87 (27.69)	0.75		
	BE9	0.87 (26.29)	0.76		
	BE10	0.82 (26.39)	0.67		
	BE11	0.78 (24.95)	0.61		
	BE12	0.83 (27.07)	0.70		
Perceived Product Quality	PPQ1	0.85*	0.73	0.92	0.74
	PPQ2	0.85 (33.40)	0.72		
	PPQ3	0.87 (31.72)	0.75		
	PPQ4	0.87 (32.49)	0.76		
Product Performance Risk	PPR1	0.79*	0.62	0.88	0.70
	PPR2	0.88 (21.32)	0.77		
	PPR3	0.84 (21.22)	0.70		
Purchase Intention	PI1	0.82*	0.68	0.89	0.67
	PI2	0.84 (28.86)	0.71		
	PI3	0.79 (25.82)	0.63		
	PI4	0.83 (28.27)	0.70		

goodness-of-fit: SB Chi-Square (df): 1953.36 (474); RMSEA: 0.061; IFC: 0.98; NFI: 0.98; NNFI: 0.98; and IFI: 0.98. Table 2 shows the values for the standardized coefficients, individual reliability, CR, and AVE. Values with * were not calculated because the parameter was established at 1 in order to set the scale for the latent variable.

Discriminant validity was evaluated using the Discriminant Validity Test proposed by Fornell and Larcker (1981), which indicates the extent to which a given construct differs significantly from the rest of the constructs. To conduct this test, it is necessary to build a matrix in which the diagonal reflects the square root of the AVE of the constructs, whose value must be higher than the values located below the diagonal, which correspond to the correlations between constructs. It can be concluded from the results of this test that the proposed measurement model shows acceptable discriminant validity (Table 3). The heterotrait-monotrait (HTMT) method was also used to assess the discriminant validity (Netemeyer et al., 2004). The HTMT values were below the threshold value of 0.85 (Henseler et al., 2015), thus confirming the discriminant validity.

4.2. Analysis of the structural model

To test the research hypotheses, we estimated the proposed model. We used the bootstrap method with 5000 samples and a 95% confidence interval to assess the overall model fit. All the overall goodness-of-fit indicators were within the ranges recommended in the literature (Hair et al., 2010). However, the Satorra-Bentler Chi-square value was not significant, which may be due to the sensitivity of this indicator to sample size. In such scenarios, the normed Chi-square indicator can be used, which entails analyzing the discrepancy between the degrees of freedom, with a recommended threshold value of less than 5 (Schumacker and Lomax, 2004). In the present study, the normed Chi-square was 4.42, which indicates a good level of fit in terms of degrees of freedom. The results of the overall model estimation were as follows: GFI = 0.81; NFI = 0.97; NNFI = 0.98; IFI = 0.98; RFI = 0.97; CFI = 0.98; and RMSEA = 0.064.

To further ensure the reliability of the statistical approach, a power analysis was conducted using G*Power. With a significance level of 0.05, the analysis resulted in a power level higher than the 80% recommended minimum threshold (Cohen, 1988; Hagen et al., 2024).

Fig. 1 shows the results of the estimation of the proposed model.

Hypotheses H_1, H_2, H_3, and H_4 propose a direct and positive relationship between the quantity of reviews, source credibility, review usefulness, and brand experience on perceived product quality. Based on the results obtained, it can be confirmed that the quantity of reviews ($\beta_{QR \rightarrow PPQ}$: 0.19; $p < 0.01$), source credibility ($\beta_{SC \rightarrow PPQ}$: 0.12; $p < 0.05$), review usefulness ($\beta_{RU \rightarrow PPQ}$: 0.10; $p < 0.05$), and brand experience ($\beta_{BE \rightarrow PPQ}$: 0.39; $p < 0.001$) all positively and significantly influence perceived product quality. Thus, the results provide empirical support for H_1, H_2, H_3, and H_4. However, H_5 fails to find empirical support: the results do not support our hypothesis that a perception of high product quality has a negative influence on performance risk ($\beta_{PPQ \rightarrow PPR}$: 0.05; $p > 0.05$).

Turning to the hypotheses relating to the determinants of purchase intention, H_6 proposes that perceived product quality exerts a positive effect on purchase intention. This hypothesis can be affirmed, as the results indicate a positive and significant relationship ($\beta_{PPQ \rightarrow PI}$: 0.69; $p < 0.001$). Likewise, H_7 proposes that perceived product performance risk negatively influences purchase intention, and this too was verified by the results ($\beta_{PPR \rightarrow PI}$: 0.07; $p < 0.05$), thus confirming H_7.

Table 4 shows the results of the evaluation of the structural model. All of the hypotheses in the model were supported empirically, with the exception of H_5.

Table 3
Discriminant validity.

	QR	SC	RU	BE	PPQ	PPR	PI
QR	**0.82**						
SC	0.67	**0.84**					
RU	0.51	0.58	**0.84**				
BE	0.54	0.62	0.35	**0.85**			
PPQ	0.52	0.54	0.39	0.60	**0.86**		
PPR	0.38	0.31	0.10	0.30	0.02	**0.84**	
PI	0.37	0.36	0.36	0.30	0.69	−0.03	**0.82**

5. Discussion

The main objective of this study was to develop a theoretical model of how four of the main cues available on e-commerce platforms are processed by users heuristically or systematically to assess the quality of the products on offer. To this end, three research questions were posed.

RQ1 inquired about the effect of certain social interaction (eWOM) cues available on e-commerce platforms on perceived product quality. This study found that the number of reviews positively influences perceived product quality—this result is consistent with previous studies (Chen et al., 2004; Metzger et al., 2010). The present research model's inclusion of this variable as a signal of quality extends the existing literature, as it does not focus on a specific product (Flanagin et al., 2014) but is relevant to any type of product that can be purchased on e-commerce platforms. Thus, we can generalize that the number of customer reviews that a product has attracted is an important factor that consumers look out for when seeking information about the desired product quality, as suggested in the extant literature (Xie et al., 2016). This conclusion directly contradicts the aforementioned finding from the literature that the number of reviews, while relevant, is an insufficient signal in its own right to generate perceived quality (Flanagin et al., 2014). Thus, consumers employ heuristic processing to obtain product information.

The findings also reveal that source credibility positively and significantly impacts perceived product quality, which is in line with previous research (Duarte and e Silva, 2020). This result demonstrates that consumers trust the word of other consumers in a context—e-commerce—that is characterized by high uncertainty (Cheung and Lee, 2010; Kaushik et al., 2018). Thus, it expands the literature by addressing the recognized uncertainty about whether consumers do, in fact, systematically process information to assess the credibility of the information source when judging product quality. This study reveals that they do. Review usefulness is also shown here to positively influence perceived product quality. This result is in accordance with previous studies (Filieri, 2015; Jiang and Benbasat, 2007), indicating that consumers systematically evaluate the quality of reviews to identify their usefulness in the evaluation of product quality (Sussman and Siegal, 2003). Finally, brand experience is positively and significantly related to perceived product quality, which, again, is in line with previous research findings (Beig and Nika, 2022; Duarte and e Silva, 2020; Tran et al., 2023).

Thus, the results reveal that the quantity of reviews, source credibility, review usefulness, and brand experience all act as cues via which the consumer can perceive the quality of the products available on e-commerce platforms. Specifically, brand experience is the cue that most strongly influences perceived product quality, followed by the quantity of reviews, source credibility, and review usefulness. It is found here that consumers use both systematic and heuristic processing to evaluate such information in e-commerce platforms but that they prefer to make a greater cognitive effort to perceive brand experience because this conveys higher product quality. Therefore, it is extremely important for firms to generate a good brand experience for the consumer, since this will lead them to perceive the products on offer to be of higher quality. That said, it is also shown that it is important for the consumer to perceive easy-to-process signals such as the number of reviews. These results are in line with our expectations, given the impact that these cues are known to have on consumer purchasing behavior (Siering et al., 2018; Zhang and Watts, 2008; Zhang et al., 2014). The importance of the

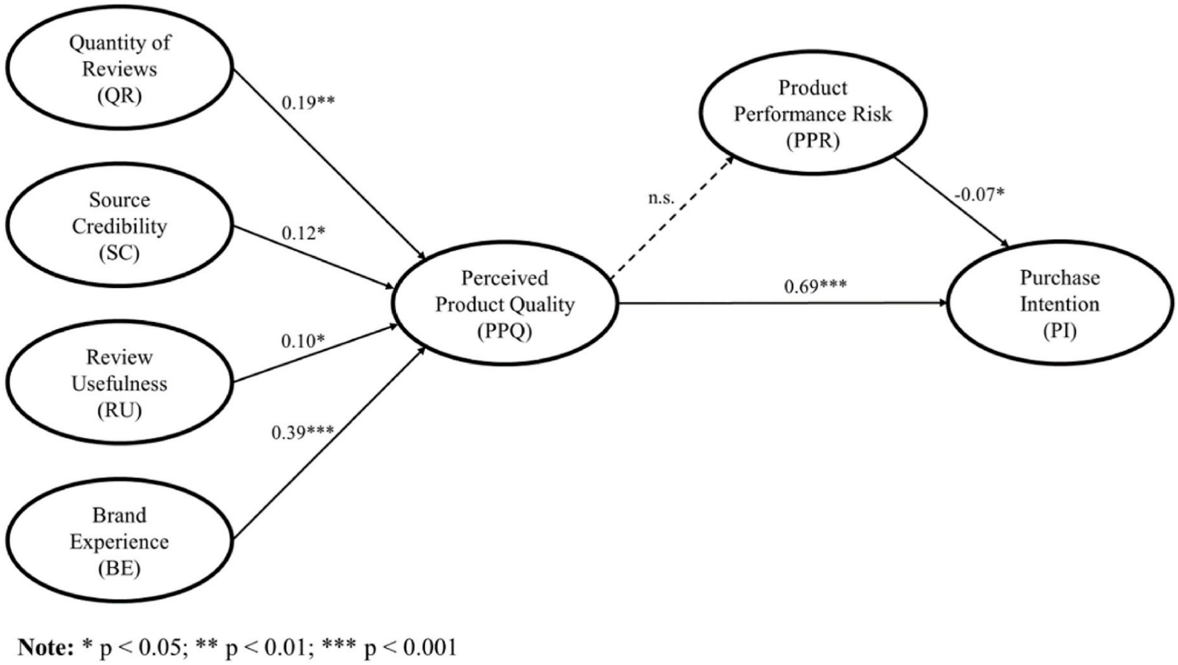

Fig. 1. Estimated structural equation model.

Table 4
Results of the SEM estimation.

Hypothesis: Relationship		Coefficient (β)	t-value	Result
H_1:	Quantity of reviews → Perceived product quality	0.19	3.15	Supported
H_2:	Source credibility → Perceived product quality	0.12	2.24	Supported
H_3:	Review usefulness → Perceived product quality	0.10	2.18	Supported
H_4:	Brand experience → Perceived product quality	0.39	6.85	Supported
H_5:	Perceived product quality → Product performance risk	0.05	1.14	Not Supported
H_6:	Perceived product quality → Purchase intention	0.69	17.88	Supported
H_7:	Product performance risk → Purchase intention	−0.07	−2.33	Supported

eWOM generated by other users in influencing consumer purchasing behavior is thus confirmed, due to its potential as a recommendation system.

RQ2 was concerned with the influence of perceived product quality on perceived product performance risk and purchase intention. According to the results, perceived product quality does not significantly influence the consumer's perception of product performance risk. Despite the fact that the literature observes that perceived product quality reduces perceptions of risk (Chen and Dubinsky, 2003; Snoj et al., 2004) and specifically that perceived product quality reduces the perception of performance risk (Eryiğit and Fan, 2021; Nepomuceno et al., 2014), we were unable to confirm this relationship. This means that perceived quality will not imply a reduction in perceived product performance risk. One reason for this result may be that, during the COVID-19 pandemic, consumers were forced to adopt e-commerce in many cases, which may have significantly changed the drivers of risk perceptions. Furthermore, the results indicate that, if it were to exert a significant influence, its effect would be positive. This seems coherent, given that, when the consumer perceives greater product quality in e-commerce, they may sense a greater risk of non-compliance with the product standard claimed by the seller than if they perceive the product to be of low quality. In the latter case, the consumer has no expectation that the product will meet the standard it claims to meet.

The present study also finds that perceived product quality is a positive determinant in the purchase intention of the e-commerce consumer, which confirms previous research findings (Boon et al., 2018; Chen et al., 2023; Flanagin et al., 2014; Nofrizal et al., 2023; Yuniarti et al., 2022). This finding also indicates that it is important to identify those cues that are able to convey product quality in order to reduce the typical consumer uncertainty that is associated with the e-commerce context.

Finally, RQ3 inquired about the impact of product performance risk on purchase intention in e-commerce. According to the results of this study, perceived performance risk is a negative determinant of purchase intention among e-commerce consumers, which is consistent with the results obtained by Hong and Cha (2013), Dai et al. (2014), Ariffin et al. (2018), Ahmad et al. (2020), Lakchan and Samaraweera (2022), and Yuniarti et al. (2022). This finding reflects the importance of reducing the perception of product risk to encourage consumer purchase.

5.1. Theoretical implications

This study proposes new cues for consumers' evaluation of product quality in e-commerce platforms. We now outline the theoretical implications of the work.

Previous studies have analyzed the effect of heuristic and systematic cues (such as the quantity of reviews, source credibility, review usefulness, and brand experience) on variables other than perceived product quality, such as perceived value (Vijay et al., 2017), satisfaction (Jin et al., 2009), or purchase intention (Fan et al., 2024). Regarding perceived quality, most previous studies have examined, for example, the effect of brand experience together with other brand-related variables such as brand attachment (Beig and Nika, 2022; Tran et al., 2023) or source credibility (Duarte and e Silva, 2020). The present research is the first to analyze the effect of certain key signals that can be processed heuristically or systematically on perceived product quality, showing that the quantity of reviews, source credibility, review usefulness, and brand experience all positively influence product quality. Thus, the results indicate that consumers can process information both heuristically and systematically, which differentiates it from the widely studied

Elaboration Likelihood Model.

More specifically, it is found here that the systematic signal of brand experience has the greatest effect on the consumer when evaluating the quality of the product, followed by the heuristic signal of quantity of reviews. This answers the question of which consumer eWOM-related signals available on the platforms reflect the quality of the product offered. By analyzing these variables, we expand on the previous literature and contribute to clarifying contradictory results that require further elaboration to better understand how signals such as the quantity of reviews or the credibility of the sources that post those reviews influence perceived product quality in e-commerce (Flanagin et al., 2014; Loureiro et al., 2018). In short, the work facilitates our understanding of the role of these elements as cues that help consumers gauge the quality of a product that cannot be tried or tested through a computer screen. This study contributes to the gap in the literature by combining signaling theory with the HSM model, taking both heuristic and systematic cues into account and verifying their importance as indicators of product quality in the e-commerce context, thus providing a basis for future research.

Furthermore, this research satisfies the need to delve deeper into the types of risks perceived by consumers in e-commerce (Guru et al., 2020; Paluch and Wünderlich, 2017). More specifically, it responds to the gap relating to the effect of perceived product quality on one of the most important risk types in e-commerce, which is closely linked to product quality: perceived product performance risk. Previous studies have mainly addressed the effect of different types of risks on different variables such as attitude toward the seller or the brand (Cho et al., 2015) and on perceived usefulness (Biucky et al., 2017). However, very few studies have analyzed the effect of certain variables such as perceived product quality on the different types of risks existing in e-commerce. In this study, we focus on performance risk. Similarly, considering this type of risk also addresses the gap in the literature on the effect of performance risk on purchase intention among e-commerce consumers in the wake of the major changes in purchasing habits undergone during the COVID-19 pandemic.

Finally, this research addresses the gap concerning the role of perceived product quality on purchase intention in the e-commerce context, since there are scant studies that analyze perceived product quality in e-commerce. Perhaps one of the reasons for this paucity is the complexity of measuring this variable, but, as the present study shows, it is possible to measure perceived product quality in this environment despite the fact that consumers cannot test the product physically.

5.2. Practical implications

This study holds a number of important implications for e-commerce professionals. First, they should encourage consumers to post comments online after their purchase, since the more comments the product attracts, the greater the perception of quality among other consumers on the platform and, therefore, the greater their purchase intention. In addition, when the product offered attracts a large volume of useful comments and these come from sources perceived to be credible, the perceived product quality will be higher, which will lead to a favorable attitude toward the brand and motivate purchase intention.

It is evident from the results here that it is essential for firms to implement interactive systems that enable high volumes of reviews to be posted and, above all, that the reviews should be useful and come from reliable sources so that they are perceived by consumers to be credible. To achieve this, sellers on e-commerce platforms should establish filters that permit only verified reviews—that is, only those reviews that are posted by genuine consumers who have actually purchased the product in question—and leverage those authenticated reviews in their product advertising. This would enable firms to disseminate true and credible product information, by incentivizing customers to describe the product, for example, using photos.

Sellers must give these components of the online context the importance they deserve, since, thanks to such cues, consumers are able to assess the quality of the products before they make a purchase, despite being at a physical distance—via a computer, tablet, or cellphone. In this way, if the consumer can be encouraged to leave comments and provide information, as a credible source, this will help sellers to increase their sales, which translates into increased profits. In addition, it is important for sellers to generate a good brand experience for the consumer on the e-commerce platform so that the latter can perceive high product quality, as the brand experience acts as a strong signal of this variable. In fact, the brand experience is the factor that will most reflect the quality of the products, indicating that marketers should devote significant efforts to achieving a pleasant brand experience for the consumer.

Although it cannot be confirmed that perceived product quality helps to ameliorate perceived product performance risk, sellers are advised to reduce customer perceptions of product performance risk because this perception cools purchase intention. One way to reassure consumers of product standards and thus reduce the perception that they may not comply with them could be to offer quality guarantees. In addition, achieving the perception of quality through the aforementioned signals generates greater purchase intention, underlining the importance of emitting these signals in this context.

In short, marketing professionals and sellers alike must take great care over the eWOM elements analyzed in this study—namely, the quantity, credibility, and usefulness of customer reviews and brand experience conveyed on these platforms, as the social interaction tools integrated into them enable consumers to act, in effect, as promotional agents. Therefore, professionals must know how to treat consumers so that they continue to function as promotional agents automatically, thus reducing the need to hire external agents. This will contribute to increasing profits.

5.3. Limitations and future research

This study has several limitations that should be addressed in future research. For example, while it collected information from the United States and Spain, no analysis was carried out to examine whether there are differences between consumers from these two countries. Consequently, looking to the future, a multigroup analysis by country could be performed to compare it with the results obtained from the proposed model.

Another limitation is that we did not analyze whether there are differences in consumers' processing of product information when attempting to discern its quality, depending on the type of products in question—whether they are search goods or experience goods. The attributes of the former type lend themselves to providing full product information, helping the consumer to more readily make purchase decisions prior to purchase. The nature of experience goods, in contrast, renders them more difficult to evaluate in advance of actually consuming them. Thus, it would be interesting to conduct a multigroup analysis to assess whether there are any differences in the perception of product quality after having processed the information available on the e-commerce platform, according to these two types of goods.

Finally, it would be helpful to include in a future study other elements that have more recently become available on e-commerce platforms, such as gamification systems, to analyze their impact as a quality cue.

CRediT authorship contribution statement

Elena Rosillo-Díaz: Writing – original draft, Methodology, Funding acquisition, Formal analysis. **Juan Francisco Muñoz-Rosas:** Writing – review & editing, Supervision, Methodology. **Francisco Javier Blanco-Encomienda:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of Competing interest

The authors declare that there is no conflict of interest.

Data availability

Data will be made available on request.

Acknowledgments

This study was supported via a F.P.U. grant from the Spanish Ministry of Science, Innovation and Universities (grant number FPU17/03002). Funding for open access charge: Universidad de Granada / CBUA.

References

Ahmad, A.H., Fauzi, R.U.A., Ditta, A.S.A., Idris, I., Yazid, M.F.M., 2020. The role of perceived benefits and perceived risks towards the consumers' purchase intention via e-commerce: an evidence from Indonesia. Solid State Technol. 63 (2), 3257–3274.

Alrawad, M., Lutfi, A., Alyatama, S., Al Khattab, A., Alsoboa, S.S., Almaiah, M.A., Ramadan, M.H., Arafa, H.M., Ahmed, N.A., Alsyouf, A., Al-Khasawneh, A.L., 2023. Assessing customers perception of online shopping risks: a structural equation modeling–based multigroup analysis. J. Retailing Consum. Serv. 71, 103188.

Ariffin, S.K., Mohan, T., Goh, Y.N., 2018. Influence of consumers' perceived risk on consumers' online purchase intention. Journal of Research in Interactive Marketing 12 (3), 309–327.

Atulkar, S., 2020. Brand trust and brand loyalty in mall shoppers. Market. Intell. Plann. 38 (5), 559–572.

Baek, H., Ahn, J., Choi, Y., 2012. Helpfulness of online consumer reviews: Readers' objectives and review cues. Int. J. Electron. Commer. 17 (2), 99–126.

Baek, T.H., King, K.W., 2011. Exploring the consequences of brand credibility in services. J. Serv. Market. 25 (4), 260–272.

Beig, F.A., Nika, F.A., 2022. Impact of brand experience on brand equity of online shopping portals: a study of select e-commerce sites in the state of Jammu and Kashmir. Global Bus. Rev. 23 (1), 156–175.

Beneke, J., Brito, A., Garvey, K.A., 2015. Propensity to buy private label merchandise: the contributory effects of store image, price, risk, quality and value in the cognitive stream. Int. J. Retail Distrib. Manag. 43 (1), 43–62.

Berger, J., Humphreys, A., Ludwig, S., Moe, W.W., Netzer, O., Schweidel, D.A., 2020. Uniting the tribes: using text for marketing insight. J. Market. 84 (1), 1–25.

Biucky, S.T., Abdolvand, N., Harandi, S.R., 2017. The effects of perceived risk on social commerce adoption based on the TAM model. International Journal of Electronic Ccommerce Studies 8 (2), 173–196.

Boon, L.K., Fern, Y.S., Meng, Y.W., 2018. A study of purchasing intention of private label brands in Malaysia. Global Business and Management Research: Int. J. 10 (3), 1025–1034.

Brakus, J.J., Schmitt, B.H., Zarantonello, L., 2009. Brand experience: what is it? How is it measured? Does it affect loyalty? J. Market. 73 (3), 52–68.

Brislin, R.W., 1970. Back-translation for cross-cultural research. J. Cross Cult. Psychol. 1 (3), 185–216.

Brown, J., Broderick, A.J., Lee, N., 2007. Word of mouth communication within online communities: Conceptualizing the online social network. J. Interact. Market. 21 (3), 2–20.

Bryman, A., Cramer, D., 2012. Quantitative Data Analysis with IBM SPSS 17, 18 & 19: A Guide for Soial Scientists. Routledge.

Buil, I., Martínez, E., de Chernatony, L., 2013. The influence of brand equity on consumer responses. J. Consum. Market. 30 (1), 62–74.

Byrne, B.M., 2016. Structural Equation Modelling with AMOS: Basic Concepts, Applications and Programming. Routledge.

Cai, X., Cebollada, J., Cortiñas, M., 2023. Impact of seller- and buyer-created content on product sales in the electronic commerce platform: the role of informativeness, readability, multimedia richness, and extreme valence. J. Retailing Consum. Serv. 70, 103141.

Cao, Q., Duan, W., Gan, Q., 2011. Exploring determinants of voting for the "helpfulness" of online user reviews: a text mining approach. Decis. Support Syst. 50 (2), 511–521.

Chaiken, S., 1980. Heuristic versus systematic information processing and the use of source versus message cues in persuasion. Journal of Personality and Social Psychology 39 (5), 752–766.

Chang, H.H., Chen, S.W., 2008. The impact of online store environment cues on purchase intention. Trust and perceived risk as a mediator. Online Inf. Rev. 32 (6), 1468–4527.

Chang, S., 2018. Experience economy in hospitality and tourism: gain and loss values for service and experience. Tourism Manag. 64, 55–63.

Cheah, J.H., Lim, X.J., Ting, H., Liu, Y., Quach, S., 2022. Are privacy concerns still relevant? Revisiting consumer behaviour in omnichannel retailing. J. Retailing Consum. Serv. 65, 102242.

Chen, Z., Dubinsky, A.J., 2003. A conceptual model of perceived customer value in e-commerce: a preliminary investigation. Psychol. Market. 20 (4), 323–347.

Chen, L., Rashidin, M.S., Song, F., Wang, Y., Javed, S., Wang, J., 2021. Determinants of consumer's purchase intention on fresh e-commerce platform: perspective of UTAUT model. Sage Open 11 (2), 1–17.

Chen, X., Shen, J., Wei, S., 2023. What reduces product uncertainty in live streaming e-commerce? From a signal consistency perspective. J. Retailing Consum. Serv. 74, 103441.

Chen, P.Y., Wu, S.Y., Yoon, J., 2004. The impact of online recommendations and consumer feedback on sales. In: Proceedings of the International Conference on Information Systems. Association for Information Systems, pp. 711–724.

Cheong, J.W., Muthaly, S., Kuppusamy, M., Han, C., 2020. The study of online reviews and its relationship to online purchase intention for electronic products among the millennials in Malaysia. Asia Pac. J. Mark. Logist. 32 (7), 1519–1538.

Cheung, C.M., Lee, M.K., 2010. A theoretical model of intentional social action in online social networks. Decis. Support Syst. 49 (1), 24–30.

Cheung, C.M.K., Lee, M.K.O., Rabjohn, N., 2008. The impact of electronic word-of-mouth. The adoption of online opinions in online customer communities. Internet Res. 18 (3), 229–247.

Chevalier, J.A., Mayzlin, D., 2006. The effect of word of mouth on sales: online book reviews. J. Market. Res. 43 (3), 345–354.

Chiu, C.M., Wang, E.T., Fang, Y.H., Huang, H.Y., 2014. Understanding customers' repeat purchase intentions in B2C e-commerce: the roles of utilitarian value, hedonic value and perceived risk. Inf. Syst. J. 24 (1), 85–114.

Cho, Y.S., Rha, H.S., Burt, S., 2015. The impact of customer awareness of manufacturer name disclosure on retail brand attitudes and loyalty in Korea. J. Retailing Consum. Serv. 22, 128–137.

Chong, S.C., Yeow, C.C., Low, C.W., Mah, P.Y., Tung, D.T., 2022. Non-Muslim Malaysians' purchase intention towards halal products. Journal of Islamic Marketing 13 (8), 1751–1762.

Chua, A.Y., Banerjee, S., 2016. Helpfulness of user-generated reviews as a function of review sentiment, product type and information quality. Comput. Hum. Behav. 54, 547–554.

Cohen, J., 1988. Statistical Power Analysis for the Behavioral Sciences. Erlbaum Associates.

Colamatteo, A., Cassia, F., Sansone, M., 2021. Near-shoring versus far-shoring: effects on customer perceived quality and purchase intention. The TQM Journal 34 (5), 1416–1431.

Cui, G., Lui, H.K., Guo, X., 2012. The effect of online consumer reviews on new product sales. Int. J. Electron. Commer. 17 (1), 39–58.

Dai, B., Forsythe, S., Kwon, W.S., 2014. The impact of online shopping experience on risk perceptions and online purchase intentions: does product category matter? J. Electron. Commer. Res. 15 (1), 13–24.

Dean, D.H., 1999. Brand endorsement, popularity, and event sponsorship as advertising cues affecting consumer pre-purchase attitudes. J. Advert. 28 (3), 1–12.

Duan, W., Gu, B., Whinston, A.B., 2008. Do online reviews matter? An investigation of panel data. Decis. Support Syst. 45 (4), 1007–1016.

Duarte, P., e Silva, S.C., 2020. Need-for-touch and online purchase propensity: a comparative study of Portuguese and Chinese consumers. J. Retailing Consum. Serv. 55, 102122.

Elshaer, I.A., Alrawad, M., Lutfi, A., Azazz, A.M.S., 2024. Social commerce and buying intention post COVID-19: evidence from a hybrid approach based on SEM – fsQCA. J. Retailing Consum. Serv. 76, 103548.

Eryiğit, C., Fan, Y., 2021. The effects of convenience and risk on e-loyalty through the mediating role of e-service quality: a comparison for China and Turkey. J. Int. Consum. Market. 33 (5), 613–626.

Fan, L., Wang, Y., Mou, J., 2024. Enjoy to read and enjoy to shop: an investigation on the impact of product information presentation on purchase intention in digital content marketing. J. Retailing Consum. Serv. 76, 103594.

Filieri, R., 2015. What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM. J. Bus. Res. 68, 1261–1270.

Flanagin, A.J., Metzger, M.J., Pure, R., Markov, A., Hartsell, E., 2014. Mitigating risk in ecommerce transactions: perceptions of information credibility and the role of user-generated ratings in product quality and purchase intention. Electron. Commer. Res. 14 (1), 1–23.

Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. J. Market. Res. 18 (1), 39–50.

Forsythe, S.M., Shi, B., 2003. Consumer patronage and risk perceptions in Internet shopping. J. Bus. Res. 56 (11), 867–875.

Fuller, C.M., Simmering, M.J., Atinc, G., Atinc, Y., Babin, B.J., 2016. Common methods variance detection in business research. J. Bus. Res. 69 (8), 3192–3198.

Garbarino, E., Strahilevitz, M., 2004. Gender differences in the perceived risk of buying online and the effects of receiving a site recommendation. J. Bus. Res. 57 (7), 768–775.

Gursoy, D., 2019. A critical review of determinants of information search behavior and utilization of online reviews in decision making process. Int. J. Hospit. Manag. 76, 53–60.

Guru, S., Nenavani, J., Patel, V., Bhatt, N., 2020. Ranking of perceived risks in online shopping. Decision 47 (2), 137–152.

Hagen, D., Spierings, B., Weltevreden, J., Risselada, A., Atzema, O., 2024. What drives consumers to use local online retail platforms? The influence of non-place-specific and place-specific motives. J. Retailing Consum. Serv. 77, 103649.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2010. Multivariate Data Analysis. Pearson Prentice Hall.

Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., Danks, N.P., Ray, S., 2021. Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook. Springer.

Hellofs, L.L., Jacobson, R., 1999. Market share and customers' perceptions of quality: when can firms grow their way to higher versus lower quality? J. Market. 63 (1), 16–25.
Henseler, J., Ringle, C.M., Sarstedt, M., 2015. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J. Acad. Market. Sci. 43 (1), 115–135.
Hong, I.B., Cha, H.S., 2013. The mediating role of consumer trust in an online merchant in predicting purchase intention. Int. J. Inf. Manag. 33 (6), 927–939.
Hussain, S., Ahmed, W., Jafar, R.M.S., Rabnawaz, A., Jianzhou, Y., 2017. eWOM source credibility, perceived risk and food product customer's information adoption. Comput. Hum. Behav. 66, 96–102.
Huyen, T.T., Costello, J., 2017. Quality versus quantity: an investigation into electronic word of mouth's influence on consumer buying intention. Journal of Promotional Communications 5 (2), 137–155.
Hwang, J., Hyun, S.S., 2012. The antecedents and consequences of brand prestige in luxurt restaurants. Asia Pac. J. Tourism Res. 17 (6), 656–683.
Ismagilova, E., Slade, E., Rana, N.P., Dwivedi, Y.K., 2020. The effect of characteristics of source credibility on consumer behavior: a meta-analysis. J. Retailing Consum. Serv. 53, 101736.
Jeong, H.J., Kwon, K.N., 2012. The effectiveness of two online persuasion claims: limited product availability and product popularity. J. Promot. Manag. 18 (1), 83–99.
Jiang, Z., Benbasat, I., 2004. Virtual product experience: effects of visual and functional control of products on perceived diagnosticity and flow in electronic shopping. J. Manag. Inf. Syst. 21 (3), 111–147.
Jiang, Z., Benbasat, I., 2007. Research note—investigating the influence of the functional mechanisms of online product presentations. Inf. Syst. Res. 18 (4), 454–470.
Jin, X., Cheung, C.M.K., Lee, M.K.O., Chen, H., 2009. How to keep members using the information in a computer-supported social network. Comput. Hum. Behav. 25 (5), 1172–1181.
Kaushik, K., Mishra, R., Rana, N.P., Dwivedi, Y.K., 2018. Exploring reviews and review sequences on e-commerce platform: a study of helpful reviews on Amazon. J. Retailing Consum. Serv. 45, 21–32.
Kemp, S., 2021. Digital 2021. Global overview report: the latest insights into how people around the world use the Internet, social media, mobile devices, and ecommerce. https://wearesocial.com/digital-2021. (Accessed 10 January 2022).
Khan, I., Rahman, Z., 2016. Retail brand experience: scale development and validation. J. Prod. Brand Manag. 25 (5), 435–451.
Kim, R.Y., 2021. When does online review matter to consumers? The effect of product quality information cues. Electron. Commer. Res. 21, 1011–1030.
King, R.A., Racherla, P., Bush, V.D., 2014. What we know and don't know about online word-of-mouth: a review and synthesis of the literature. J. Interact. Market. 28, 167–183.
Kock, F., Berbekova, A., Assaf, A.G., 2021. Understanding and managing the threat of common method bias: detection, prevention and control. Tourism Manag. 86, 104330.
Konuk, F.A., 2018. The role of store image, perceived quality, trust and perceived value in predicting consumers' purchase intentions towards organic private label food. J. Retailing Consum. Serv. 43, 304–310.
Kordrostami, E., Rahmani, V., 2020. Investigating conflicting online review information: evidence from Amazon.com. J. Retailing Consum. Serv. 55, 102125.
Lakchan, U.G.C., Samaraweera, G.C., 2022. The influence of customer perceived risk on online purchasing intention, moderating effect of electronic word of mouth: with reference to fast fashion retail industry in Sri Lanka. Peradeniya Management Review 4 (1), 88–114.
Lee, J.E., Goh, M.L., Noor, M.N.B.M., 2019a. Understanding purchase intention of university students towards skin care products. PSU Research Review 3 (3), 161–178.
Lee, Y.F., Ha, S., Johnson, Z., 2019b. Antecedents and consequences of flow state in e-commerce. J. Consum. Market. 36 (2), 264–275.
Lee, G.G., Lin, H.F., 2005. Customer perceptions of e-service quality in online shopping. Int. J. Retail Distrib. Manag. 33 (2), 161–176.
Lee, H., Moon, H., 2015. Perceived risk of online apparel mass customization: scale development and validation. Cloth. Text. Res. J. 32 (2), 115–128.
Li, X., Hitt, L.M., 2008. Self-selection and information role of online product reviews. Inf. Syst. Res. 19 (4), 456–474.
Li, Y., Wei, Z., Zhao, J., Zhang, C., Liu, Y., 2013. Ambidextrous organizational learning environmental munificence and new product performance: moderating effect of managerial ties in China. Int. J. Prod. Econ. 14 (1), 95–105.
Lim, X.J., Cheah, J.W., Dwivedi, Y.K., Richard, J.E., 2022. Does retail type matter? Consumer responses to channel integration in omni-channel retailing. J. Retailing Consum. Serv. 67, 102992.
Liu, X., Wei, K.K., 2003. An empirical study of product differences in consumers' e-commerce adoption behavior. Electron. Commer. Res. Appl. 2 (3), 229–239.
Loureiro, S.M.C., Cavallero, L., Miranda, F.J., 2018. Fashion brands on retail websites: customer performance expectancy and e-word-of-mouth. J. Retailing Consum. Serv. 41, 131–141.
Lu, B., Chen, Z., 2021. Live streaming commerce and consumers' purchase intention: an uncertainty reduction perspective. Inf. Manag. 58 (7), 103509.
MacKenzie, S.B., Podsakoff, P.M., Jarvis, C.B., 2005. The problem of measurement model misspecification in behavioral and organizational research and some recommended solutions. J. Appl. Psychol. 90 (4), 710–730.
Malik, M.S., Hussain, A., 2017. Helpfulness of product reviews as a function of discrete positive and negative emotions. Comput. Hum. Behav. 73, 290–302.
Mavlanova, T., Benbunan-Fich, R., Koufaris, M., 2012. Signaling theory and information asymmetry in online commerce. Inf. Manag. 49 (5), 240–247.
Mavlanova, T., Benbunan-Fich, R., Lang, G., 2016. The role of external and internal signals in e-commerce. Decis. Support Syst. 87, 59–68.
Metzger, M.J., Flanagin, A.J., Medders, R.B., 2010. Social and heuristic approaches to credibility evaluation online. J. Commun. 60, 413–439.
Miyazaki, A.D., Grewal, D., Goodstein, R.C., 2005. The effect of multiple extrinsic cues on quality perceptions: a matter of consistency. J. Consum. Res. 32 (1), 146–153.
Moro, S., Rita, P., Coelho, J., 2017. Stripping customers' feedback on hotels through data mining: the case of Las Vegas Strip. Tourism Manag. Perspect. 23, 41–52.
Mudambi, S.M., Schuff, D., 2010. What makes a helpful online review? A study of customer reviews on amazon.com. MIS Q. 34 (1), 185–200.
Munikrishnan, U.T., Huang, K., Mamun, A.A., Hayat, N., 2023. Perceived risk, trust, and online food purchase intention among Malaysians. Business Perspectives and Research 11 (1), 28–43.
Nayeem, T., Murshed, F., Dwivedi, A., 2019. Brand experience and brand attitude: examining a credibility-based mechanism. Market. Intell. Plann. 37 (7), 821–836.
Nepomuceno, M.V., Laroche, M., Richard, M.O., 2014. How to reduce perceived risk when buying online: the interactions between intangibility, product knowledge, brand familiarity, privacy and security concerns. J. Retailing Consum. Serv. 21 (4), 619–629.
Netemeyer, R.G., Brashear, T., Boles, J., 2004. A cross-national test of work and family roles: a retail context. J. Acad. Market. Sci. 32, 49–60.
Nofrizal, N., Juju, U., Sucherly, S., Arizal, N., Waldermi, I., Aznuriyandi, A., 2023. Changes and determinants of consumer shopping behavior in e-commerce and social media product Muslimah. J. Retailing Consum. Serv. 70, 103146.
Paluch, S., Wünderlich, N.V., 2017. Contrasting risk perceptions of technology-based service innovations in inter-organizational settings. J. Bus. Res. 69 (7), 2424–2431.
Pan, Y., Zhang, J.Q., 2011. Born unequal: a study of the helpfulness of user-generated product reviews. J. Retailing 87 (4), 598–612.
Park, J., Hong, E., Park, Y., 2023. Toward a new business model of retail industry: the role of brand experience and brand authenticity. J. Retailing Consum. Serv. 74, 103426.
Park, D.H., Kim, S., 2008. The effects of consumer knowledge on message processing of electronic word-of-mouth via online consumer reviews. Electron. Commer. Res. Appl. 7 (4), 399–410.
Petty, R.E., Cacioppo, J.T., 1986. The elaboration likelihood model of persuasion. Adv. Exp. Soc. Psychol. 19, 123–205.
Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., Podsakoff, N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J. Appl. Psychol. 88 (5), 879–903.
Rahayu, R., Day, J., 2017. E-commerce adoption by SMEs in developing countries: evidence from Indonesia. Eurasian Business Review 7 (1), 25–41.
Rosillo-Díaz, E., Blanco-Encomienda, F.J., Muñoz-Rosas, J.F., 2022. Analysis of the evolution and impact of product quality in business. Total Qual. Manag. Bus. Excel. 33 (7–8), 907–928.
Ruiz-Mafe, C., Bigné-Alcañiz, E., Currás-Pérez, R., 2020. The effect of emotions, eWOM quality and online review sequence on consumer intention to follow advice obtained from digital services. J. Serv. Manag. 31 (3), 465–487.
Sadiq, M., Bharti, K., Adil, M., Singh, R., 2021. Why do consumers buy green apparel? The role of dispositional traits, environmental orientation, environmental knowledge, and monetary incentive. J. Retailing Consum. Serv. 62, 102643.
Schmitt, H., Ferdinand, N.K., Kray, J., 2015. The influence of monetary incentives on context processing in younger and older adults: an event-related potential study. Cognit. Affect Behav. Neurosci. 15, 416–434.
Schumacker, R.E., Lomax, R.G., 2004. A Beginner's Guide to Structural Equation Modeling. Lawrence Erlbaum Associates.
Sen, S., Lerman, D., 2007. Why are you telling me this? An examination into negative consumer reviews on the web. J. Interact. Market. 21 (4), 76–94.
Siering, M., Muntermann, J., Rajagopalan, B., 2018. Explaining and predicting online review helpfulness: the role of content and reviewer-related signals. Decis. Support Syst. 108, 1–12.
Sigurdsson, V., Larsen, N.M., Alemu, M.H., Gallogly, J.K., Menor, R.V., Fagerstrom, A., 2020. Assisting sustainable food consumption: the effects of quality signals stemming from consumers and stores in online and physical grocery retailing. J. Bus. Res. 112, 458–471.
Snoj, B., Korda, A.P., Mumel, D., 2004. The relationships among perceived quality, perceived risk and perceived product value. J. Prod. Brand Manag. 13 (3), 156–167.
Sullivan, Y.W., Kim, D.J., 2018. Assessing the effects of consumers' product evaluations and trust on repurchase intention in e-commerce environments. Int. J. Inf. Manag. 39, 199–219.
Sussman, S.W., Siegal, W.S., 2003. Informational influence in organizations: an integrated approach to knowledge adoption. Informational Systems Research 14 (1), 47–65.
Tang, Y., Zhang, Y., Ning, X., 2023. Uncertainty in the platform market: the information asymmetry perspective. Comput. Hum. Behav. 148, 107918.
Todorov, A., Chaiken, S., Henderson, M.D., 2002. The heuristic-systematic model of social information processing. In: Dillard, J.P., Pfau, M. (Eds.), The Persuasion Handbook: Developments in Theory and Practice. Sage, pp. 195–211.
Tran, T., Sen, S., Steenburg, E.V., 2023. This ad's for you: how personalized SNS advertisements affect the consumer-brand relationship. J. Consum. Market. 40 (4), 458–469.
Uhm, J.P., Kim, S., Do, C., Lee, H.W., 2022. How augmented reality (AR) experience affects purchase intention in sport E-commerce: roles of perceived diagnosticity, psychological distance, and perceived risks. J. Retailing Consum. Serv. 67, 103027.
Vazquez, E.E., Patel, C., Alvidrez, S., Siliceo, L., 2023. Images, reviews, and purchase intention on social commerce: the role of mental imagery vividness, cognitive and affective social presence. J. Retailing Consum. Serv. 74, 103415.

Vijay, T.S., Prashar, S., Parsad, C., Kumar, M., 2017. An empirical examination of the influence of information and source characteristics on consumers' adoption of online reviews. Pac. Asia J. Assoc. Inf. Syst. 9 (1), 75–94.
Vo, T.T.N., Nguyen, C.T.K., 2015. Factors influencing customer perceived quality and purchase intention toward private labels in the Vietnam market: the moderating effects of store image. Int. J. Market. Stud. 7 (4), 51–63.
Wang, S., Cunningham, N.R., Eastin, M.S., 2015. The impact of eWOM message characteristics on the perceived effectiveness of online consumer reviews. J. Interact. Advert. 15 (2), 151–159.
Wang, Y.J., Hernandez, M.D., Minor, M.S., 2010. Web aesthetics effects on perceived online service quality and satisfaction in an e-tail environment: the moderating role of purchase task. J. Bus. Res. 63 (9/10), 935–942.
Wathen, C.N., Burkell, J., 2002. Believe it or not: factors influencing credibility on the web. J. Am. Soc. Inf. Sci. Technol. 53 (2), 134–144.
Wells, J.D., Valacich, J.S., Hess, T.J., 2011. What signal are you sending? How website quality influences perceptions of product quality and purchase intentions. MIS Q. 35 (2), 373–396.
Xiao, L., Guo, Z., D'Ambra, J., Fu, B., 2016. Building loyalty in e-commerce: towards a multidimensional trust-based framework for the case of China. Program 52 (4), 431–461.
Xiao, L., Lin, X., Mi, C., Akter, S., 2023. The effect of dynamic information cues on sales performance in live streaming e-commerce: an IFT and ELM perspective. Electron. Commer. Res. https://doi.org/10.1007/s10660-023-09774-6.
Xie, K.L., Chen, C., Wu, S., 2016. Online consumer review factors affecting offline hotel popularity: evidence from tripadvisor. J. Trav. Tourism Market. 33 (2), 211–223.
Xu, H., Zhang, K.Z.K., Zhao, S.J., 2020. A dual systems model of online impulse buying. Industrial Management & Data 120 (5), 845–861.
Xu, X., Yao, Z., 2015. Understanding the role of argument quality in the adoption of online reviews. An empirical study integrating value-based decision and needs theory. Online Inf. Rev. 39 (7), 885–902.
Yang, J., Sarathy, R., Lee, J., 2016. The effect of product review balance and volume on online shoppers' risk perception and purchase intention. Decis. Support Syst. 89, 66–76.
Yeon, J., Park, I., Lee, D., 2019. What creates trust and who gets loyalty in social commerce? J. Retailing Consum. Serv. 50, 138–144.
Yin, D., Bond, S.D., Zhang, H., 2014. Anxious or angry: effects of discrete emotions on the perceived helpfulness of online reviews. MIS Q. 38 (2), 539–560.
Yu, S., Hudders, L., Cauberghe, V., 2018a. Selling luxury products online: the effect of a quality label on risk perception, purchase intention and attitude toward the brand. J. Electron. Commer. Res. 19 (1), 16–35.
Yu, S., Hudders, L., Cauberghe, V., 2018b. Are fashion consumers like schooling fish? The effectiveness of popularity cues in fashion e-commerce. J. Bus. Res. 85, 105–116.
Yuniarti, F., Arief, H.R., Meydia, H., Yevis, M.O., 2022. Online retailers' ethics and its effect on repurchase intention: the mediating role of perceived risk. Cogent Business & Management 9 (1), 2051691.
Zhang, W., Watts, S.A., 2008. Capitalizing on content: information adoption in two online communities. J. Assoc. Inf. Syst. Online 9 (2), 73–94.
Zhang, K.Z.K., Zhao, S.J., Cheung, C.M.K., Lee, M.K.O., 2014. Examining the influence of online reviews on consumers' decision-making: a heuristic-systematic model. Decis. Support Syst. 67, 78–89.
Zhao, Y., Chen, J., Shi, P., Hou, R., 2022. The value of information acquisition and sharing on an online intermediary platform. Electron. Commer. Res. https://doi.org/10.1007/s10660-022-09620-1.
Zheng, X., Zhu, S., Lin, Z., 2013. Capturing the essence of word-of-mouth for social commerce: assessing the quality of online e-commerce reviews by a semi-supervised approach. Decis. Support Syst. 56, 211–222.
Zhu, F., Zhang, X., 2010. Impact of online consumer reviews on sales: the moderating role of product and consumer characteristics. J. Market. 74 (2), 133–148.