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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

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1. Introduction

E-commerce has been growing fast in recent years. Taking Amazon.com as an example, the first-party e-commerce net scales on this platform have increased 3.2 times from 2014 to 2021 (Statista, 2021). During the lockdown caused by COVID-19, e-commerce accelerated its growth as new and existing customers chose to purchase products via available channels (Barnes, 2020). Therefore, it is not surprising to see that the net sales on Amazon.com increased dramatically (1.4 times) in 2020 compared with 2019 (Statista, 2021). More importantly, given the early lessons from China (Stewart, 2020), post-COVID-19 consumers may be more willing to accept e-commerce as a purchase channel (Barnes, 2020).

The rapid development of e-commerce greatly impacts sellers' marketing strategies. In the old years, customers were predominantly passive receivers of marketing and media information, and companies could avoid negative information because they almost completely controlled the brand-sharping messages (Hennig-Thurau et al., 2010). However, nowadays, companies have lost absolute control over the product information: consumers are using several portals to share comments and reviews about products or services, such as the comment area of online retailers and third-party channels (Hennig-Thurau et al., 2010). These new sources of information are essential for consumers when purchasing experience goods like video games (Zhu and Zhang, 2006, 2010) because, for experience goods, it is relatively difficult and costly to obtain information on product quality before interacting with the product (Mudambi and Schuff, 2010).

Consumers now find on e-commerce platforms two types of content, which are seller-created and buyer-created content (Chen and Chang, 2018; Chen and Xie, 2008). In the social media context, these two types of content are also called marketer-generated and user-generated content (Choi and Lee, 2017; Goh et al., 2013). Researchers have conducted a series of studies about their relationships to consumer behaviour and product sales regarding seller-created and buyer-created content.

On the side of buyer-created content, researchers have found that many determinants are associated with product sales on e-commerce platforms. Several meta-analyses have been conducted to summarise the primary metrics of consumer reviews that affect product sales (Floyd et al., 2014; Rosario et al., 2016; You et al., 2015). Recent evidence suggests that review informativeness[1] is positively related to review helpfulness (Sun et al., 2019; Yi and Oh, 2021), which affects product sales (Kaushik et al., 2018). Informativeness, also called information richness, refers to the amount of information embedded in seller-created and buyer-created contents (Goh et al., 2013). Moreover, readability (Ghose and Ipeirotis, 2011), multimedia richness (Xu et al., 2015), and valence (Floyd et al., 2014; Rosario et al., 2016; You et al., 2015) of buyer-created content are positively associated with product sales. Additionally, researchers found that review valence moderated the relationship between review informativeness and product evaluations (Kim and Gupta, 2012).

On the side of seller-created content, researchers have found that information presentation of products is related to mood, perceived risk, and purchase intention (Park et al., 2005). Meanwhile, vividness and interactivity are two critical components of information presentation in customers' purchase patterns (Jiang and Benbasat, 2007). Besides, image-text presentation outperforms text-only presentation in terms of shorter information searching time on product listing pages (Hong et al., 2004). Besides, media richness positively affects purchase intention through satisfaction with seller-created content (Chen and Chang, 2018). Moreover, researchers found that high-quality product

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[1] In this article, we call the informativeness embedded in buyer-created content as review informativeness, and that from seller-created content as product description informativeness. We also use the same logic to denominate readability, multimedia richness, and valence embedded in the two types of contents throughout the article.

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descriptions affected purchase intention through product involvement (Mou et al., 2019).

Seller-created content and buyer-created content also jointly affect consumers' trust (Choi and Lee, 2017), purchase intention (Chen and Chang, 2018), purchase decision (Chen and Xie, 2008), and product sales (Goh et al., 2013). Additionally, the psychological and informational distances between the two types of information affect review helpfulness (Alzate et al., 2021a).

Despite the rich theoretical and empirical evidence regarding the impacts of seller-created and buyer-created content on product sales on e-commerce platforms, several research gaps are noted. First, although the information from seller-created and buyer-created content could be complementary or substitutionary (Chen and Xie, 2008), the empirical evidence is scant. Second, although researchers speculated that more readable content enhanced the relationship between informativeness and product sales (Ghose and Ipeirotis, 2011), the moderating role of readability is not empirically verified. Third, existing evidence suggests that multimedia richness affects purchase intention through the perception of consumer reviews (Xu et al., 2015). Nevertheless, the relationship between multimedia richness and product sales remains explored. Forth, although researchers have found the moderating role of review valence between informativeness and product evaluations (Kim and Gupta, 2012), researchers still do not know whether the same moderating role exists between informativeness and product sales.

Therefore, this research aims to verify:

(1) whether the impacts of the informativeness in seller-created and buyer-created content (product description informativeness/review informativeness) on product sales are complementary or substitutionary.
(2) the moderating role of the readability of seller-created and buyer-created content (product description readability/review readability) between the corresponding informativeness (product description informativeness/review informativeness) and product sales.
(3) the moderating role of the multimedia richness in seller-created and buyer-created content (product multimedia richness/review multimedia richness) between the corresponding informativeness (product description informativeness/review informativeness) and product sales.
(4) the moderating role of valence in buyer-created content (review valence) between the informativeness (review informativeness) in buyer-created content and product sales.

To achieve the mentioned goals, we created a conceptual framework combining the dual processing theory (Chaiken and Trope, 1999) and the dual coding theory (Paivio, 1990), through which the hypotheses were proposed. To test the hypotheses in our conceptual framework, we collected data of video game products from Amazon.com using a third-party API service: the Rainforest API. Then, we operationalised the constructs and measured the variables, including creating the lexicons of video game attributes. Finally, we estimated the empirical model using partial least squares structural equation modelling (PLS-SEM).

This research makes several contributions to the e-commerce literature as well as to practitioners and researchers in this field. On the theoretical side, our empirical findings suggest that review informativeness fully mediates the influence of product description informativeness on product sales, which complements the previous normative model of the interactions between seller-created and buyer-created content (Chen and Xie, 2008). On the practical side, based on the empirical results, we provide concrete guidance for marketers to enhance their strategies on e-commerce platforms. Moreover, as an additional product of the research process, we developed the lexicons of video game attributes, which can help practitioners and researchers to understand and study the attributes of video game products.

2. Theoretical background and hypothesis

2.1. Dual processing theory, dual coding theory, and conceptual framework

In electronic commerce literature, scholars have used dual processing theory (Chaiken and Trope, 1999) and dual coding theory (Paivio, 1990) to address a series of research issues. On the one hand, electronic commerce researchers use dual processing theory to explore review helpfulness (Bigne et al., 2021), customers' evaluation and recall (Book et al., 2018), and product sales (Topaloglu and Dass, 2019). On the other hand, dual coding theory is used to explore review helpfulness (Yang et al., 2017), review enjoyment (Yang et al., 2017), and examine product listing page design (Hong et al., 2004). In the study, we used the mentioned two theories to construct our conceptual framework.

The dual processing theory in the social psychology literature suggests two distinct processes in human cognition that influence peoples' attitudes: System 1 process and System 2 process (Chaiken and Trope, 1999). While System 1 is characterised as unconscious and perceptual, System 2 is conscious and analytic (Evans, 2008). Different authors have proposed distinct names for the two processes (Evans, 2008), and in line with some researchers (Epstein and Pacini, 1999), we call System 1 as experiential process and System 2 as rational process in this study. Marketing researchers have used dual processing theory to explain how informativeness and valence of consumer reviews affect product sales (Topaloglu and Dass, 2019): while informativeness generates the rational process, valence generates the experiential process.

Since consumers usually face incomplete information when purchasing a product (Kivetz and Simonson, 2001), they rely on both seller-created and buyer-created content to reduce uncertainties (Goh et al., 2013). In this research, we classified the widespread informativeness on e-commerce platforms into two categories: product description informativeness from seller-created content and review informativeness from buyer-created content. While product description informativeness includes product-related information (e.g., introduction and specifications of the product), review informativeness contains customers' experience of the product and e-commerce platform (e.g., product features and shopping experience) (Goh et al., 2013).

Moreover, consumers' purchasing decision on e-commerce platforms is affected by the valence of the information received (Floyd et al., 2014; Rosario et al., 2016; You et al., 2015). Valence is the favourability, sentiment, and polarity in a piece of information, which can be either positive, negative, or neutral (Rosario et al., 2016). On the one hand, consumers' attitude towards a product is formed, reinforced, or altered from the exposure to positive or negative reviews from other consumers (Rosario et al., 2016). On the other hand, although we acknowledge that there is a stream of research suggesting the positive effects of negative information (Crowley and Hoyer, 1994), we assume that seller-created content always has positive valence on e-commerce platforms. In general, negative marketing communication is used to denigrate a product in an attempt to either discourage some attitude/behaviour or to establish some alternative attitude/behaviour (Weinberger et al., 1981). Therefore, it is not an optimal strategy for retailers to place negative information about the product on the page where consumers place the order.

Dual processing theory explains the relationship between text information and product sales on e-commerce platforms. However, in many cases, there is not only text information but also multimedia information on the product page, such as images created by both sellers and buyers. To complete the conceptual framework, we embedded the dual coding theory. According to dual coding theory (Paivio, 1990), there are two ways that an individual could expand on learned material, which are verbal associations and visual imagery. Two cognitive systems are involved in processing textual and visual information. While the verbal system involves sequential processing following a certain direction, the non-verbal system involves parallel or synchronous processing, in which the available information is processed up to some limit. On the one hand, as both verbal and non-verbal systems can be activated without the other, they can be functionally independent (Paivio, 1990). On the other hand, as one system can activate another, they also can be functionally interconnected (Paivio, 1990). Information system researchers have applied the dual coding theory to explore the influence of product listing page design and sales (Hong et al., 2004).

Consumers make purchasing decisions relying on a combination of information stored in the memory and information that is available from current external cues (Biehal and Chakravarti, 1982, 1983). Moreover, the information may vary in media richness (Maity and Dass, 2018). Compared with text information, multimedia, including images and videos, present more realistic visual cues and dynamic movements for conveying product information, which is expected to have a powerful impact on consumers' perception (Xu et al., 2015).

Fig. 1 demonstrates the theoretical foundations, dual processing theory and dual coding theory, and the corresponding theoretical components: product description/review informativeness, product description/review readability, product/review multimedia richness, and review valence. Fig. 1 also shows the sources that the theoretical components come from (Seller-created/Buyer-created content).

2.2. Hypotheses

The following sections explain the relationships among the essential factors and product sales on e-commerce platforms before proposing the hypotheses. The hypotheses are visualised in Fig. 2.

2.2.1. Direct and mediating effects

Product information positively affects purchase intention through perceived quality and perceived value (Chang and Wildt, 1994). Dual processing theory suggests that a deliberate and conscious cognitive process also influences peoples' attitude formation (Chaiken and Trope, 1999). Cognitive content significantly impacts new product sales (Topaloglu and Dass, 2019). Additionally, previous empirical evidence suggests that the dimensions of informativeness, including information length (Fang et al., 2016; Liu and Park, 2015; Pan and Zhang, 2011; Wu, 2013) and number of attributes (Sun et al., 2019; Yi and Oh, 2021), are positively associated with helpfulness, which is a critical component in consumers' decision process when purchasing products (Kaushik et al., 2018; Lee and Choeh, 2018; Topaloglu and Dass, 2019). Thus, we infer that informativeness, whether from seller-created or buyer-created content, is positively associated with product sales on e-commerce platforms. The following hypotheses are formed:

H1a. Product description informativeness is positively associated with product sales on e-commerce platforms.

H1b. Review informativeness is positively associated with product sales on e-commerce platforms.

Product description informativeness and review informativeness is correlated. Previously, researchers found that subjective norms were positively related to customers' intention to write online reviews (Dixit et al., 2019). Subjective norms refer to the belief that an important person or group will approve and support a particular behaviour (Ham et al., 2015). Moreover, subjective norms are determined by the social pressure that individuals perceive when conducting certain behaviour (Ham et al., 2015). Therefore, as subjective norms are related to perceived social pressure, marketers' initiatives not only increase the number of customer reviews but also increase the social sense of responsibility in review writing (Dixit et al., 2019). Thus, we infer that when seller-created content is more informative, customers perceive a social pressure that sharps their subjective norms when writing their reviews. The result of this behavioural process will be a more comprehensive and informative review. Therefore, the following hypothesis is formed:

H2. Product description informativeness is positively associated with review informativeness on e-commerce platforms.

While seller-created content is product-oriented, consumer-generated information is consumer-oriented (Bickart and Schindler, 2001). Therefore, buyer-created content is more relevant to consumers than marketer-generated information (Chen and Xie, 2008). Previous empirical evidence suggests that buyer-created content exhibits a stronger impact than seller-created content on consumer purchase behaviour (Goh et al., 2013). Thus, we infer that, as the seller-created and buyer-created content coexist on e-commerce platforms, the effect of product description informativeness can be transmitted with the help of review informativeness. In other words, review informativeness partially or completely absorb the effect of product description informativeness on product sales. Therefore, the following hypothesis is formed:

H3. Review informativeness mediates the relationship between product description informativeness and product sales on e-commerce platforms.

Customer reviews should be precise and easy to understand without possible conflicts (Fang et al., 2016). In the e-commerce context, readability evaluates how easy it is to read and comprehend a piece of text

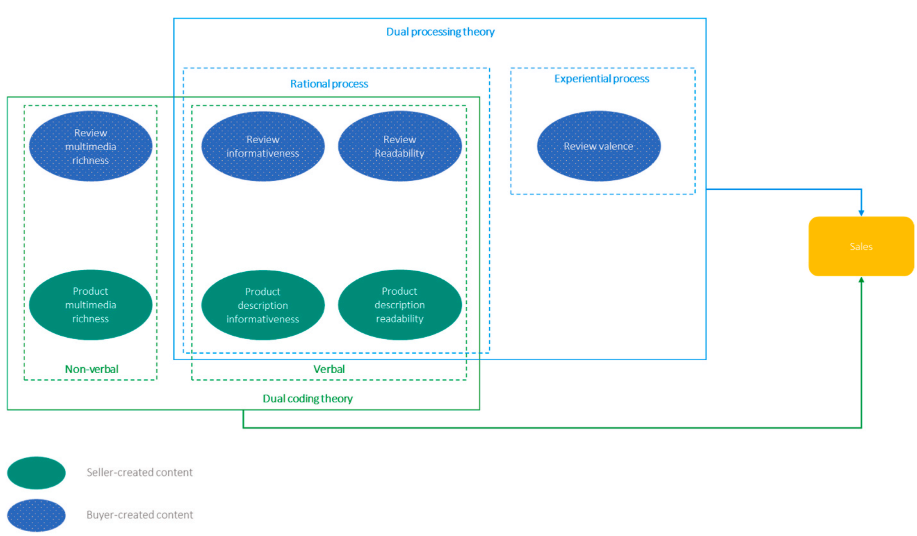

Fig. 1. Conceptual framework.

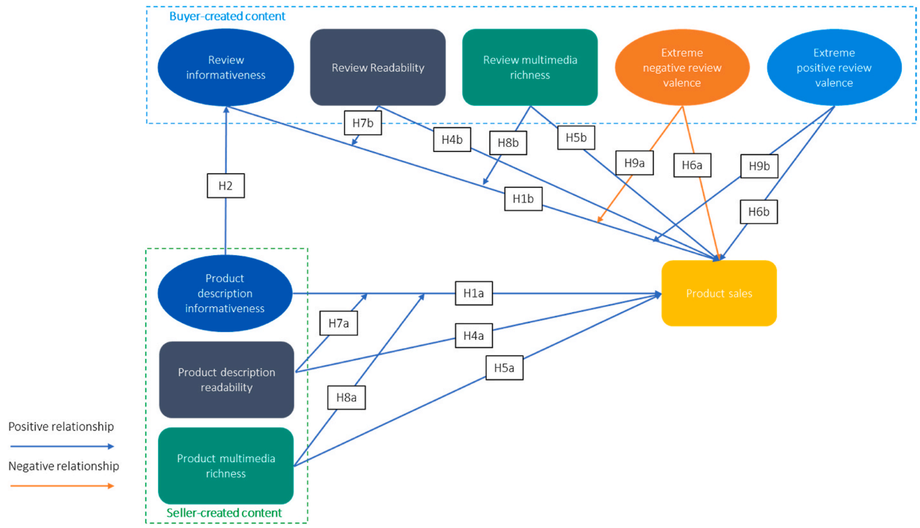

Fig. 2. Visualisation of the hypotheses.

information about the product (Korfiatis et al., 2012). The readability of the text information reflects its author's social status, education level, and social hierarchy (Fang et al., 2016). The readability of a piece of information is positively associated with helpfulness (Fang et al., 2016; Ghose and Ipeirotis, 2011; Korfiatis et al., 2012; Liu and Park, 2015; Wu, 2013). Meanwhile, the helpfulness of information influences product sales on e-commerce platforms (Kaushik et al., 2018). Thus, we infer that the readability of the text content, no matter seller-created or buyer-created, is positively associated with product sales on e-commerce platforms. The following hypotheses are formed:

H4a. Product description readability is positively associated with product sales on e-commerce platforms.

H4b. Review readability is positively associated with product sales on e-commerce platforms.

On e-commerce platforms, multimedia, including seller-created and buyer-created images and videos, coexist with text content to convey important product information to consumers. Multimedia has a significant effect on individuals' intention to visit websites (Lu et al., 2014), which eventually leads to purchase. Moreover, empirical results reveal that the number of images, such as foods and beverages, is positively related to review helpfulness (Yang et al., 2017), which further enhances product sales (Kaushik et al., 2018). Therefore, we infer that multimedia, from either seller-created or buyer-created content, is positively associated with product sales. Thus, we propose the following hypotheses:

H5a. Product multimedia richness is positively associated with product sales on e-commerce platforms.

H5b. Review multimedia richness is positively associated with product sales on e-commerce platforms.

Apart from the conscious cognitive process, dual processing theory also suggests that unconscious and emotional process also influences peoples' attitude formation (Chaiken and Trope, 1999). Valence is an indicator of a product's reputation and expected product quality (Kim and Gupta, 2012; Liu, 2006). Positive reviews enhance consumers' perceived quality and attitude towards the product, while negative reviews usually have an unfavourable impact on the attitude towards the product (Liu, 2006). Regarding the types of valence, on the one hand, researchers found that platform-related valence affected the trust in the seller (Ba and Pavlou, 2002). On the other hand, researchers found that product-related consumer reviews' valence was significantly associated with mobile game sales (Jang et al., 2019). Additionally, existing empirical evidence from meta-analysis studies suggests that, in general, positive valence is positively associated with product sales, and negative valence is negatively associated with product sales (Floyd et al., 2014; Rosario et al., 2016; You et al., 2015). The influence of review valence is even more strong when the valence is extreme (Hong et al., 2017). Extreme valence refers to the evaluation that contains either extremely positive or extremely negative sentiment (Filieri et al., 2018). Empirical evidence reveals that extreme rating leads to more helpfulness (Filieri et al., 2018), which leads to higher product sales (Kaushik et al., 2018). Therefore, we infer that the proposition of extreme review valence is associated with product sales. Thus, we propose the following hypotheses:

H6a. Proportion of extreme negative valence in customer reviews is negatively associated with product sales on e-commerce platforms.

H6b. Proportion of extreme positive valence in customer reviews is positively associated with product sales on e-commerce platforms.

2.2.2. *Moderating effects*

The readability of text content could influence its value (Fang et al., 2016). Information is easier to be processed and evaluated when it contains explicit statements (Mackiewicz and Yeats, 2014). Customers are "*cognitive misers*", who take the easiest path to a solution, such as a purchasing decision, especially when they are goal-oriented (Mackiewicz and Yeats, 2014). The cognitive fit occurs when the information in the text matches customers' own information-processing strategy (Korfiatis et al., 2012). Cognitive fit suggests that, for the most effective and efficient problem solving to occur, the problem representation and any aids employed should support the strategies required to perform that task (Vessey and Galletta, 1991). Therefore, we consider that higher readability of the text information will trigger the cognitive fit of customers. The cognitive fit further leads to effective and efficient problem solving, which in the e-commerce setting is the purchasing decision. Thus, we infer that the readability of the text information, whether from seller-created or buyer-created content, empowers the connection between informativeness and product sales on e-commerce platforms. The following hypotheses are formed:

H7a. Product description readability strengthens the effect of product description informativeness on product sales on e-commerce platforms.

H7b. Review Readability strengthens the effect of review informativeness on product sales on e-commerce platforms.

A vivid product presentation offers consumers more informational cues about a product and stimulates more sensory channels than a pallid product presentation (Jiang and Benbasat, 2007). Generally, multimedia is used on e-commerce platforms to create vividness of product presentation (Jiang and Benbasat, 2004). Multimedia conveys non-verbal information using a richer set of symbol systems and, therefore, better preserves the original meanings, which reduces the chances of misinterpretation (Lim et al., 2000). According to dual coding theory, imagery stimuli are more likely to be coded visually and verbally, and text information is less likely to be coded visually (Paivio, 1990). Thus, the dual coding process makes images easier to remember, generating the "Picture superiority effect": visual information is more likely to be remembered than words (Paivio, 1990). Moreover, "*the greater number of memory codes for images acts as multiple retrieval routes to those images, and therefore enhances information retention and recall* (Hong et al., 2004, p. 484, p. 484)". Thus, we infer that the multimedia content, no matter seller-created or buyer-created, empower the connection between text information and product sales on e-commerce platforms. Therefore, we propose the following hypotheses:

H8a. Product multimedia richness strengthens the effect of product description informativeness on product sales on e-commerce platforms.

H8b. Review multimedia richness strengthens the effect of review informativeness on product sales on e-commerce platforms.

Apart from the direct effects of review informativeness and review valence on product sales, they may also interact. According to the attribution theory, consumers may attribute emotions internally or externally (Folkes, 1988). While internal emotion refers to the personal disposition of reviews, external emotion refers to the reviewed product (Kim and Gupta, 2012). Researchers found that people tended to attribute other peoples' negative behaviour internally and other peoples' positive behaviour externally (Zuckerman, 1979). Therefore, whether consumers attribute reviewers' emotions internally or externally depends on the review valence (Kim and Gupta, 2012). Empirical evidence revealed that negative valence in a single review tended to decrease its informativeness, making the evaluation less negative (Kim and Gupta, 2012). Following this analogy, we propose that positive valence in a review tends to increase its informativeness, which makes the evaluation more positive. Therefore, we propose the following hypotheses:

H9a. Extreme negative review valence weakens the effect of review informativeness on product sales on e-commerce platforms.

H9b. Extreme positive review valence strengthens the effect of review informativeness on product sales on e-commerce platforms.

2.3. Control variables

Apart from the potential relationships between the mentioned essential factors and product sales, previous empirical evidence suggests a series of other variables affecting product sales. In line with the previous empirical evidence, we included the following control variables in the empirical model: price (Chevalier and Goolsbee, 2003; Chong et al., 2016; Kaushik et al., 2018), product average rating (Kaushik et al., 2018; Li et al., 2019), product rating volume (Kaushik et al., 2018; Rosario et al., 2016), top review[2] rating variance (Rosario et al., 2016; Wang et al., 2015), summed amount of helpfulness in top reviews (Kaushik et al., 2018), and top review volume (Floyd et al., 2014; Rosario et al., 2016; You et al., 2015).

3. Methodology

3.1. Data source

We collected data from Amazon.com (United States). Amazon data, including product descriptions (Seller-created content) and consumer reviews (Buyer-created content), were obtained using a third-party API: Rainforest API.[3] Amazon data was used because data from this e-commerce platform had been widely used in previous studies to explore the relationships between determinants and product sales (Chong et al., 2016; Dhar and Chang, 2009; Kaushik et al., 2018). Additionally, we focused on products in the video games category because video games are experience goods, which are relatively difficult and costly for customers to obtain information on their quality before interacting with them (Mudambi and Schuff, 2010). Therefore, reviews from other customers are especially important for buyers when purchasing experience goods (Zhang et al., 2013). Moreover, we selected the samples from the American site of Amazon because the United States was the largest video game market by global revenues, with $36.9 billion in 2009 (Newzoo, 2019). Driven by the growth in console game revenues, it overtook China for the #1 position (Newzoo, 2019).

Like many other e-commerce platforms, Amazon samples some reviews that receive the highest helpfulness votes in the top review section of the product page. The mentioned approach saves consumers' time in accessing quality reviews (Saumya et al., 2018). It is worth mentioning that, in this research, all the consumer reviews come from the top review section of the product page instead of including all reviews of a video game title. We only included top reviews of a video game title because it is difficult for consumers to go through all the reviews to make purchase decisions (Singh et al., 2017). According to Brightlocal (2020), 80% of consumers read less than ten reviews before trusting a product or service. Moreover, when a piece of eWOM information is immediately visible and displayed in a structured way, it has a greater impact (Rosario et al., 2016).

3.2. Data collection and data screening

We collected the data on July 2, 2021. On Amazon.com, every product has a unique identifier called the ASIN code. We searched all the physical video game software (memory card or disc) in the following categories on Amazon: "PlayStation 4″, "PlayStation 5″, "Xbox One", "Xbox Series X & S″, and "Nintendo Switch". In this step, 9639 observations were found and included in the dataset. Due to network issues, sometimes the API returned duplicated observations with the same ASIN code. After screening out the duplicated observations, there were 9565 observations in the dataset. Moreover, due to the maintenance and other factors related to sellers, some product pages on Amazon did not contain the essential information, including ranking, product description, and price. Therefore, the mentioned observations needed to be further screened out, and 7717 observations remained in the dataset.

In this research, we only focused on the products with description in English, as it is the most commonly used language in the United States. Therefore, we screened out the observations in which the product description was written in non-English languages. To achieve this object, we used the Amazon Comprehend service,[4] a natural-language processing (NLP) service that uses machine learning to uncover information in unstructured data. Commercial solutions like Amazon Web Services (AWS) require fewer or no training examples and less technical expertise to implement and calibrate the machine learning methods (Hartmann et al., 2019). Specifically, in this case, we used the function of Language Detection, which automatically identifies text written in over 100 languages and returns the dominant language in the text with a confidence

[2] Top reviews are the selected customer reviews in the "Top review section" of the product page, which are ranked by the volume of helpfulness.

[3] URL: https://www.rainforestapi.com/.

[4] URL: https://aws.amazon.com/comprehend/.

score. We first screened out the observations with confidence scores lower than 0.9 (7539 observations remained) and removed the observations in which the description was not written in English (7506 observations remained).

Then, we removed the outliers in the dataset. The outliers should be removed from the dataset because the extreme values may have an unfavourable influence on the estimated results, even when using a robust method like partial least squares structural equation modelling (PLS-SEM) (Ghasemy et al., 2020; Hair et al., 2016). To remove the outliers, we conducted two operations. First, we removed the observations with the extraordinary price: either too low (less than $10) or too high (more than $100) because the products outside the normal price range suggest that they are not the regular retailing games in the market.[5] At this step, 6771 observations remained in the dataset. Second, we removed the observations without customer reviews (5271 observations remained) and applied a machine learning approach, isolation forest (Liu et al., 2008), to detect the multivariate outliers in the dataset. We set the sub-sampling size as 256 and the number of trees as 100, as these are the recommended parameters based on the previous empirical evidence (Liu et al., 2008). Then, we fed the algorithm on all the items that measure the variables and factors mentioned, which will be introduced in the following section. We screened out the observations with anomaly scores[6] larger than 0.65. Finally, 5248 observations remained in the dataset. Table 1 shows the whole data screening procedure.

3.3. Operationalisation, measurement, and structural model

Regarding the operationalisation of the theoretical components in our conceptual framework, in line with previous researchers (Bergkvist and Rossiter, 2007), we classified the components into two types: concrete singular components and abstract collective components. While the concrete singular component refers to the component with only one object to be rated, the abstract collective component is a set of concrete singular components that collectively form a higher-level theoretical category (John R, 2002). Thus, according to this classification, informativeness and valence belong to the abstract collective components, while readability, multimedia richness, product sales, and other control variables in our conceptual framework, are the concrete singular components.

Table 1
Screening procedure.

Step	Operation	n
1	Original number of observations.	9639
2	Remove the observations with duplicated ASIN code.	9565
3	Remove the observations that: 1. Do not have the ranking information. 2. Do not have any product description. 3. Do not have the price.	7717
4	Remove the observations with low language confidence score (<0.9).	7539
5	Remove the observations in which the product description is not written in English.	7506
6	Remove the observations with extraordinary price (less than $10 or higher than $100).	6771
7	Remove the observations without customer reviews.	5271
8	Remove the outliers.	5248

Regarding the operationalisation of the informativeness, there are different approaches in the literature, including information length (Fang et al., 2016; Filieri et al., 2019; Korfiatis et al., 2012; Pan and Zhang, 2011; Sun et al., 2019; Wu, 2013) and the number of attributes (Nikolay et al., 2011; Sun et al., 2019; Yi and Oh, 2021). However, according to the definition of informativeness (Goh et al., 2013), it is an abstract concept in nature, which implies that it is not directly observable, and we can only obtain indirect evidence of its relationship with other concepts through its operationalisation (Podsakoff et al., 2016). The ubiquitous one indicator approach of operationalising informativeness as a manifest variable in the literature may be conceptually deficient, as this approach fails to articulate all the essential properties of the concept. Therefore, in this research, we operationalised the concept of informativeness as a reflective latent factor, which captures the two dimensions in the content domain of the concept in the current literature.

Regarding the measurement of the two indicators of informativeness, on the one hand, the information length was measured by the total number of words in a product description or consumer review. On the other hand, the number of attributes was measured by our self-developed lexicons (See Appendix I for the developing process and Appendix II for the developed lexicons). As for the specific data source of the two types of informativeness, we measured product description informativeness using the pooled text content from the purchase section (See Fig. 3), the “From the manufacturer” section (See Fig. 4), and the “Product description” section (See Fig. 5). Similarly, we measured review informativeness using the pooled text content from the consumer review section (See Fig. 6).

To measure the readability, we used a readability equation, the automated readability index (ARI) (Smith and Senter, 1967). The ARI was originally developed to measure the readability of written materials in the American Air Force, which is positively associated with the educational grade level (Smith and Senter, 1967). We selected ARI to measure readability in this study because it was one of the most commonly used equations in academic research (Zhou et al., 2017). In the e-commerce context, a lower score of ARI indicates a more readable text (Korfiatis et al., 2012; Liu and Park, 2015). The rationale behind this logic is that when a text can be easily comprehended by readers with fewer years of formal education, it implies that the text contains less complicated vocabulary, which makes it more readable (Fang et al., 2016).

As for the operationalisation of review valence, researchers have quantified this concept in various ways (Rosario et al., 2016). Some researchers used relative measures to quantify the valence, such as the ratio of one-star and the ratio of five-star rating (Chen et al., 2011; Chevalier and Mayzlin, 2006), text sentiment (Goh et al., 2013), and hierarchical approach (Eslami and Ghasemaghaei, 2018). Due to the abstract definition and non-observable nature of valence, in line with the previous research (Eslami and Ghasemaghaei, 2018), we also operationalised extreme valence as a reflective latent factor. We used the ratio of five-star rating and the ratio of positive text sentiment to measure extreme positive valence, while we used the ratio of one-star rating and the ratio of negative text sentiment to measure extreme negative valence. To acquire the sentiment labels for the text, we used the Amazon Comprehend service.[7] Previous empirical results suggest that, compared with lexicon-based approaches (LIWC, in particular), machine learning methods significantly improve prediction accuracy (Hartmann et al., 2019).

Regarding multimedia richness, we measured this variable using the number of images from the seller-created and buyer-created content. Specifically, we measured product multimedia richness using the pooled multimedia content from the purchase section (See Fig. 3), the “From the manufacturer” section (See Fig. 4), and the “Product description” section

[5] For example, they could either be the redeem cards attached to a specific game, or be the games bundled with video game consoles.

[6] The anomaly score in the isolation tree method is ranging from 0 to 1. The scores close to 1 indicates that they are more likely to be the anomalies, while the score close to 0 indicates that they are more likely to be the normal cases (Liu et al., 2008).

[7] URL: https://aws.amazon.com/comprehend/.

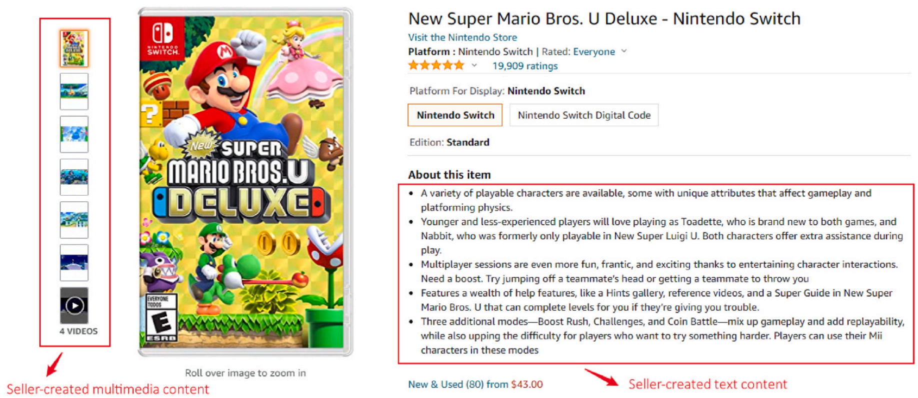

Fig. 3. Example of the content displayed in the purchase section.

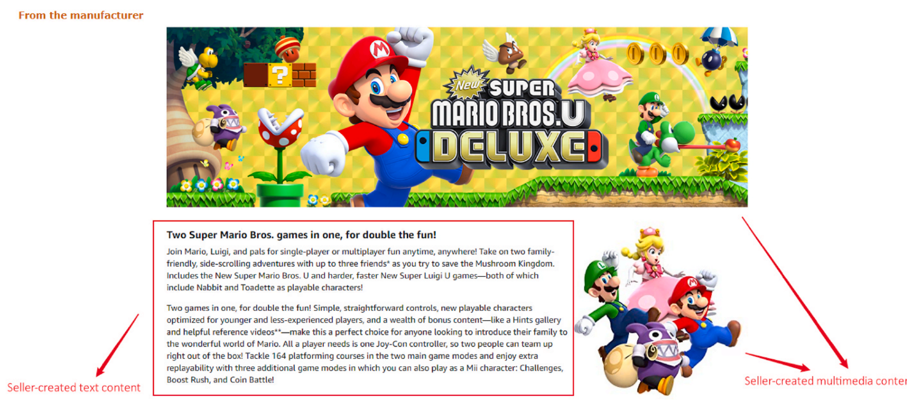

Fig. 4. Example of the content displayed in the “From the manufacturer” section.

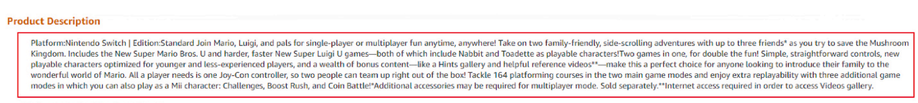

Fig. 5. Example of the content displayed in the “Product description” section.

(See Fig. 5). Similarly, we measured review multimedia richness using the pooled multimedia content from the consumer review section (See Fig. 6).

To measure product sales, we used the logarithmic inverse sales ranking of Amazon.com as a proxy of actual product sales. The rationale behind this approach is that the log curves between sales ranking and actual product sales are approximately linear (Chevalier and Goolsbee, 2003). Besides, this approach is also in line with previous empirical studies, in which product sales on e-commerce platforms is the dependent variable (Alzate et al., 2021b; Chen et al., 2004; Chong et al., 2016; Cui et al., 2012; Kaushik et al., 2018).

In terms of the measurement of the control variables, we used the corresponding numerical data from Amazon.com.

Table 2 summarises the operationalisation, measurement, abbreviation, and description of the variables in the empirical model.

The empirical model is visualised in Fig. 7. This figure demonstrates the measurement model of the variables and the structural model that specifies the hypothesised relationships between the variables and product sales.

3.4. Estimation method and software environment

In this research, we used PLS-SEM to estimate the empirical models that we proposed. PLS-SEM has become a quasi-standard in marketing and management research (Hair et al., 2011). PLS-SEM is suggested to be used when (1) the objective is to extend the existing theories; (2) the structural model is complex; (3) the research is based on secondary/archival data; (4) distribution issues are a concern. (Ghasemy et al., 2020; Hair et al., 2011, 2019; Sarstedt et al., 2014). As the research purpose and the data characteristics of our study meet the mentioned points, PLS-SEM was used.

In terms of the software environment, we implemented the API application to obtain Amazon data from Rainforest API using Python in Spyder. Moreover, we called the requests from Amazon Comprehend and conducted the early data analysis using R in RStudio. We used the package *aws.comprehend* to call the Amazon Comprehend API. Furthermore, we used SmartPLS to estimate the empirical model.

3.5. Results

The descriptive statistics for the items that measure the variables in the empirical model are summarised in Table 3.

The empirical model in this research consists of measurement and structural models. Therefore, it is important to assess the measurement model before moving to the evaluation of the structural model (Hair et al., 2016; Martínez-López et al., 2013).

PLS-SEM model assessment initially focuses on the measurement models, including the examination of internal consistency, convergent

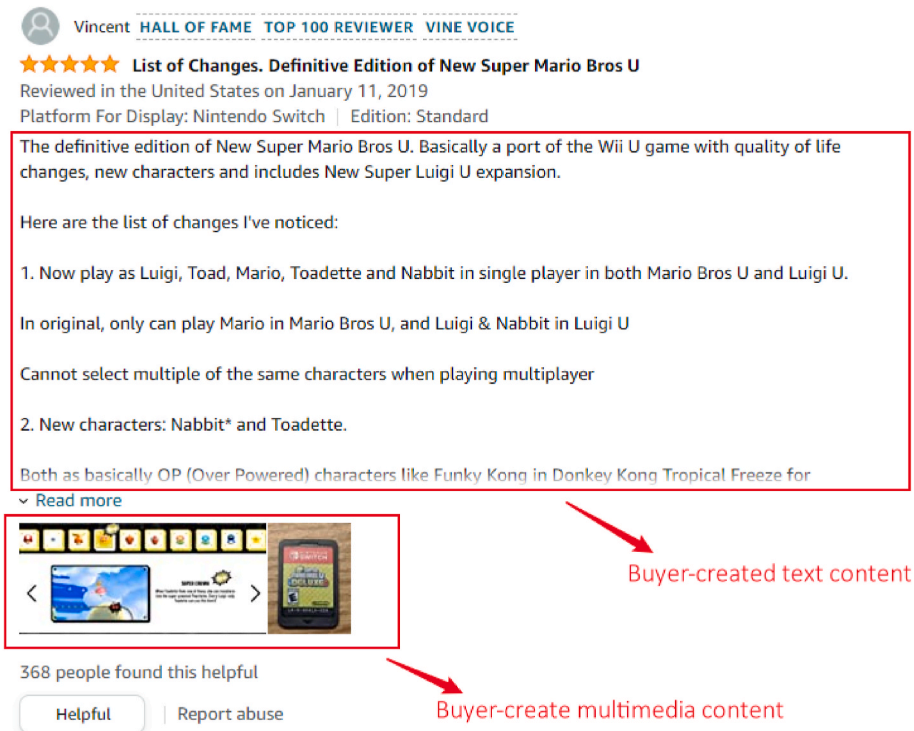

Fig. 6. Example of the content displayed in the consumer review section.

validity, and discriminant validity (Hair et al., 2016). Table 4 summarises the results for the measurement model of the latent variables. According to the results, all the values of composite reliability and Cronbach's alpha are higher than 0.7, indicating desirable internal consistency (Hair et al., 2016). Moreover, the values of outer-loadings are higher than 0.7, while the values of average variance extracted (AVE) are higher than 0.5, indicating desirable convergent validity (Hair et al., 2016). Regarding the discriminant validity, we used both the Fornell-Larcker criterion (Fornell and Larcker, 1981) and the Heterotrait-monotrait ratio (HTMT) (Henseler et al., 2015). While the Fornell-Larcker criterion is widely used in the literature to assess discriminant validity (Hair et al., 2013), HTMT is a more sensitive and reliable approach (Ab Hamid et al., 2017; Hair et al., 2016; Henseler et al., 2015). Table 5 shows the correlation matrix with AVE. On the one hand, all the values of AVE are greater than the squared correlation estimates of the corresponding variables, which provides evidence for good discriminant validity according to the Fornell-Larcker criterion. On the other hand, to implement the HTMT approach, we first checked the HTMT values (See details in Appendix III). All the values are below the conservative threshold of 0.85 (Hair et al., 2016; Henseler et al., 2015), providing the initial evidence for good discriminant validity based on HTMT. Additionally, we conducted a bootstrapping procedure, which will be explained in the following paragraph, to conduct the formal statistical discriminant tests based on HTMT. According to the results (See details in Appendix III), none of the confidence interval includes the value 1, providing the further evidence for good discriminant validity.

After ensuring the reliability and validity of the construct measures, we moved to assess the structural model, which includes the examination of collinearity, size and significance of path coefficients, coefficient of determination (R^2), f^2 effect sizes, predictive relevance (Q^2), and global model fit (Hair et al., 2016). The mentioned results were returned from the bootstrapping procedure. We conducted the bias-corrected and accelerated (BCA) bootstrapping procedure (two-tailed testing and a significance level of 0.05) with the number of subsamples as 10000, which is in line with the suggestion in the literature: the number of subsamples should be higher than the number of observations (5248 in this case) (Hair et al., 2016).

Regarding the collinearity assessment, we checked the values of the variance inflation factor (VIF) of the predictors. According to the results shown in Fig. 8, all values of VIF are below the threshold of 5, which does not indicate the multicollinearity problem in the PLS-SEM context (Hair et al., 2011).

To verify the proposed hypotheses, we assessed the path coefficients. The results are shown in Table 6 and are visualised in Fig. 8. Among the results, it is worth mentioning that the total indirect effect of product description informativeness (PDI) on product sales (LISR) is significant (0.023, $p < 0.001$), while the direct effect of the same relationship is not significant (−0.016, $p = 0.162$). These results suggest that a full mediated effect (Hair et al., 2016; Nitzl et al., 2016): review informativeness (RI) fully mediates the relationship between product description informativeness (PDI) and product sales (LISR). Thus, H3 is supported. Additionally, the direct effect (−0.154, $p < 0.001$) as well as moderating effect (−0.139, $p < 0.001$) of review readability (RR) are negatively significant. In line with the previous studies (Korfiatis et al., 2012; Liu and Park, 2015), these results suggest that when the text of customer reviews requires fewer years of formal education to be understood, the reviews are associated with more product sales and also enhances the relationship between review informativeness (RI) and product sales (LISR). Hence, H4b and H7b are supported. Moreover, although the coefficients of H6a and H8b are significant, the signs are opposite to the hypothesised relationships. Therefore, the two mentioned hypotheses are not supported.

The R^2 value of the structural model is 0.413, indicating a moderate explanatory power in the marketing context (Hair et al., 2011). Moreover, the values of f^2, which assesses the exogenous variables' contribution to the endogenous variables' R^2 value, are shown in Appendix III.

To calculate the Q^2, in line with the literature (Hair et al., 2016), we conducted the blindfolding procedure with the omission distance of 7. According to the results, the Q^2 value of product sales (LISR) equals 0.407, indicating a medium-high predictive relevance for the endogenous variables in the structural model (Hair et al., 2017, 2019).

In terms of the global model fit, the standardised root mean residual

Table 2
Operationalisation and measurement of the variables.

Concept	Operationalisation and measurement			Description
Seller-created content	Product description informativeness (PDI)	←	Information length (PDI1)	Total number of words in the seller-created text content.
			Number of attributes (PDI2)	Matching the seller-created text with the custom lexicons of video game attributes.
	Product description readability (PDR)	←	Readability	Value of automated readability index (ARI) of the seller-created text content.
	Product multimedia richness (PMR)	←	Number of images	Total number of images shown in the seller-created section.
Buyer-created content	Review informativeness (RI)	←	Information length (RI1)	Total number of words in the buyer-created text content.
			Number of attributes (RI2)	Matching the buyer-created text content with the custom lexicons of video game attributes.
	Review Readability (RR)	←	Readability	Value of automated readability index (ARI) of the buyer-created text content.
	Review multimedia richness (RMR)	←	Number of images	Total number of images shown in the consumer review section.
	Extreme negative review valence (ENRV)	←	Ratio of one-star rating (ENRV1)	Ratio of one-star rating in the top review section.
			Ratio of negative sentiment (ENRV2)	Ratio of negative sentiment, returned by the Amazon Comprehend, in the top review section.
	Extreme positive review valence (EPRV)	←	Ratio of five-star rating (EPRV1)	Ratio of five-star rating in the top review section.
			Ratio of positive sentiment (EPRV2)	Ratio of positive sentiment, returned by the Amazon Comprehend, in the top review section.
Control variables	Price (PRI)			Video game price in US dollars.
	Product average rating (PAR)			Average rating of customer reviews in the product page.
	Product rating volume (PRV)			Total volume of customer reviews in the product page.
	Top review rating variance (TRRV)			Variance of customer review ratings in the “Top reviews” section.
	Summed amount of helpfulness in top reviews (SAHTR)			Total volume of helpfulness in the “Top reviews” section.
	Top reviews volume (TRV)			Total volume of customer reviews in the “Top reviews” section.
Dependent variable	Logarithmic inverse sales ranking (LISR)			A proxy variable of actual product sales using logarithmic inverse product ranking in the video game category.

(SRMR) is 0.096.[8]

4. Discussion

In this research, we used dual processing theory and dual coding theory as theoretical foundations to establish our conceptual framework, which helped determine the interrelationships among the key factors driving product sales on e-commerce platforms. To verify the hypotheses, we collected the data (n = 5248) from Amazon.com and estimated the empirical model using PLS-SEM. In the following paragraphs, we discuss the highlighted results of this research.

In terms of the relationship between informativeness and product sales, we found that with the presence of customer reviews on product pages, review informativeness fully mediated the influence of product description informativeness on product sales. In other words, the influence of product description informativeness on product sales should completely pass-through review informativeness. Therefore, in contrast to earlier findings (Chen and Xie, 2008), the relationship between seller-created and buyer-created information is not simply complementary or substitutionary. Our finding suggests that review informativeness not only positively affects product sales (Kaushik et al., 2018) but also is positively influenced by product description informativeness.

As for the relationship between readability and product sales, several insightful results are found. First, the relationship between product description readability and product sales is insignificant. We infer that, quite possibly, like product description informativeness, the influence of product description readability on product sales is absorbed by customer reviews. Further work is required to explore the mentioned relationship. Second, the moderating role of product description readability in the relationship between product description informativeness and product sales is not significant, as the direct relationship mentioned is not significant. Third, the coefficient of the direct effect of review readability is negative, indicating that it is positively associated with product sales, as a lower score of ARI indicates a more readable text (Korfiatis et al., 2012; Liu and Park, 2015). Although this result differs from the previous study (Ghose and Ipeirotis, 2011), it is in line with the results from other studies, which indicate that more readable texts generate a positive marketing outcome: they are positively associated with helpfulness (Fang et al., 2016; Korfiatis et al., 2012; Liu and Park, 2015; Reinartz, 2016). This discrepancy may be due to the explosive growth of customer review volume in e-commerce platforms in recent years leads to information overload, which forces customers to select reviews to read (Alzate et al., 2021b). In this case, more readable reviews enjoy more helpfulness (Fang et al., 2016; Korfiatis et al., 2012; Liu and Park, 2015; Reinartz, 2016), which consequently leads to more product sales (Kaushik et al., 2018). Forth, the coefficient of the moderating effect of review readability is also negative. This result reveals another pathway by which review readability affects product sales: it enhances the relationship between review informativeness and product sales. Therefore, customers, as cognitive misers, employ not only readable reviews to assist their purchase (Mackiewicz and Yeats, 2014) but also find readable reviews with high informativeness valuable (Fang et al., 2016), which finally drives purchase behaviour.

Multimedia richness, either from seller-created or buyer-created content, is positively associated with product sales. This finding is in line with the previous findings (Yang et al., 2017), which indices that multimedia richness from customer reviews is positively associated with

[8] The model fit indices, including SRMR, are still in early research stage in the PLS-SEM context. Although some researchers are starting to report the model fit indices in the PLS-SEM context (Henseler et al., 2014), others point out that reporting them should be very cautious (Hair et al., 2016). For instance, a value less than 0.08 is generally considered a good fit in the CB-SEM context (Hu and Bentler, 1998), this threshold is considered too low for PLS-SEM (Hair et al., 2016).

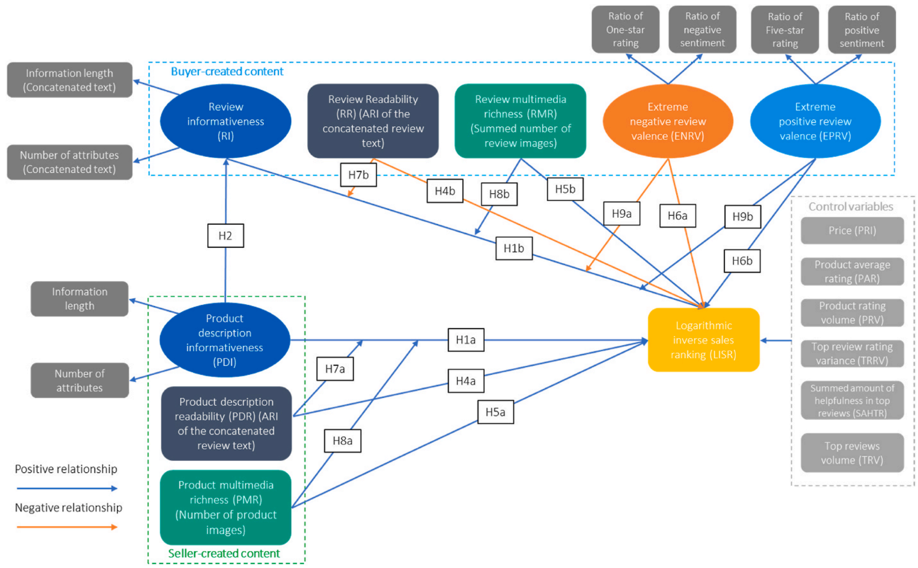

Fig. 7. Visualisation of the measurement and structural models.

Table 3
Descriptive statistics for the items.

Item	Minimum	Q1	Median	Q3	Maximum	Mean	Sd	Skewness	Kurtosis
Information length of product description (PDI1)	2	140	202	284.25	1454	226.085	136.986	2.388	12.719
Number of attributes in product description (PDI2)	0	9	15	24	335	18.890	16.655	4.545	56.402
Product description readability (PDR)	−4.8	9.625	11.691	13.913	74.011	12.006	3.887	1.960	17.993
Product multimedia richness (PMR)	1	5	7	11	46	8.416	5.611	1.254	3.317
Information length of customer reviews (RI1)	1	146	399	877	4632	614.919	640.691	1.712	3.504
Number of attributes in customer reviews (RI2)	0	9	23	45	205	31.657	29.439	1.485	2.575
Review Readability (RR)	−5.162	4.975	6.510	8.140	75.209	6.844	3.794	3.905	40.536
Review multimedia richness (RMR)	0	0	0	0	23	0.473	1.454	5.634	47.724
Ratio of one-star rating in customer reviews (ENRV1)	0	0	0	0.2	1	0.132	0.200	2.159	5.245
Ratio of negative sentiment in customer reviews (ENRV2)	0	0	0.111	0.3	1	0.200	0.231	1.474	2.105
Ratio of five-star rating in customer reviews (EPRV1)	0	0.4	0.6	0.8	1	0.577	0.282	−0.303	−0.651
Ratio of positive sentiment in customer reviews (ENRV2)	0	0.4	0.6	0.8	1	0.585	0.279	−0.329	−0.590
Price (PRI)	10	21.2	29.905	41.175	99.99	34.499	18.017	1.365	1.754
Product average rating (PAR)	1	4.3	4.5	4.7	5	4.430	0.367	−2.708	15.692
Product rating volume (PRV)	1	48	156	501	30088	548.592	1351.681	9.653	149.978
Top review rating variance (TRRV)	0	0.278	1.511	2.456	8	1.569	1.406	1.128	2.275
Summed amount of helpfulness in top reviews (SAHTR)	0	0	8	29	5192	32.808	109.244	24.757	1020.514
Top reviews volume (TRV)	1	5	9	10	10	7.492	3.277	−0.945	−0.737
Logarithmic inverse sales ranking (LISR)	−13.513	−10.973	−10.238	−9.199	−4.357	−10.017	1.318	0.764	0.536

positive marketing outcomes, including review enjoyment and usefulness. Additionally, our results indicate that influences from the seller side do not fade completely: the seller-created multimedia content is still positively influencing product sales with the presence of customer reviews on product pages. Nevertheless, as the relationship between product description informativeness and product sales is not significant, the moderating role of product multimedia richness is not found. Surprisingly, review multimedia reduces the influence of review informativeness on product sales. We speculate that, like review texts, images created by buyers also convey positive (e.g., the impressive graphic performance of a game) and negative valence (e.g., a broken package of a game). If images convey negative valence, they cloud eventually decrease the positive effect of review informativeness on product sales. Therefore, researchers are encouraged to further study the double-edged role of multimedia in customer reviews in future e-commerce studies.

Regarding the valence of customer reviews, it is unanticipated that while the ratio of extreme positive review valence is not significantly associated with product sales, the ratio of extreme negative review valence is positively associated with product sales. A possible explanation for this is the defensive behavioural process (Wilson et al., 2017). Researchers found that customers with high self-brand connections consider negative brand information as a threat to their positive self-view (Cheng et al., 2012), and defensive purchase is a response: they counter-argued/derogated the message source and re-affirmed their own positive attitude (Wilson et al., 2017). Researchers have found a positive relationship between negative customer reviews and product sales in several product categories, including clothing, smartphones, hotel stay (Wilson et al., 2017), and books (Berger et al., 2010). As the mentioned positive relationship also exists in the video game context, it is possible that high self-brand connections ubiquitously exist in the population of video game players. Future studies on the current topic are, therefore, recommended. Moreover, in line with the previous study (Cui et al., 2012), negative reviews are more influential than positive reviews, which further supports the existence of the negativity bias (Paul Rozin and Edward B. Royzman, 2001) in the e-commerce context. Additionally, in contrast to earlier findings (Kim and Gupta, 2012), while the ratio of extreme positive valence enhances the relationship between review informativeness and product sales, the moderating role of the ratio of extreme negative valence is not found. A possible explanation for this is that video game players might generally have high self-brand connections, who attribute negative emotions internally to reviewers' personal disposition rather than to the reviewed products.

Table 4
Summary of the results for the measurement model.

Latent variable	Item	Internal consistency		Convergent validity		Discriminant validity
		Composite reliability	Cronbach's alpha	Loadings	AVE	
		>0.70	>0.70	>0.70	>0.50	HTMT confidence interval does not include 1
Product description informativeness (PDI)	Information length of product description (PDI1)	0.913	0.808	0.913	0.839	Yes
	Number of attributes in product description (PDI2)			0.919		
Review informativeness (RI)	Information length of customer reviews (RI1)	0.984	0.967	0.983	0.968	Yes
	Number of attributes in customer reviews (RI2)			0.985		
Extreme negative review valence (ENRV)	Ratio of one-star rating in customer reviews (ENRV1)	0.946	0.887	0.94	0.898	Yes
	Ratio of negative sentiment in customer reviews (ENRV2)			0.954		
Extreme positive review valence (EPRV)	Ratio of five-star rating in customer reviews (EPRV1)	0.936	0.88	0.897	0.88	Yes
	Ratio of positive sentiment in customer reviews (ENRV2)			0.978		

Table 5
Correlation matrix with AVE.

	PDI	RI	ENRV	EPRV	PDR	PMR	RR	RMR	PRI	PAR	PRV	TRRV	SAHTR	TRV	LISR
PDI	**0.839**	0.019	0.002	0.004	0.085	0.015	0	0	0.001	0.007	0.007	0.001	0.002	0.012	0.005
RI	0.136	**0.968**	0	0.05	0.004	0.118	0.024	0.046	0.002	0.026	0.081	0.001	0.148	0.32	0.143
ENRV	0.047	−0.014	**0.898**	0.497	0	0	0	0	0.002	0.172	0.003	0.253	0.012	0	0.003
EPRV	−0.061	−0.224	−0.705	**0.88**	0	0.016	0.009	0.001	0.004	0.138	0.005	0.142	0.023	0.014	0.007
PDR	0.291	0.066	−0.017	0.013	N/A	0.001	0.001	0	0	0.004	0	0	0	0.001	0
PMR	0.124	0.343	0.02	−0.125	0.029	N/A	0.004	0.013	0	0.004	0.027	0.001	0.023	0.055	0.058
RR	0.018	0.153	−0.007	−0.094	0.03	0.061	N/A	0	0.001	0	0	0	0.001	0	0.003
RMR	0.009	0.214	0.012	−0.031	0.009	0.113	−0.004	N/A	0.009	0.021	0.034	0.003	0.023	0.028	0.066
PRI	0.027	−0.039	−0.044	0.064	−0.01	0.008	0.037	0.094	N/A	0.006	0.001	0.005	0.001	0.008	0.014
PAR	0.081	0.161	−0.414	0.372	0.061	0.067	−0.007	0.146	0.076	N/A	0.044	0.022	0.008	0.036	0.108
PRV	0.082	0.284	0.059	−0.074	0.017	0.166	−0.013	0.185	−0.026	0.21	N/A	0.007	0.118	0.058	0.212
TRRV	0.032	0.025	0.503	−0.377	−0.008	0.035	0.011	0.052	−0.071	−0.15	0.087	N/A	0.005	0.031	0.016
SAHTR	0.04	0.385	0.11	−0.151	0.008	0.152	0.024	0.152	−0.027	0.09	0.344	0.072	N/A	0.039	0.093
TRV	0.11	0.566	−0.002	−0.117	0.037	0.234	0.018	0.168	−0.087	0.189	0.241	0.176	0.197	N/A	0.152
LISR	0.068	0.378	0.053	−0.083	0.017	0.24	−0.051	0.257	−0.119	0.328	0.461	0.128	0.306	0.39	N/A

Note.
1Lower triangle shows the correlation coefficients.
2Upper triangle shows the squared values of the correlation coefficients.
3Diagonal of the matrix shows the average variance extracted (AVE).
4AVE, Composite reliability, and Cronbach's alpha are not meaningful criteria for single-item measures. Therefore, the corresponding cells are presented with "N/A".

5. Implications

5.1. Theoretical implications

This research makes several theoretical contributions to the e-commerce literature.

First, our research reveals that review informativeness fully mediates the influence of product description informativeness on product sales. This empirical finding is an important complement to the previous normative model of the interactions between seller-created and buyer-created content in the e-commerce context (Chen and Xie, 2008). This finding confirms the viewpoint of previous researchers: sellers are losing control over their brands and products (Hennig-Thurau et al., 2010) because the information in the description they created can no longer directly influence product sales. Nevertheless, the situation is not so adverse: the text content that sellers create can still influence product sales with the help of information from customer reviews.

Second, previous empirical studies on the joint influence of seller-created and buyer-created content take place in either social media (Choi and Lee, 2017; Goh et al., 2013) or the tourism (Chen and Chang, 2018) context. In turn, our research is one of the pioneer studies to quantify the influences of both seller-created and buyer-created content in the e-commerce context. Therefore, the results of this research reveal better the economic value of the two types of content on e-commerce platforms.

Third, we found that previous researchers either used dual processing theory (Topaloglu and Dass, 2019) or dual coding theory (Yang et al., 2017) to approach their objectives in the e-commerce context. In contrast, our research highlights the necessity to combine both theories when studying various marketing phenomena in the e-commerce context. The reason behind this logic is that e-commerce platforms contain diverse components on the same product page, and omitting either theory may weaken the explainability.

5.2. Practical implications

This research also makes several practical contributions to e-commerce markers and researchers.

First, we used the bigram analysis to develop the lexicons of video game attributes. The developed lexicons help to understand and study

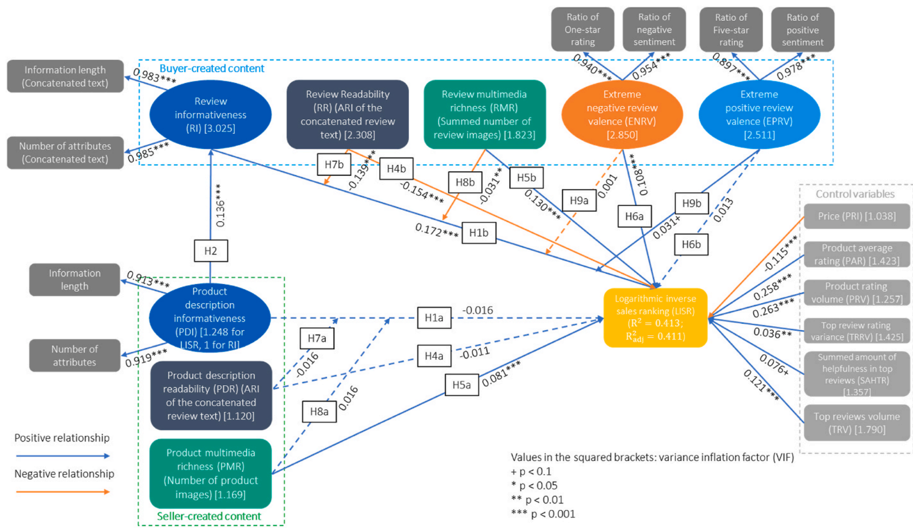

Fig. 8. Results of the estimation of VIF, R^2, loading, and path.

Table 6
Results of significance tests of the path coefficients.

Hypothesis	Relationship	Path coefficient	Standard deviation	t statistics	95% confidence intervals	p value	Is the hypothesis supported?
H1a	PDI → LISR	−0.016	0.012	1.399	[-0.039, 0.008]	0.162	No
H1b	RI → LISR	0.172	0.028	6.238	[0.106, 0.212]	**<0.001**	**Yes**
H2	PDI → RI	0.136	0.015	9.073	[0.108, 0.167]	**<0.001**	**Yes**
H3	RI mediates PDI → LISR	0.023	0.004	5.242	[0.014, 0.031]	**<0.001**	**Yes**
H4a	PDR → LISR	−0.011	0.011	0.972	[-0.032, 0.011]	0.331	No
H4b	RR → LISR	−0.154	0.017	9.022	[-0.186, −0.119]	**<0.001**	**Yes**
H5a	PMR → LISR	0.081	0.011	7.078	[0.058, 0.102]	**<0.001**	**Yes**
H5b	RMR → LISR	0.130	0.016	7.962	[0.099, 0.163]	**<0.001**	**Yes**
H6a	ENRV → LISR	0.108	0.022	5.012	[0.059, 0.143]	**<0.001**	No
H6b	EPRV → LISR	0.013	0.016	0.813	[-0.021, 0.042]	0.416	No
H7a	PDR moderates PDI → LISR	−0.016	0.010	1.499	[-0.036, 0.004]	0.134	No
H7b	RR moderates RI → LISR	−0.139	0.021	6.479	[-0.180, −0.096]	**<0.001**	**Yes**
H8a	PMR moderates PDI → LISR	0.016	0.011	1.491	[-0.005, 0.038]	0.136	No
H8b	RMR moderates RI → LISR	−0.031	0.010	3.062	[-0.052, −0.012]	**0.002**	No
H9a	ENRV moderates RI → LISR	0.001	0.022	0.036	[-0.050, 0.034]	0.971	No
H9b	EPRV moderates RI → LISR	0.031	0.017	1.838	[-0.007, 0.060]	**0.066**	**Yes**
Control variables	PRI → LISR	−0.115	0.011	10.540	[-0.136, −0.093]	**<0.001**	N/A
	PAR → LISR	0.258	0.015	17.242	[0.227, 0.285]	**<0.001**	
	PRV → LISR	0.263	0.027	9.841	[0.205, 0.310]	**<0.001**	
	TRRV → LISR	0.036	0.013	2.734	[0.011, 0.063]	**0.006**	
	SAHTR → LISR	0.076	0.039	1.934	[0.031, 0.169]	**0.053**	
	TRV → LISR	0.121	0.014	8.759	[0.094, 0.148]	**<0.001**	

the attributes of video game products, which have several practical applications, including product development, product maintenance (Lawless and Civille, 2013), marketing research (Sun et al., 2019; Yi and Oh, 2021), and video game research (Bedwell et al., 2012; Marlow et al., 2016; Wilson et al., 2009). For instance, with the assistance of our lexicons, researchers are able to conduct replication studies to verify whether the established knowledge from other contexts (Sun et al., 2019; Yi and Oh, 2021) are applicable in the video game context, which is a process that is increasingly valued by marketing researchers (Easley et al., 2000; Evanschitzky and Scott Armstrong, 2013). Moreover, our lexicons can also serve as a corpus that allows video game researchers to develop a more parsimonious taxonomy of video game attributes, which remains a research gap in the video game literature (Marlow et al., 2016).

Second, our results align with the viewpoint that sellers are losing control over their brands and products with the presence of customer reviews (Hennig-Thurau et al., 2010). Therefore, relying exclusively on markers' own content may not be the most effective way to drive product sales (Goh et al., 2013). Nevertheless, practitioners can still increase product sales by describing in detail their products, as the informativeness in product description increases the informativeness in customer reviews, which eventually drives product sales. Moreover, markers are encouraged to incorporate more images of their products on the product page, which directly drives product sales.

Third, the results indicate that informativeness and readability of customer reviews are two crucial factors that drive product sales in e-commerce platforms. Therefore, markers should attach great importance to buyer-created content. In line with the suggestions from previous researchers (Choi and Lee, 2017; Goh et al., 2013), we also recommend practitioners implement an appropriate marketing initiative that combines seller-created and buyer-created content. Specifically, marketing managers are encouraged to consider developing customer incentive programmes like Amazon Vine,[9] in which the informativeness and readability in the reviews that participants write should be highly valued.

[9] Amazon Vine invites the most trusted reviewers on Amazon to post reviews about new and pre-release products to help other customers make informed purchase decisions. URL: https://www.amazon.com/vine/about.

6. Limitations and future research

Despite the implications that this research offers, some limitations are identified.

First, the empirical model of this research specifies the interrelationships between the key components of seller-created and buy-created content that affect product sales. However, according to the standpoint of social cognitive theory (Bandura, 1986), individuals' behaviour is not only influenced by environmental factors (which are included in this research) but also is influenced by personal factors (e.g., cognition, beliefs, skills, affects). Therefore, we encourage future researchers to extend our conceptual framework by incorporating psychometric factors, such as attitude and behavioural intention. This approach helps to reveal the reciprocal interactions among the three sets of influences in the e-commerce context.

Second, we observed the mediating role of review informativeness between product description informativeness and product sales. However, as this is an observational study, it is not possible to estimate the causal effect of buyer-created content on product sales. The casual inference is important in the marketing discipline because researchers are interested in certain exposures to customer behaviour (Varian, 2016). Future researchers are encouraged to adopt the following approaches to make causal inferences for the results of our research. On the one hand, as randomised controlled trials are considered the gold standard approach (Austin, 2011), it is recommended to replicate our study in the experimental setting. On the other hand, researchers can also use propensity score matching to analyse the observational data to mimic some characteristics of a randomised controlled trial (Austin, 2011).

Third, we detected the double-edged role of buyer-created images. We speculate that buyer-created images can also convoy positive or negative valence. Computer vision techniques have been used to automatically classify images on social media for marketing research (Argyris et al., 2020). Therefore, in future research, it is recommended to use deep learning algorithms to automatically classify the images with positive or negative valence and explore their relationships with product sales when the corresponding training set in the e-commerce context is available. Moreover, in line with previous researchers (Hartmann et al., 2019), we also encourage future researchers to monitor closely the development of commercial cloud computing services, like the image classification algorithm of the AWS[10], which may be another solution to approach the research objective.

Forth, we focused on products in the video games category on the electronic commerce platform. Products from the mentioned category are experience goods, which require sampling or purchase to evaluate the product quality (Mudambi and Schuff, 2010). Customer reviews are essentially crucial for buyers before purchasing experience goods like video games (Zhu and Zhang, 2006, 2010), which makes this product category adequate to study the mediating and moderating roles of the factors derived from both seller-created and buyer-created content. Nevertheless, the sample selection is double-edged. Customer reviews are expected to influence product sales only when consumers' reliance on customer reviews is sufficiently high, which is further influenced by product characteristics (Zhu and Zhang, 2010). Therefore, although results in this research are expected to generalise to experience goods, future researchers are suggested to verify whether the results of this research are generalisable to search goods, such as digital cameras, laser printers, and mobile phones. Unlike experience goods, consumers have the ability to obtain information on product quality before purchasing search goods (Mudambi and Schuff, 2010). Especially, researchers are encouraged to determine whether product type (experience/search goods) serves as a moderator between the essential factors and product sales in this research, as product type has been verified as an important moderator between various factors and the helpfulness of customer review (Filieri et al., 2018; Mudambi and Schuff, 2010; Sun et al., 2019).

[10] URL: https://docs.aws.amazon.com/sagemaker/latest/dg/image-classification.html.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jretconser.2022.103141.

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