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Content-Rating Consistency of Online Product Review and Its Impact on Helpfulness: A Fine-Grained Level Sentiment Analysis

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Abstract

Aim/Purpose	The objective of this research is to investigate the effect of review consistency between textual content and rating on review helpfulness. A measure of review consistency is introduced to determine the degree to which the review sentiment of textual content conforms with the review rating score. A theoretical model grounded in signaling theory is adopted to explore how different variables (review sentiment, review rating, review length, and review rating variance) affect review consistency and the relationship between review consistency and review helpfulness.
Background	Online reviews vary in their characteristics and hence their different quality features and degrees of helpfulness. High-quality online reviews offer consumers the ability to make informed purchase decisions and improve trust in e-commerce websites. The helpfulness of online reviews continues to be a focal research issue regardless of the independent or joint effects of different factors. This research posits that the consistency between review content and review rating is an important quality indicator affecting the helpfulness of online reviews. The review consistency of online reviews is another important requirement for maintaining the significance and perceived value of online reviews. Incidentally, this parameter is inadequately discussed in the literature. A possible reason is

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	that review consistency is not a review feature that can be readily monitored on e-commerce websites.
Methodology	More than 100,000 product reviews were collected from Amazon.com and pre-processed using natural language processing tools. Then, the quality reviews were identified, and relevant features were extracted for model training. Machine learning and sentiment analysis techniques were implemented, and each review was assigned a consistency score between 0 (not consistent) and 1 (fully consistent). Finally, signaling theory was employed, and the derived data were analyzed to determine the effect of review consistency on review helpfulness, the effect of several factors on review consistency, and their relationship with review helpfulness.
Contribution	This research contributes to the literature by introducing a mathematical measure to determine the consistency between the textual content of online reviews and their associated ratings. Furthermore, a theoretical model grounded in signaling theory was developed to investigate the effect on review helpfulness. This work can considerably extend the body of knowledge on the helpfulness of online reviews, with notable implications for research and practice.
Findings	Empirical results have shown that review consistency significantly affects the perceived helpfulness of online reviews. The study similarly finds that review rating is an important factor affecting review consistency; it also confirms a moderating effect of review sentiment, review rating, review length, and review rating variance on the relationship between review consistency and review helpfulness. Overall, the findings reveal the following: (1) online reviews with textual content that correctly explains the associated rating tend to be more helpful; (2) reviews with extreme ratings are more likely to be consistent with their textual content; and (3) comparatively, review consistency more strongly affects the helpfulness of reviews with short textual content, positive polarity textual content, and lower rating scores and variance.
Recommendations for Practitioners	E-commerce systems should incorporate a review consistency measure to rank consumer reviews and provide customers with quick and accurate access to the most helpful reviews.
Impact on Society	Incorporating a score of review consistency for online reviews can help consumers access the best reviews and make better purchase decisions, and e-commerce systems improve their business, ultimately leading to more effective e-commerce.
Future Research	Additional research should be conducted to test the impact of review consistency on helpfulness in different datasets, product types, and different moderating variables.

Keywords	review helpfulness, review consistency, regression analysis, sentiment analysis, signaling theory

INTRODUCTION

Consumer-generated online reviews have become an important source of product information and a standard on the vast majority of e-commerce websites (Chou et al., 2022). They are also considered an electronic "word of mouth" through which consumers share their positive or negative experiences (Aghakhani et al., 2021). A major advantage of online reviews is that they assist consumers in the purchase decision-making process (Erkan & Evans, 2016), as they are proven to reduce the risk and uncertainty associated with online purchases (Eslami et al., 2018; Salehan & Kim, 2016). However, the considerable reviews posted on different e-commerce websites cause online consumers to be overloaded with contradictory information concerning the same product, and they end up having to deal with many reviews of unpredictable quality (Baek et al., 2012; Chou et al., 2022; S. Yang et al., 2019). The number of online reviews is growing exponentially (Singh et al., 2017). On the one hand, these reviews provide more useful information to consumers and make online businesses more attractive (Ghasemaghaei et al., 2018). On the other hand, the number of online reviews overwhelms consumers and creates information overload that is difficult for consumers to process (Malik & Hussain, 2018; X. Sun et al., 2019). Paget, S. (2023) reported that approximately 85% of consumers read only the first few reviews before purchasing products, and they potentially miss more helpful reviews that appear later in the reviews section.

The common form of an online review consists of three main parts: the rating, content, and helpfulness of the review. The rating of a review is commonly a five-point scale, represented in stars, through which consumers rate their experience or view of a product as negative, moderate, or positive (Mudambi & Schuff, 2010). The content of the online review should provide information about the product based on personal experience. The content of the review should also provide an explanation and context to the star rating associated with the review, indicating the quality of such a review (Mudambi & Schuff, 2010). The helpfulness score of the review aims to provide indications about the quality of an online review as helpful or not helpful from the perspective of other consumers apart from the one who wrote the review. Therefore, this part is a form of consumer interaction as one consumer writes a review, whereas other consumers rate its helpfulness and utilize the helpfulness vote to select the most helpful reviews to read. The helpfulness of online reviews has received increasing attention in the literature over the years (Lee et al., 2018; Mousavizadeh et al., 2022). Helpful reviews can improve the value of the intended product, contribute to the sustainability of an e-commerce website (Lee et al., 2018), and attract more consumers seeking useful information for better purchase decisions (Qazi et al., 2016).

Online reviews differ in their characteristics and thus vary in their quality and helpfulness. High-quality and helpful online reviews afford consumers the opportunity to make informed purchase decisions and improve trust in e-commerce websites. The factors affecting online review helpfulness continue to be a popular research hotspot. In this study, the consistency between review content and review rating as an important quality indicator affecting review helpfulness is posited. This research further posits that the consistency of an online review is important in maintaining the relevance and perceived value of the review. In cases in which the review rating is inconsistent with the textual content, consumers are hindered from acquiring helpful information. The link between review consistency and perceived helpfulness and their correlation must be investigated and established, respectively, allowing the problem to be resolved and the review quality to be improved. Various factors influencing the helpfulness of online reviews were examined in past studies, but only a few of them emphasize the consistency of reviews.

On the one hand, quality online reviews with high review consistency help consumers access the most helpful reviews and make informed purchase decisions; on the other hand, they allow firms to improve their e-commerce websites and overall business operations. In particular, consistent reviews raise consumer satisfaction in the following ways: decreased search cost when seeking the most helpful reviews; reduced cognitive effort when reading and evaluating review information; and improved purchase decisions. Among firms, incorporating a parameter for assessing the consistency of online reviews can help improve the value of their products posted online and their overall business operation while affording their consumers the opportunity to convey their trust in the firm. Thus, e-platforms need to focus on the consistency between written reviews and the assignment of ratings.

This study mainly investigates the effect of a review of textual content and its associated rating score on review helpfulness; explores how review sentiment, review rating, and review length are associated with review consistency; and determines whether review sentiment, review rating, review length, and review rating variance, moderate the relationship between review consistency and review helpfulness.

This research posits that when consumers read online product reviews, they simultaneously analyze and consider signals related to the textual content of an online review and its associated rating score during the purchase decision-making process (Erkan & Evans, 2016). A variety of signals embedded in online reviews can be used by readers to judge which one may help evaluate product quality (L. Fan & Zhang, 2020). Within a specific review, textual content and rating score are operated as signals that are simultaneously considered by receivers (review readers) during the purchase decision-making process (Ko & McKelvie, 2018). Therefore, the interaction between the review content and the review rating signals is introduced as a review consistency signal to indicate the ability of the textual content of an online review and correctly explain its associated rating score of the review. Signaling theory provides an adequate theoretical perspective on review helpfulness, as it allows modeling and exploring the relationship between different signals and review helpfulness (Siering et al., 2018). Signaling theory also enables researchers to extend previous research and hypothesize on the moderating role of other signaling environmental variables.

This study contributes to the literature in several ways. First, this study introduces a mathematical measure for the consistency between the textual content of a review and its associated rating. Second, this study investigates review helpfulness from a holistic perspective by combining review textual and numerical scalar characteristics simultaneously. Third, this study proposes a signaling theory-based model to explore the impacts of several characteristics on review consistency, which aids e-commerce websites in presenting more consistent reviews to consumers. This case can help consumers lower their search costs and find the most helpful reviews. Fourth, the research findings contribute to the literature on the helpfulness of online reviews and provide useful insights and practical implications.

The remaining content of this paper is organized as follows. First, a literature review is presented to establish the research background and key concepts and examine previous studies in depth. Then, the research hypothesis, the research methodology, and the data analysis and results are presented. Finally, the findings and their implications are comprehensively discussed.

LITERATURE REVIEW

SIGNALING THEORY

Signaling theory primarily draws on information economics theory (Nguyen-Viet, 2022), which is considered a suitable theoretical framework for understanding how to reduce the uncertainty associated with products by providing quality information that supports the purchasing decision-making process (Mudambi & Schuff, 2010; Nelson, 1970). In the literature, review helpfulness is "a measure of perceived value in the decision-making process" and resembles the diagnosticity of the online review related to the reduction of uncertainty (Mudambi & Schuff, 2010; Siering et al., 2018). Signaling theory is also used for information interaction and transmission (L. Wang et al., 2019), which provides a framework to understand how signals are used to convey hidden or limited quality information from one party to another for effective exchange or purchase (L. Fan & Zhang, 2020). In the context of online reviews, signals are the visible features a review can communicate and carry information from those with more information to those with less information (Spence, 2002).

Signaling theory proposes that signals help reduce the information asymmetry between two parties (Spence, 2002; L. Wang et al., 2019). Information asymmetry exists between buyers and sellers in the market transaction, considering that different parties often possess a different amount of information regarding a specific product (Connelly et al., 2011; Keeler, 1976). In general, sellers are aware of essential information about products, but consumers may not be fully informed about such information. Consumers often seek relevant cues/signals to infer the potential quality of a product to reduce their perceived risks (Kirmani & Rao, 2000), as signals disclose the review messages that can assist consumers in making better decisions. In the context of online reviews, consumers are senders, the review characteristic information represents the signal transmitted, and potential consumers or review readers represent receivers (Numminen & Sällberg, 2017). When information is conveyed to review readers, high-quality information should be selected, which can be extracted by signaling theory to improve purchasing decisions (L. Wang et al., 2019). Online retailers encourage their consumers to deliver product recommendation information through online reviews mainly in the forms of text descriptions and quantitative ratings to facilitate the product purchasing processes of consumers (L. Fan & Zhang, 2020). As a result, textual and quantitative review characteristics have become the major types of information on e-commerce websites.

This study draws upon signaling theory to investigate the effect of the simultaneous interaction between textual and numerical types of signals on review helpfulness. The sentiment polarity of the review text and rating score are conceptualized as textual and numerical signals, respectively. The effect of consistency between these two types of signals on review helpfulness is also investigated to help consumers reduce product uncertainty. Meanwhile, this study posits that other review characteristic signals, such as length, polarity, and rating, may enhance review consistency, which may further moderate the relationships between review consistency and review helpfulness. Signaling theory is utilized in this research to explain how signals of online reviews influence the perceptions of consumers, and domain-specific signals have been recognized in extant studies (Cheung et al., 2014; Choi et al., 2018; Liu et al., 2016; Mavlanova et al., 2016; Mou & Shin, 2018; L. Wang et al., 2019). Mavlanova et al. (2016) and Spence (2002) argued that the essence of signaling theory lies in analyzing various types of signals and the situations where they are applied. Several studies in the literature have utilized signaling theory (Choi et al., 2018; Mou & Shin, 2018). For instance, Cheung et al. (2014) and Numminen and Sällberg (2017) selected peer consumer reviews and ratings to establish a signaling framework that generates perceived product and service quality. L. Fan and Zhang (2020) used review length and the number of images in the review to establish their signaling framework and found that such signals can help the review gain more helpful votes. In addition, Siering et al. (2018) considered review content-related signals (i.e., specific review content and writing styles) and reviewer-related signals (i.e., reviewer expertise and non-anonymity) in their signaling framework. They further observed that this content and reviewer-related signals influence review helpfulness.

Review Helpfulness

Many researchers have attempted to explain the various factors and reasons that make online reviews helpful, with a particular focus on review content, length, linguistic features, readability, emotions, relevancy, factuality, currency, rating score, and related photographs or illustrations (Filieri et al., 2018; Ma et al., 2018; Malik & Hussain, 2017; Srivastava & Kalro, 2019; S.-B. Yang et al., 2017). Regarding the use of research variables, previous works on review helpfulness have emphasized the impact of review scores on review helpfulness. Zhou and Yang (2019) and Y. Wang et al. (2019) revealed that extreme review ratings significantly affect review helpfulness. Furthermore, prior studies determined that lower-rating reviews tend to be perceived as more helpful than other reviews (Cao et al., 2011; Sen & Lerman, 2007; Willemsen et al., 2011). In general, consumers depend on the textual content of reviews rather than ratings (Chevalier & Mayzlin, 2006). Thus, other textual factors, such as review readability (Fang et al., 2016; X. Wang et al., 2019) and review sentiment, must be investigated, as they are important determinants of review helpfulness (Al-Smadi et al., 2019; Ren & Hong, 2019). W. Fan et al. (2021) have recently shown that reviews with positive sentiments are perceived as more helpful than those with negative sentiments. Siering and Muntermann (2013) revealed that positive review sentiments positively affect online review helpfulness. Textual length can also affect review helpfulness (X. Wang et al., 2019), with long online reviews containing many more words and expressions being perceived as more helpful than short reviews (Cao et al., 2011; Kang & Zhou, 2016; Peng et al., 2014; Siering & Muntermann, 2013). However, Bilal et al. (2020) found a negative correlation between review length and review helpfulness, which is similar to the finding of S. Yang et al. (2019), who found that review length negatively affects review helpfulness. Several other studies have addressed the rating variance of online reviews, proving that the similarity between review ratings and the average rating of a product raises the review's helpfulness (Baek et al., 2012, 2015). On the client side, the findings suggest that consumers tend to consider a review helpful when its rating is close to the average rating of a product.

Given the relevance of the review consistency variable, some studies have investigated review consistency from different perspectives. Zhou et al. (2020), for example, examined the influence of review title-content sentiment consistency on review helpfulness. The results show that review helpfulness is enhanced when the review title and content are consistent. Quaschning et al. (2015) examined the influence of similar reviews on review helpfulness compared with prior studies that considered individual reviews only. Their results confirmed that the consistency of the sentiment of a review with that of other available reviews affects and improves the helpfulness of the review. Shen et al. (2019) used review consistency to evaluate the reliability of reviewers, not for the helpfulness effect. The authors observed that large discrepancies between the review rating score and sentiment score can be an indicator of low-quality reviews without addressing the impact on perceived helpfulness. Aghakhani et al. (2021) investigated the effects of consistent and inconsistent reviews on the consumer decision-making process but ignored the factors that might affect, improve, or moderate review consistency. Their results showed that consistent reviews positively affect review helpfulness as a proxy for review quality. However, the focus of this study is mainly to measure review consistency, how it can affect perceived review helpfulness, and how review consistency is affected by several review characteristics. To the best of our knowledge, previous research that measured review consistency and investigated its impact on review helpfulness is very limited. Moreover, this study is the first to investigate the effect of review rating, review sentiment, and review length on review consistency and investigate their moderating effect on the relationship between review consistency and review helpfulness. The effect of such variables on review helpfulness has been commonly investigated in the literature with mixed results.

The present study contributes to the literature by introducing a review consistency score and investigating its impact on perceived review helpfulness. In particular, this research simultaneously assesses the impact of review content and review rating on review helpfulness. Past works focused independently on either rating scores or textual content. The current study expands the current body of knowledge by simultaneously exploring the importance of review consistency and how it affects perceived review helpfulness. The direct and mediated impacts of different review characteristics on review consistency and their correlations with perceived review helpfulness represent the other important contributions of this work. Moreover, this study introduces a regression model to address review consistency based on its characteristics.

Hypothesis Development and Research Model

Drawing on the findings of previous research and theoretical reasoning, this section presents the development of the research hypothesis, which jointly forms the theoretical research model for this study. First, the direct effect of review consistency on review helpfulness is checked. Then, the effects of review sentiment polarity, review rating score, and review length on review consistency are examined. Finally, the moderating effects of review sentiment, review rating, review length, and review rating variance on the relationship between review consistency and review helpfulness are explored.

Review Consistency

Online customer reviews consist of quantitative and qualitative aspects represented by the rating, text, and helpfulness of the review. Review ratings and helpfulness are quantitative scores useful in attracting the attention of consumers and offering sufficient information to make a decent first impression (Zhou et al., 2020). The textual content presents a detailed description of the product features and functionalities and should provide cues and explanations for the rating of the review (Dor, 2003). The text of a review and its associated rating should be consistent to provide more value for the customer. Inconsistency between review rating and review textual content can create conflicting signals for potential customers when reading the review, which negatively affects their purchasing decisions.

In the literature, individuals are interested in having consistent attitudes, thoughts, and actions over time (Abelson et al., 1968). Several studies have addressed reducing such tensions; for example, Hogenboom et al. (2014) argued that the sentiment of a review can be used as an alternative to the rating score of that review. Another study by Ghasemaghaei et al. (2018) found that the sentiment of a review can be a good predictor for a review rating score. Thus, writers are expected to provide a rating score that is consistent with the sentiment that they have incorporated in that review.

To describe the extent to which the sentiment of review textual content is consistent with its associated rating, the concept of "content-rating consistency" is introduced in this study, which is also referred to as "review consistency" for short where it is unambiguous. This study posits that review consistency will be positively associated with perceived review helpfulness and useful to attract the attention of consumers. That is, when consistent reviews are presented to consumers, their perception of review helpfulness increases. Hence, the following is hypothesized:

H_1: Review consistency will positively affect review helpfulness.

Review Sentiment

Review sentiment is defined as "the consumers' tone reflected in the text of a review" (Hu et al., 2014) and is considered an important factor that influences review helpfulness. Sentiment polarity is a score ranging from -1 to 1 obtained using sentiment analysis and reflects the emotions and opinions of consumers about their usage experiences of the reviewed product (Yin et al., 2014). Positive review sentiment is represented by a sentiment polarity score (1), and negative review sentiment is represented by a sentiment polarity score (-1). Consumers (review readers) can detect the emotions of reviewers (review writers) from certain cues and expressions existing in the text of the review (Salehan & Kim, 2016). Sentiment analysis has been consistently employed to calculate sentiment polarity scores of reviews to investigate its influence on reading customers and their purchasing decision process (Eslami et al., 2018; Nakayama & Wan, 2019; Saumya et al., 2020).

In the context of review helpfulness evaluation, the literature has reported that consumers (review readers) perceive negative reviews as more diagnostic and helpful than positive reviews (Eslami et al., 2018; Hong et al., 2017; Yin et al., 2016). Moreover, negativity bias theory proposes that individuals are more likely to be concerned with negative cues than positive cues (Rozin & Royzman, 2001). By contrast, consistency mainly depends on the reviewer (review writers); instead, from the perspective of a reviewer, people normally tend to praise and compliment others more than they criticize. The main reason could be that it is easier to provide positive expressions that are consistent with the rating assessment, particularly in the case of a good experience with the product. In comparison, in the case of bad experiences, people find it difficult to write appropriately passive, pungent, or slanderous expressions and cues; consequently, neutral descriptions become more dominant. Even when reviewers are offensive, they prefer utilizing neutral words. Thus, the sentiment of content will likely be positively associated with the consistency of the review, where positive reviews are more likely to be consistent with their rating. Thus, the following is hypothesized:

H_2: The positive sentiment of a review content will positively affect review consistency.

H_3: The effect of review consistency on review helpfulness is stronger when review sentiment polarity is higher.

Review Rating

Another factor influencing the perceptions of consumers regarding review consistency and helpfulness is the review rating score. In general, the review rating is a score (usually ranging from 1 to 5) that reflects the overall assessment of a reviewer (review writer) about product quality (Mudambi & Schuff, 2010). In this regard, lower scores indicate a negative evaluation of the reviewer about the quality and vice versa. According to negativity bias theory, individuals tend to evaluate negative opinions and expressions higher than positive or neutral ones (Chen et al., 2020). This case implies that consumers will pay more attention to negativity (Rozin & Royzman, 2001) when reading a review and evaluating its helpfulness. Salehan and Kim (2016) found that consumers perceive reviews with lower review rating scores to be more helpful. By contrast, a high rating score can be easily decided and provided by a reviewer compared with a negative low-rating score, which results in more accurate state harmony. The reason is that people (e.g., reviewers) normally tend to praise and compliment others more than they criticize them, and thus, it is easier to provide a positive review. Reviews with extremely positive or negative ratings are often considered more informative and thus are perceived as more helpful (Chua & Banerjee, 2015). Hence, a positive relationship is expected between review rating and review consistency such that reviews with higher rating scores (extreme positive rating) can be more consistent with their textual content. Additionally, review rating is expected to play a moderating role in the review consistency and review helpfulness relationship, such that a positive review rating with a higher score strengthens review consistency. The following is hypothesized:

H_4: Review extremity has a positive effect on review consistency.

H_5: The effect of review consistency on review helpfulness is stronger for extreme-rated reviews.

REVIEW LENGTH

The textual content of a review can be used as an alternative to evaluating its helpfulness for consumers to make robust purchasing decisions (Eastin, 2006; Park & Lee, 2009; Reinhard & Sporer, 2010). Review helpfulness is dependent on the amount of information available in the review's textual content, i.e., the length of a review is positively correlated with the perceived review helpfulness of consumers, as longer reviews are likely to contain more cues than shorter ones (Chevalier & Mayzlin, 2006; Mudambi & Schuff, 2010; Park & Lee, 2009; Salehan & Kim, 2016). For consistency, longer reviews that contain more cues imply more potentially consistent reviews, particularly when reviewers express and provide more detailed and accurate cues and expressions explaining their usage experience without the need for any summarization. Thus, the review consistency can be positively dependent on the amount of information available in its textual content. The longer the reviews, the more potentially consistent the reviews. Therefore, on the balance of these arguments, the following is hypothesized:

H_6: Review length has a positive effect on review consistency.

H_7: The effect of review consistency on review helpfulness is stronger for longer reviews.

RATING VARIANCE

The variance of rating is considered to further confirm the effect of the review consistency on review helpfulness perceived by review readers. Rating distribution represents variance, or heterogeneity, in the evaluations by consumers (Luo et al., 2013), which can be represented statistically as the standard deviation of rating scores. Several consumers provide several ratings in their reviews about a certain product, and having harmony and consistency between these ratings is preferred. Consumers can form their initial reaction to product quality based on the average rating or visualized rating distribution (Yin et al., 2016). Providing a rating score of a product that is in line with or close to other scores for that product presents an indication of the correctness of this assessment, which could be measured as the mathematical variance of those ratings (Moe et al., 2011; M. Sun, 2012). Lower rating variance presents harmony among the reviews about that product. Thus, the following is proposed:

H_8: The effect of review consistency on review helpfulness is stronger for reviews with lower variance.

RESEARCH MODEL

The conceptual research model developed on the basis of the proposed hypothesis is shown in Figure 1. Testing and validating this model with empirical evidence is the main objective of this study. The following main sections document the implementation of this study, provide methodological detail, present data analytical results, and discuss the research findings.

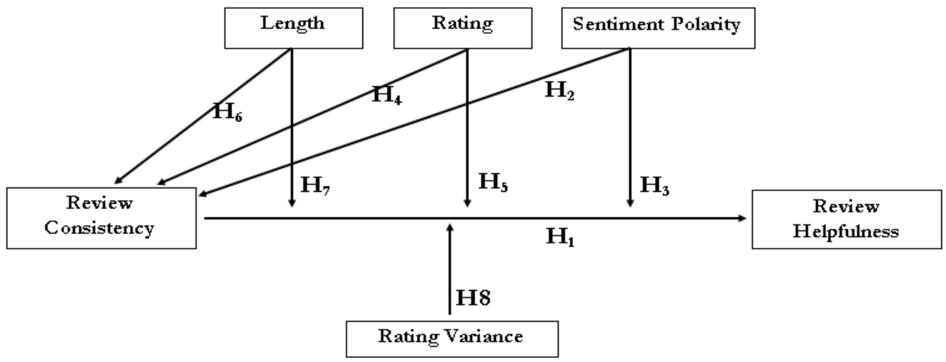

Figure 1. Research model

METHODOLOGY

To evaluate the proposed model by virtue of testing the hypothesis, several steps are performed using several tools and instruments, including: (1) data preprocessing, which is performed to select and prepare reviews for extraction; (2) data extraction, which is performed to identify quality reviews and extract their required features that correspond to the study variables; and (3) training and prediction, which is aimed at performing predictive analysis and measuring a consistency score for each review.

The dataset obtained from Amazon.com consists of 104,856 product reviews for 25,788 products. T he mobile electronics category is selected from several categories such as electronics, toys, furniture, a nd cameras; it consists of approximately 48,500 product reviews extracted from Amazon.com (Amaz on Customer Reviews Dataset, n.d.; He & McAuley, 2016). The review data are divided into training and target datasets. The training dataset consists of voted reviews, which include the actual helpfulne ss values provided by users. By contrast, the target dataset, which represents the non-voted reviews, l acks the helpfulness values. With the aim of improving the reliability and quality of the results, traini ng reviews are classified on the basis of the number of individuals who voted for review helpfulness, the number of words that describe the product or service in the review, and the number of product a spects mentioned in the review. Only high-quality reviews containing valuable information for trainin g (i.e., reviews with more than 20 votes, reviews with 5 words or more, and reviews that include at lea st 1 product aspect) are adopted. The final sample training dataset comprises 1,180 reliable, non-bias ed reviews.

Then, for each review in the training dataset, the review textual content (Ti) is obtained by tokenizing the original text; that is, segmenting it into sentences and words and removing the punctuation marks and stop words, review rating score (Ri), number of helpful votes, and total votes. All operations were performed based on natural language processing (NLP) functions by using RStudio, version 3.0 of the Python software via Jupyter Notebook, and two Python libraries: spaCy and TextBlob. The other required study variables (e.g., review helpfulness, length, sentiment, rating variance, and consistency) are not directly available and were calculated as follows. Review helpfulness (Hi) was calculated by the ratio of helpfulness to total votes (Mudambi & Schuff, 2010). Review length (Li) was calculated by counting the number of words in the textual review content. Review sentiment is represented as a sentiment polarity score (Spi) that ranges from −1 to 1 and is calculated using TextBlob (Mundra et al., 2019). TextBlob is a Python-based library for performing NLP functions, which has been proven to be an effective sentiment analysis tool (Gauba et al., 2017; Mundra et al., 2019) and provides a sentiment score for a text based on a Naïve Bayes analyzer (Gauba et al., 2017). The lower the polarity score, the more negative the review sentiment is. The rating variance for each review is mathematically calculated by finding the deviation of a rating score from the mean of other rating scores for that product.

Finally, review consistency is introduced in this study to determine the extent to which the sentiment of review textual content is in harmony with the review rating or its ability to explain the review rating score. Finding precise and fine-grained consistency values is key to performing this study efficiently and obtaining reliable results. Thus, regression analysis was employed as a machine-learning technique to perform predictive analysis and measure review consistency (Ci). Regression analysis is a machine learning technique commonly used to conduct predictive analysis, investigate the relationship between the research variables, and efficiently obtain a predicted value based on their correlation (Maulud & Abdulazeez, 2020).

In this study, a linear regression (LR) model is formulated and applied to predict a new rating score (R_d) resulting from a linear combination of the review sentiment score (Sp) and actual rating score (R) of the training reviews (Palmer & O'Connell, 2009). The solution involves training the LR model to understand and learn the rating behavior for training reviews and predict the suitable ideal rating score (R_d). Understanding the rating behavior requires sentiment polarity and the corresponding actual rating score originally provided by the review provider for each review. The LR uses such values and predicts an ideal rating score for each review that best represents its sentiment polarity, as shown in Eq. (1).

$$R_{di} = (m*Sp_i)+b, \qquad (1)$$

where R_d is the ideal rating score, Sp is the sentiment polarity score for review (i), and b and m are LR-related parameters, such as b: intercept parameter and m: slope coefficient. The obtained error values among predicted and actual rating scores were used to represent the dissimilarity and inconsistency that exist for that review. Finally, the error is normalized and inversed to determine a consistency value for such a review, as shown in Eq. (2).

$$C_i = 1- [abs(R_i- R_{di})], \qquad (2)$$

where C_i is the review consistency, (R_i) is the actual rating score, and R_{di} is the predicted ideal rating score for a review (i). Table 1 shows the summary statistics of the sample. Figure 2 represents the proposed framework that summarizes the overall data collection, preprocessing, extraction, learning, and prediction processes.

Table 1. Descriptive statistics for dataset (n = 1,180)

Review characteristics	**Description**	**Instrument**	**Min**	**Max**	**Mean**	**SD**
Helpfulness (H_i)	Ratio of helpful votes to total votes	Ratio calculation	0	1	0.828	0.241
Review Consistency (C_i)	Ability of the review text to explain its rating score.	Regression analysis	0	0.997	0.721	0.17
Sentiment polarity (Sp_i)	Emotions of consumers about usage experiences of a product range from negative (−1) to positive (1) score	TextBlob Python-based library	−0.875	1	0.17	0.175
Rating score (R_i)	5-point quantitative assessment of a consumer about product quality		1	5	3.59	1.618

Review characteristics	Description	Instrument	Min	Max	Mean	SD
Length	Number of words in a review	Word count calculation	6	2654	231.6	271.9
Rating variance	Rating distribution represented as the standard deviation of the review rating	Variance calculation	0.409	2.591	1.449	0.720

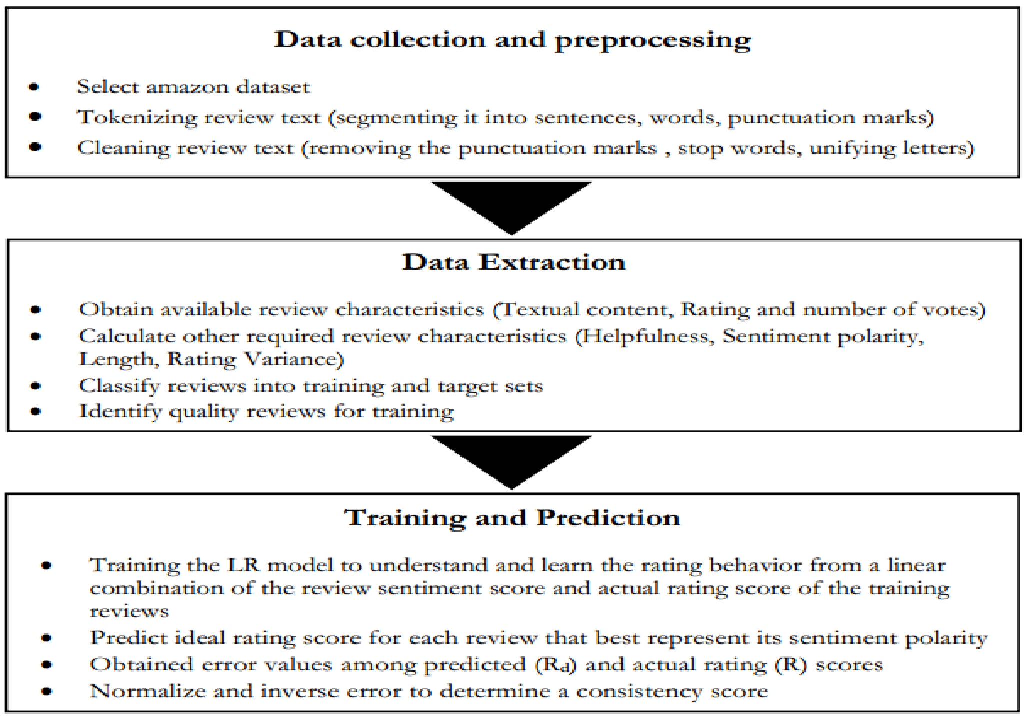

Figure 2. Study framework
(data collection, preprocessing, extraction, learning, and prediction)

DATA ANALYSIS AND RESULTS

MEASUREMENT MODEL EVALUATION

Regarding the proposed model of the study, the obtained data were analyzed using the method of robust path analysis (Hair et al., 2009; McDonald, 1996). The multivariate statistical analysis software WarpPLS 8.0 (Kock, 2022) was used to conduct a robust path analysis with a linear inner model analysis algorithm and stable3 resampling. This algorithm allows for the testing of the entire model, including the quick determination of the mediating effect, an estimation of all P values via distribution-neutral nonparametric procedures, and a direct estimation of the P value associated with the mediating effect by resampling. The variance inflation factor (VIF) values are calculated to test for the multicollinearity, as they can affect the final analysis. All VIF values are less than 5 in the multicollinearity analysis, as shown in Table 2. This finding suggests that all latent variables in the model can measure the indices differently, which is an important precondition for validity analysis (Kock, 2022). Therefore, multicollinearity does not seem to have an effect on the research analysis. Table 3 further shows that the research model has a good fit based on the suggested model fit quality indices and their recommended criteria standard levels (Kock, 2022).

Table 2. Full collinearity VIFs

		VIFs
1	Review consistency	2.34
2	Review length	1.176
3	Review rating	1.098
4	Review sentiment polarity	4.17
5	Review helpfulness	2.922

Table 3. Model fit evaluation result

Measure	Value	p-Values
Average path coefficient (APC)	0.115	$p = 0.002$
Average R-squared (ARS)	0. 118	$p < 0.001$
Average adjusted R-squared (AARS)	0.115	$p < 0.001$
Average block VIF (AVIF)	1.530	Good if ≤ 5, ideally ≤ 3.3
Average full collinearity VIF (AFVIF)	3.004	Acceptable if ≤ 5, ideally ≤ 3.3
TenenhausGoF (GoF)	0.344	Small ≥ 0.1, medium ≥ 0.25, large ≥ 0.36
Simpson's paradox ratio (SPR)	0.875	Acceptable if ≥ 0.7, ideally = 1
R-squared contribution ratio (RSCR) (experimental index)	0.971	Acceptable if ≥ 0.9, ideally = 1
Statistical suppression ratio (SSR)	1.000	Acceptable if ≥ 0.7
Nonlinear bivariate causality direction ratio (NLBCDR)	0.813	Acceptable if ≥ 0.7

Table 3 presents the ten fit quality indices of the model provided by WarpPLS 8.0 (Kock, 2022) together with their recommended criteria and acceptable levels for assessing the fit of the model with the data. The obtained results indicate that all quality indices have reached the required model fit, and all criteria have been met. The proposed model has a good fit with the data, as depicted by the APC, ARS, and AARS (i.e., scores lower than 0.05, significant at the 0.05 level). AVIF and AFVIF are both lower than the recommended value of 3.3; GoF has a medium score (between 0.25 and 0.36); SPR has a score greater than 0.7 (i.e., at least 70 percent of the paths in the model are free from Simpson's paradox); RSCR has a score greater than 0.9 (i.e., at least 90 percent of the paths in the model are not associated with negative R-squared contributions); SSR has a score greater than 0.7 (i.e., at least 70 percent of the paths in the model are free from statistical suppression); and NLBCDR has a score greater than 0.7 (i.e., there is at least 70 percent of path-related instances in the model; this indicator is used to support or reject the reverse hypothesis based on the causal direction or degree of weakness).

Hypothesis Testing

The final statistical results prove that the model can be carried forward safely for hypothesis testing. Thereafter, the following research objectives were analyzed and tested using robust path analysis with a linear inner model analysis algorithm and stable3 resampling: (a) the effect of review consistency on review helpfulness (H_1); (b) the effect of review sentiment, review rating, and review length on review consistency (H_2, H_4, and H_6); and (c) whether review sentiment, review rating, review length, and review rating variance moderate the relationship between review consistency and review helpfulness (H_3, H_5, H_7, and H_8). Figure 3 and Table 4 show the results of the hypothesis testing.

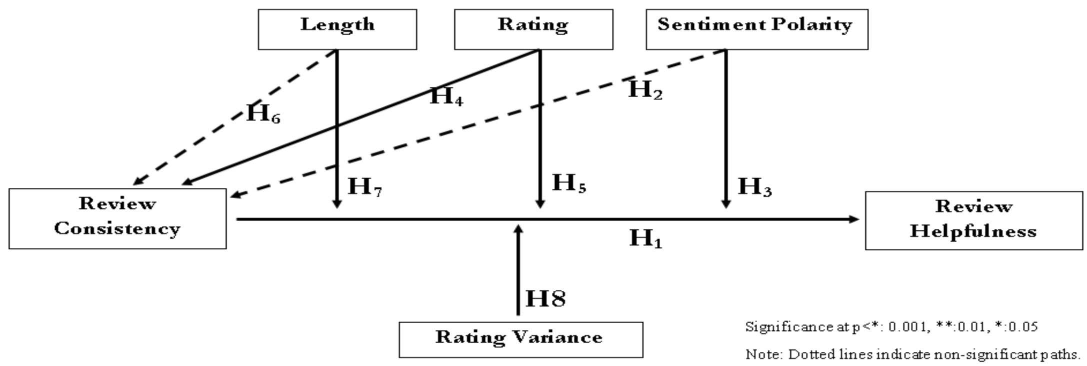

Figure 3. Research model with hypothesis testing results

Table 4. Detailed results of testing hypothesis

No.	Independent variables	Dependent variables	Moderators	Path coefficient	Supported
H_1	Review Consistency	Review Helpfulness		0.141***	Yes
H_2	Sentiment Polarity	Review Consistency		0.031	No
H_3	Review Consistency	Review Helpfulness	Sentiment Polarity	0.066*	Yes
H_4	Rating	Review Consistency		0.405***	Yes
H_5	Review Consistency	Review Helpfulness	Rating	-0.162***	Yes
H_6	Length	Review Consistency		0.013	No
H_7	Review Consistency	Review Helpfulness	Length	−0.033*	Yes
H_8	Review Consistency	Review Helpfulness	Rating Variance	−0.070*	Yes

Significance at ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

Table 4 presents the results of the analyses. Review consistency is important to perceived review helpfulness; thus, H_1 is supported. This finding also suggests that reviews are perceived as more helpful by potential consumers (readers) when the textual content sentiment is consistent with its rating score. Furthermore, review rating is an important factor for improving review consistency; therefore, H_4 is supported. This result suggests that reviews with extreme ratings are more likely to be consistent with the textual content of the same review. However, review sentiment and review length do not have a significant effect on review consistency; thus, H_2 and H_6 are not supported. This result indicates that review consistency is independent of the length and sentiment of textual content.

Moreover, as shown in Table 4, review sentiment (H_3), review rating (H_5), review length (H_7), and review rating variance (H_8) have significant moderating effects on the relationship between review consistency and review helpfulness. Review consistency has a relatively strong impact on the helpfulness of reviews with short textual content, positive polarity textual content, and low rating scores and variance.

DISCUSSION

The objectives of this study were to: (a) investigate the effect of review consistency on review helpfulness; (b) investigate the effect of review sentiment, review rating, and review length on review consistency; and (c) determine whether review sentiment, review rating, review length, and review rating variance moderate the relationship between review consistency and review helpfulness.

First, this study has attempted to examine the effect of review consistency on review helpfulness. On this basis, H_1 is proposed as a means of determining whether a positive relationship exists between the two variables. The results show a significantly positive effect of review consistency on review helpfulness (H_1: $\beta = 0.141$, $p < 0.001$). Consistent with the findings of Aghakhani et al. (2021), the results of the present research confirm that review consistency plays an important role in the evaluation of consumers, particularly whether a review is indeed helpful. From the perspective of consumers, reviews with textual content that can correctly explain the associated rating tend to be more helpful and informative. Indeed, review consistency can be used as an indicator for readers to trust the opinion presented in the review. Consumers are probably more willing to trust and accept a review if they find that the textual content is in line with the rating and that the opinion in this review is suitable for the purchase decision-making process. From the perspectives of e-commerce websites and review aggregators, more attention should be given to providing real evidence as a means of achieving consistency in each review. This approach can help potential consumers enhance their purchasing experience, thereby increasing the acceptance rate of the products posted on online platforms.

Second, this study examined the effects of review sentiment, review rating, and review length on review consistency. On this basis, three hypotheses (H_2, H_4, and H_6) have been presented to provide insights into how these variables affect review consistency. The research results indicate that extreme rating scores positively affect review consistency (H_4: $\beta = 0.405$, $p < 0.001$), proving that reviews with extreme ratings are highly likely to be consistent with the textual content of those reviews. Zhou and Yang (2019) and Y. Wang et al. (2019) revealed that reviews with extreme ratings are perceived as more helpful by review readers. The results of the current research provide additional support for the role of extreme review ratings in review consistency. A good explanation is that reviews with extreme ratings can be easily expressed and correctly explained via textual content (e.g., a review depicting good or bad product usage experience). A medium rating may indicate an uncertain, cannot be determined, or neutral opinion, which hinders reviewers from balancing the provided opinion despite the sharing of textual context.

Review sentiment and review length do not significantly affect review consistency; thus, H_2 and H_6 are not supported (H_2: $\beta = 0.031$, $p > 0.05$), (H_6: $\beta = 0.013$, $p > 0.05$). Review consistency is independent of the sentiment polarity and length of its textual content. Furthermore, reviews may include positive and negative opinions, which is a common tendency, and many reviewers discuss the pros and cons of a product, which further suggests that the polarity may not necessarily affect the review's consistency. Sentiment polarity also does not directly affect review consistency. For the review length variable, reviewers express and summarize their usage experience of the products by means of the textual content of the review, but they may struggle to share the appropriate terms, resulting in varying textual content lengths. Ultimately, depending on their writing skills and whether the content is short or long, the content may not clearly explain the rating score. This topic is rarely comprehensively discussed in the literature. To the best of our knowledge, the current research is the first to investigate the effect of review sentiment and review length on review consistency. Most past studies that investigated the effect of these two variables on review helpfulness obtained mixed results. For instance, while some researchers have revealed the effect of review sentiment on review helpfulness (W. Fan et al., 2021; Siering & Muntermann, 2013), Salehan and Kim (2016) found that review sentiment does not have a significant effect on review helpfulness. Other past studies did not find a significant impact of review length on perceived helpfulness (Bilal et al., 2020; Kang & Zhou, 2016).

Finally, this study examined the moderating effect of review sentiment polarity (H_3), review rating (H_5), review length (H_7), and review rating variance (H_8) on the relationship between review consistency and review helpfulness. All four hypotheses are significant, hence providing empirical support for the significance of the interaction effect between review consistency and the aforementioned variables. This research has determined the relatively strong impact of review consistency on the helpfulness of reviews with short textual content, positive polarity textual content, and low rating scores and variance.

Sentiment polarity positively affects the relationship between review consistency and review helpfulness (H3: $\beta = 0.066$, $p < 0.05$). This result is aligned with the findings of W. Fan et al. (2021) and Siering and Muntermann (2013), who reported a significant effect of positive review sentiment on review helpfulness. A positive interaction effect between review consistency and the sentiment polarity of textual content means that review consistency has a strong effect on helpfulness when reviews have positive sentiment content. Positive sentiment reviews include positive opinions from reviewers who are discussing a good experience of a product. From the perspective of reviewers, people normally praise and compliment others more than they criticize, and it is easier to provide positive expressions that are consistent with the numerical rating assessment, particularly in the case of a good experience with the product compared with the case of bad experiences.

Rating extremity moderates the relationship between review consistency and review helpfulness (H_5: $\beta = -0.162$, $p < 0.001$). The statistical outcomes demonstrate the strong relationship between review consistency and its helpfulness for reviews with extreme rating scores, particularly lower-rated reviews. This finding is consistent with past studies that adopted negativity bias theory, which argues that consumers perceive reviews with low rating scores as more helpful than those with high rating scores (Rozin & Royzman, 2001; Salehan & Kim, 2016; Willemsen et al., 2011). Therefore, review consistency has a strong impact on review helpfulness with low rating scores.

In terms of review length, this study hypothesized a strong relationship between review consistency and review helpfulness with long reviews. However, contrary to the proposed hypothesis, the results showed that the effect is significant for short reviews (H_7: $\beta = -0.033$, $p < 0.05$). The literature on the effect of review length on review helpfulness has reported mixed findings. For instance, Mudambi and Schuff (2010) reported a positive effect of review length on review helpfulness. Although a positive effect was proposed in this research, the results are still in line with the findings of Bilal et al. (2020) and S. Yang et al. (2019), who found a negative effect of review length on review helpfulness. The relationship between review consistency and review helpfulness relies not only on the reviewer who writes the review but also on consumers who read the review as a means of evaluating and voting on its helpfulness. This result further implies that consumers can more easily understand the shorter-length content of consistent reviews and perceive it to be more helpful than those with longer textual content. Short reviews may be more understandable for consumers and require less effort compared with long reviews with more terms and expressions. For consumers dealing with confusing lengthy text content, the vote for that review can be ignored. In other words, when consumers read short reviews, a strong review consistency will affect its helpfulness.

The moderating effect of rating variance on the relationship between review consistency and review helpfulness is statistically significant (H_8: $\beta = -0.070$, $p < 0.05$). A significant interaction effect between review consistency and rating variance means that consistency has a strong impact on review helpfulness when the rating for a review is close to the average rating of a product. This result complements the finding of Baek et al. (2012, 2015), who confirmed that consumers tend to consider a review helpful when its rating is close to the average rating of a product. A low variance of a review rating score may indicate the correctness and reliability of the review, which is also preferred by consumers and thus positively affects their evaluation of the review's helpfulness. Reviewers also tend to be interested in the text content of other reviewers who use the same product. The result confirms the statistically significant moderating effect of variance on the relationship associating review consistency with review helpfulness. That is, review consistency has a stronger effect on the helpfulness of reviews with low rating variance.

CONCLUSION

The consistency between review content and review rating score is used in this study as a useful criterion to measure and represent review helpfulness. This study offers novel contributions to the literature by illustrating the importance of review consistency and how it affects perceived review helpfulness. Empirical results have proven that review consistency significantly affects perceived review helpfulness. The findings of this research also show that review rating is an important factor affecting review consistency. The moderating effects of review sentiment, review rating, review length, and review rating variance on the review consistency–review helpfulness relationship are also confirmed. The overall findings indicate that online reviews with textual content correctly explaining the associated ratings tend to be helpful; reviews with extreme ratings are highly likely to be consistent with the textual content; and review consistency has a strong impact on the helpfulness of reviews with short textual content, positive polarity textual content, and low rating scores and variance.

Backed by signaling theory, the current research can contribute to the literature by showing novel antecedents of review helpfulness that deal with the simultaneous interaction between textual and numerical types of signals, which are embodied by review consistency. This study also contributes to the literature by introducing a mathematical measure to evaluate the consistency between the textual content and the rating of a review. Moreover, this study incorporates the newly developed variable in the theoretical model grounded in signaling theory as a means of investigating the effects of different factors on review helpfulness and other relevant findings. Therefore, this study considerably extends ongoing studies on online review helpfulness and provides notable implications for research and practice. Consistent reviews are important for consumers to facilitate access to the most valuable reviews, allowing them to improve their purchase decisions, and for e-commerce websites to increase their business sustainability by attracting consumers and improving their overall satisfaction and loyalty.

In practical terms, incorporating indices on review consistency in e-commerce websites will enable firms to rank and provide online reviews for their customers. An alternative approach is to evaluate and accept reviews according to consistency before posting the reviews. A consistency evaluation system that provides real-time alerts for reviewers reporting consistency statuses can also be implemented. Furthermore, e-commerce websites can ask reviewers to initially provide rating scores before writing the textual content of their reviews. In this manner, the cognitive effort of consumers is highlighted, allowing them to stay focused and provide accurate textual content that can best explain the rating score. Incorporating review consistency for consumers facilitates access to helpful and consistent reviews and enables them to accurately evaluate the review helpfulness index.

The limitations encountered in this study may represent opportunities for future research. Although the current study provides new antecedents of review consistency, other important factors may affect review consistency; its correlation with perceived review helpfulness can be added to the model proposed in this study. For instance, the rating distribution of top reviewers can be explored in future work. The results of this study can also be generalized by applying the same method of analysis when searching for goods and products.

REFERENCES

Abelson, R. P., Aronson, E., McGuire, W. J., Newcomb, T. M., Rosenberg, M. J., & Tannenbaum, P. H. (Eds.). (1968). *Theories of cognitive consistency: A sourcebook*. Rand Mc NaJly.

Aghakhani, N., Oh, O., Gregg, D. G., & Karimi, J. (2021). Online review consistency matters: An elaboration likelihood model perspective. *Information Systems Frontiers*, *23*(5), 1287–1301. https://doi.org/10.1007/s10796-020-10030-7

Al-Smadi, M., Al-Ayyoub, M., Jararweh, Y., & Qawasmeh, O. (2019). Enhancing aspect-based sentiment analysis of Arabic hotels' reviews using morphological, syntactic and semantic features. *Information Processing & Management*, *56*(2), 308–319. https://doi.org/10.1016/j.ipm.2018.01.006

Amazon Customer Reviews Dataset. (n.d.). https://www.kaggle.com/datasets/cynthiarempel/amazon-us-customer-reviews-dataset?select=amazon_reviews_us_Mobile_Electronics_v1_00.tsv

Baek, H., Ahn, J., & Choi, Y. (2012). Helpfulness of online consumer reviews: Readers' objectives and review cues. *International Journal of Electronic Commerce*, *17*(2), 99–126. https://doi.org/10.2753/JEC1086-4415170204

Baek, H., Lee, S., Oh, S., & Ahn, J. H. (2015). Normative social influence and online review helpfulness: Polynomial modeling and response surface analysis. *Journal of Electronic Commerce Research*, *16*(4), 290–306.

Bilal, M., Marjani, M., Lali, M. I., Malik, N., Gani, A., & Hashem, I. A. T. (2020). Profiling users' behavior, and identifying important features of review "helpfulness." *IEEE Access*, *8*, 77227–77244. https://doi.org/10.1109/ACCESS.2020.2989463

Cao, Q., Duan, W., & Gan, Q. (2011). Exploring determinants of voting for the "helpfulness" of online user reviews: A text mining approach. *Decision Support Systems*, *50*(2), 511–521. https://doi.org/10.1016/j.dss.2010.11.009

Chen, L., Baird, A., & Straub, D. (2020). A linguistic signaling model of social support exchange in online health communities. *Decision Support Systems*, *130*, 113233. https://doi.org/10.1016/j.dss.2019.113233

Cheung, C. M. K., Xiao, B. S., & Liu, I. L. B. (2014). Do actions speak louder than voices? The signaling role of social information cues in influencing consumer purchase decisions. *Decision Support Systems*, *65*, 50–58. https://doi.org/10.1016/j.dss.2014.05.002

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, *43*(3), 345–354. https://doi.org/10.1509/jmkr.43.3.345

Choi, H. S., Ko, M. S., Medlin, D., & Chen, C. (2018). The effect of intrinsic and extrinsic quality cues of digital video games on sales: An empirical investigation. *Decision Support Systems*, *106*, 86–96. https://doi.org/10.1016/j.dss.2017.12.005

Chou, Y. C., Chuang, H. H. C., & Liang, T. P. (2022). Elaboration likelihood model, endogenous quality indicators, and online review helpfulness. *Decision Support Systems*, *153*, 113683. https://doi.org/10.1016/j.dss.2021.113683

Chua, A. Y. K., & Banerjee, S. (2015). Understanding review helpfulness as a function of reviewer reputation, review rating, and review depth. *Journal of the Association for Information Science and Technology*, *66*(2), 354–362. https://doi.org/10.1002/asi.23180

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of Management*, 37(1), 39–67. https://doi.org/10.1177/0149206310388419

Dor, D. (2003). On newspaper headlines as relevance optimizers. *Journal of Pragmatics*, *35*(5), 695–721. https://doi.org/10.1016/S0378-2166(02)00134-0

Eastin, M. S. (2006). Credibility Assessments of online health information: The effects of source expertise and knowledge of content. *Journal of Computer-Mediated Communication*, *6*(4). https://doi.org/10.1111/j.1083-6101.2001.tb00126.x

Erkan, I., & Evans, C. (2016). The influence of eWOM in social media on consumers' purchase intentions: An extended approach to information adoption. *Computers in Human Behavior*, *61*, 47–55. https://doi.org/10.1016/j.chb.2016.03.003

Eslami, S. P., Ghasemaghaei, M., & Hassanein, K. (2018). Which online reviews do consumers find most helpful? A multi-method investigation. *Decision Support Systems*, *113*, 32–42. https://doi.org/10.1016/j.dss.2018.06.012

Fan, L., & Zhang, X. (2020). The Combination signaling effect of text and image on mobile phone review helpfulness – The moderating effect of signaling environment. *IEEE Access*, *8*, 122736–122746. https://doi.org/10.1109/ACCESS.2020.3005951

Fan, W., Liu, Y., Li, H., Tuunainen, V. K., & Lin, Y. (2021). Quantifying the effects of online review content structures on hotel review helpfulness. *Internet Research*, *32*(7), 202–227. https://doi.org/10.1108/INTR-11-2019-0452

Fang, B., Ye, Q., Kucukusta, D., & Law, R. (2016). Analysis of the perceived value of online tourism reviews: Influence of readability and reviewer characteristics. *Tourism Management*, *52*, 498–506. https://doi.org/10.1016/j.tourman.2015.07.018

Filieri, R., Raguseo, E., & Vitari, C. (2018). When are extreme ratings more helpful? Empirical evidence on the moderating effects of review characteristics and product type. *Computers in Human Behavior*, *88*, 134–142. https://doi.org/10.1016/j.chb.2018.05.042

Gauba, H., Kumar, P., Roy, P. P., Singh, P., Dogra, D. P., & Raman, B. (2017). Prediction of advertisement preference by fusing EEG response and sentiment analysis. *Neural Networks*, *92*, 77–88. https://doi.org/10.1016/j.neunet.2017.01.013

Ghasemaghaei, M., Eslami, S. P., Deal, K., & Hassanein, K. (2018). Reviews' length and sentiment as correlates of online reviews' ratings. *Internet Research*, *28*(3), 544–563. https://doi.org/10.1108/IntR-12-2016-0394

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2009). *Multivariate data analysis*. Pearson Prentice Hall.

He, R., & McAuley, J. (2016). VBPR: Visual bayesian personalized ranking from implicit feedback. *Proceedings of the AAAI Conference on Artificial Intelligence* (pp. 144–150). AAAI Press. https://doi.org/10.1609/aaai.v30i1.9973

Hogenboom, A., Heerschop, B., Frasincar, F., Kaymak, U., & De Jong, F. (2014). Multi-lingual support for lexicon-based sentiment analysis guided by semantics. *Decision Support Systems*, *62*, 43–53. https://doi.org/10.1016/j.dss.2014.03.004

Hong, H., Xu, D., Wang, G. A., & Fan, W. (2017). Understanding the determinants of online review helpfulness: A meta-analytic investigation. *Decision Support Systems*, *102*, 1–11. https://doi.org/10.1016/j.dss.2017.06.007

Hu, N., Koh, N. S., & Reddy, S. K. (2014). Ratings lead you to the product, reviews help you clinch it? The mediating role of online review sentiments on product sales. *Decision Support Systems*, *57*, 42–53. https://doi.org/10.1016/j.dss.2013.07.009

Kang, Y., & Zhou, L. (2016, August). Longer is better? A case study of product review helpfulness prediction. *Proccedings of the Americas Conference on Information Systems, San Diego, CA, USA.*

Keeler, E. (1976). *MarketsSignaling: Informational transfer in hiring and related screening processes by A. Michael Spence. Journal of Political Economy*, *84*(1), 200–201. https://doi.org/10.1086/260427

Kirmani, A., & Rao, A. R. (2000). No pain, no gain: A critical review of the literature on signaling unobservable product quality. *Journal of Marketing*, *64*(2), 66–79. https://doi.org/10.1509/jmkg.64.2.66.18000

Ko, E.-J., & McKelvie, A. (2018). Signaling for more money: The roles of founders' human capital and investor prominence in resource acquisition across different stages of firm development. *Journal of Business Venturing*, *33*(4), 438–454. https://doi.org/10.1016/j.jbusvent.2018.03.001

Kock, N. (2022). *Model-driven data analytics: Applications with WarpPLS*. https://www.scriptwarp.com/warp-pls/UserManual_v_8_0.pdf

Lee, P.-J., Hu, Y.-H., & Lu, K.-T. (2018). Assessing the helpfulness of online hotel reviews: A classification-based approach. *Telematics and Informatics*, *35*(2), 436–445. https://doi.org/10.1016/j.tele.2018.01.001

Liu, X., Guo, X., Wu, H., & Wu, T. (2016). The impact of individual and organizational reputation on physicians' appointments online. *International Journal of Electronic Commerce*, *20*(4), 551–577. https://doi.org/10.1080/10864415.2016.1171977

Luo, X., Raithel, S., & Wiles, M. A. (2013). The impact of brand rating dispersion on firm value. *Journal of Marketing Research*, *50*(3), 399–415. https://doi.org/10.1509/jmr.12.0188

Ma, Y., Xiang, Z., Du, Q., & Fan, W. (2018). Effects of user-provided photos on hotel review helpfulness: An analytical approach with deep leaning. *International Journal of Hospitality Management*, *71*, 120–131. https://doi.org/10.1016/j.ijhm.2017.12.008

Malik, M. S. I., & Hussain, A. (2017). Helpfulness of product reviews as a function of discrete positive and negative emotions. *Computers in Human Behavior*, *73*, 290–302. https://doi.org/10.1016/j.chb.2017.03.053

Malik, M. S. I., & Hussain, A. (2018). An analysis of review content and reviewer variables that contribute to review helpfulness. *Information Processing and Management*, *54*(1), 88–104. https://doi.org/10.1016/j.ipm.2017.09.004

Maulud, D., & Abdulazeez, A. M. (2020). A review on linear regression comprehensive in machine learning. *Journal of Applied Science and Technology Trends*, *1*(4), 140–147. https://doi.org/10.38094/jastt1457

Mavlanova, T., Benbunan-Fich, R., & Lang, G. (2016). The role of external and internal signals in e-commerce. *Decision Support Systems*, *87*, 59–68. https://doi.org/10.1016/j.dss.2016.04.009

McDonald, R. P. (1996). Path analysis with composite variables. *Multivariate Behavioral Research*, *31*(2), 239–270. https://doi.org/10.1207/s15327906mbr3102_5

Moe, W. W., Trusov, M., & Smith, R. H. (2011). The value of social dynamics in online product ratings forums. *Journal of Marketing Research*, *48*(3), 444–456. https://doi.org/10.1509/jmkr.48.3.444

Mou, J., & Shin, D. (2018). Effects of social popularity and time scarcity on online consumer behaviour regarding smart healthcare products: An eye-tracking approach. *Computers in Human Behavior*, *78*, 74–89. https://doi.org/10.1016/j.chb.2017.08.049

Mousavizadeh, M., Koohikamali, M., Salehan, M., & Kim, D. J. (2022). An investigation of peripheral and central cues of online customer review voting and helpfulness through the lens of elaboration likelihood model. *Information Systems Frontiers*, *24*(1), 211–231. https://doi.org/10.1007/s10796-020-10069-6

Mudambi, S. M., & Schuff, D. (2010). Research mote: What makes a helpful online review? A study of customer reviews on amazon.com. *MIS Quarterly*, *34*(1), 185–200. https://doi.org/10.2307/20721420

Mundra, S., Dhingra, A., Kapur, A., & Joshi, D. (2019). Prediction of a movie's success using data mining techniques. In S. Satapathy, & A. Joshi (Eds.), *Information and Communication Technology for Intelligent Systems* (pp. 219–227). Springer. https://doi.org/10.1007/978-981-13-1742-2_22

Nakayama, M., & Wan, Y. (2019). The cultural impact on social commerce: A sentiment analysis on Yelp ethnic restaurant reviews. *Information & Management*, *56*(2), 271–279. https://doi.org/10.1016/j.im.2018.09.004

Nelson, P. (1970). Information and consumer behavior. *Journal of Political Economy*, *78*(2), 311–329. https://doi.org/10.1086/259630

Nguyen-Viet, B. (2022). Understanding the influence of eco-label, and green advertising on green purchase intention: The mediating role of green brand equity. *Journal of Food Products Marketing*, *28*(2), 87–103. https://doi.org/10.1080/10454446.2022.2043212

Numminen, E., & Sällberg, H. (2017, September). The impact of online ratings on downloads of free mobile apps. *Proceedings of the 11th European Conference on Information Systems Management, Genoa, Italy,* 225–232.

Paget, S. (2023, February 7). *Local consumer review survey 2023.*Brightlocal. https://www.brightlocal.com/research/local-consumer-review-survey/

Palmer, P. B., & O'Connell, D. G. (2009). Research Corner: Regression analysis for prediction: Understanding the process. *Cardiopulmonary Physical Therapy Journal*, *20*(3), 23–26. https://doi.org/10.1097/01823246-200920030-00004

Park, C., & Lee, T. M. (2009). Antecedents of online reviews' usage and purchase influence: An empirical comparison of U.S. and Korean consumers. *Journal of Interactive Marketing*, *23*(4), 332–340. https://doi.org/10.1016/j.intmar.2009.07.001

Peng, Y., Kou, G., & Li, J. (2014). A fuzzy PROMETHEE approach for mining customer reviews in Chinese. *Arabian Journal for Science and Engineering*, *39*(6), 5245–5252. https://doi.org/10.1007/s13369-014-1033-7

Qazi, A., Shah Syed, K. B., Raj, R. G., Cambria, E., Tahir, M., & Alghazzawi, D. (2016). A concept-level approach to the analysis of online review helpfulness. *Computers in Human Behavior*, *58*, 75–81. https://doi.org/10.1016/j.chb.2015.12.028

Quaschning, S., Pandelaere, M., & Vermeir, I. (2015). When consistency matters: The effect of valence consistency on review helpfulness. *Journal of Computer-Mediated Communication*, *20*(2), 136–152. https://doi.org/10.1111/jcc4.12106

Reinhard, M.-A., & Sporer, S. L. (2010). Content versus source cue information as a basis for credibility judgments: The impact of task involvement. *Social Psychology*, *41*(2), 93–104. https://doi.org/10.1027/1864-9335/a000014

Ren, G., & Hong, T. (2019). Examining the relationship between specific negative emotions and the perceived helpfulness of online reviews. *Information Processing and Management*, *56*(4), 1425–1438. https://doi.org/10.1016/j.ipm.2018.04.003

Rozin, P., & Royzman, E. B. (2001). Negativity bias, negativity dominance, and contagion. *Personality and Social Psychology Review*, *5*(4), 296–320. https://doi.org/10.1207/S15327957PSPR0504_2

Salehan, M., & Kim, D. J. (2016). Predicting the performance of online consumer reviews: A sentiment mining approach to big data analytics. *Decision Support Systems*, *81*, 30–40. https://doi.org/10.1016/j.dss.2015.10.006

Saumya, S., Singh, J. P., & Dwivedi, Y. K. (2020). Predicting the helpfulness score of online reviews using convolutional neural network. *Soft Computing*, *24*(15), 10989–11005. https://doi.org/10.1007/s00500-019-03851-5

Sen, S., & Lerman, D. (2007). Why are you telling me this? An examination into negative consumer reviews on the Web. *Journal of Interactive Marketing*, *21*(4), 76–94. https://doi.org/10.1002/dir.20090

Shen, R. P., Zhang, H. R., Yu, H., & Min, F. (2019). Sentiment based matrix factorization with reliability for recommendation. *Expert Systems with Applications*, *135*, 249–258. https://doi.org/10.1016/j.eswa.2019.06.001

Siering, M., & Muntermann, J. (2013, February). What drives the helpfulness of online product reviews ? From stars to facts and emotions. *Proceedings of the 11th International Conference on Wirtschaftsinformatik*, *Leipzig, Germany,* 103–118.

Siering, M., Muntermann, J., & Rajagopalan, B. (2018). Explaining and predicting online review helpfulness: The role of content and reviewer-related signals. *Decision Support Systems*, *108*, 1–12. https://doi.org/10.1016/j.dss.2018.01.004

Singh, J. P., Irani, S., Rana, N. P., Dwivedi, Y. K., Saumya, S., & Kumar Roy, P. (2017). Predicting the "helpfulness" of online consumer reviews. *Journal of Business Research*, *70*, 346–355. https://doi.org/10.1016/j.jbusres.2016.08.008

Spence, M. (2002). Signaling in retrospect and the informational structure of markets. *American Economic Review*, *92*(3), 434–459. https://doi.org/10.1257/00028280260136200

Srivastava, V., & Kalro, A. D. (2019). Enhancing the helpfulness of online consumer reviews: The role of latent (content) factors. *Journal of Interactive Marketing*, *48*(1), 33–50. https://doi.org/10.1016/j.intmar.2018.12.003

Sun, M. (2012). How does the variance of product ratings matter? *Management Science*, *58*(4), 696–707. https://doi.org/10.1287/mnsc.1110.1458

Sun, X., Han, M., & Feng, J. (2019). Helpfulness of online reviews: Examining review informativeness and classification thresholds by search products and experience products. *Decision Support Systems*, *124*, 113099. https://doi.org/10.1016/j.dss.2019.113099

Wang, L., Fan, L., & Bae, S. (2019). How to persuade an online gamer to give up cheating? Uniting elaboration likelihood model and signaling theory. *Computers in Human Behavior*, *96*, 149–162. https://doi.org/10.1016/j.chb.2019.02.024

Wang, X., Tang, L., & Kim, E. (2019). More than words: Do emotional content and linguistic style matching matter on restaurant review helpfulness? *International Journal of Hospitality Management*, *77*, 438–447. https://doi.org/10.1016/j.ijhm.2018.08.007

Wang, Y., Wang, J., & Yao, T. (2019). What makes a helpful online review? A meta-analysis of review characteristics. *Electronic Commerce Research*, *19*(2), 257–284. https://doi.org/10.1007/s10660-018-9310-2

Willemsen, L. M., Neijens, P. C., Bronner, F., & De Ridder, J. A. (2011). "Highly recommended!" The content characteristics and perceived usefulness of online consumer reviews. *Journal of Computer-Mediated Communication*, *17*(1), 19–38. https://doi.org/10.1111/j.1083-6101.2011.01551.x

Yang, S., Zhou, Y., Yao, J., Chen, Y., & Wei, J. (2019). Understanding online review helpfulness in omnichannel retailing. *Industrial Management & Data Systems*, *119*(8), 1565–1580. https://doi.org/10.1108/IMDS-10-2018-0450

Yang, S.-B., Hlee, S., Lee, J., & Koo, C. (2017). An empirical examination of online restaurant reviews on Yelp.com: A dual coding theory perspective. *International Journal of Contemporary Hospitality Management*, *29*(2), 817–839. https://doi.org/10.1108/IJCHM-11-2015-0643

Yin, D., Bond, S. D., & Zhang, H. (2014). Anxious or angry? Effects of discrete emotions on the perceived helpfulness of online reviews. *MIS Quarterly*, *38*(2), 539–560. https://doi.org/10.25300/MISQ/2014/38.2.10

Yin, D., Mitra, S., & Zhang, H. (2016). Research note – When do consumers value positive vs. negative reviews? An empirical investigation of confirmation bias in online word of mouth. *Information Systems Research*, *27*(1), 131–144. https://doi.org/10.1287/isre.2015.0617

Zhou, Y., & Yang, S. (2019). Roles of review numerical and textual characteristics on review helpfulness across three different types of reviews. *IEEE Access*, *7*, 27769–27780. https://doi.org/10.1109/ACCESS.2019.2901472

Zhou, Y., Yang, S., Li, Y., Chen, Y., Yao, J., & Qazi, A. (2020). Does the review deserve more helpfulness when its title resembles the content? Locating helpful reviews by text mining. *Information Processing and Management*, *57*(2), 102179. https://doi.org/10.1016/j.ipm.2019.102179

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