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What makes deceptive online reviews? A linguistic analysis perspective

Wen Zhang[1], Qiang Wang[2✉], Jian Li[1], Zhenzhong Ma[3], Gokul Bhandari[3] & Rui Peng[1]

With the rapid development of e-commerce, online reviews have become an important information source for consumers and e-commerce businesses. While the negative impact of deceptive online reviews has been well recognized, more research has to be done to help understand the linguistic manifestations of deceptive online reviews in order to help identify deceptive reviews and help increase the value and sustainability of e-commerce businesses. This study explores the linguistic manifestations of deceptive online reviews based on the reality monitoring theory, and then uses the data from Amazon.com online product reviews to examine perceptual cues, affective cues, detail cues, relevance cues, and cognitive cues of various deceptive online reviews. The results show that reviews for emotional catharsis are more extreme with affective cues, while perfunctory reviews often lack details with fewer prepositions and adjectives. In addition, deceptive reviews often lack relevance cues when these reviews are made to obtain the rewards provided by the vendors while paid posters tend to use more cognitive cues in deceptive reviews. Moreover, deceptive online reviews under all motives often lack perceptual cues. These findings provide a deeper understanding of the linguistic manifestations of deceptive online reviews and provide significant managerial implications for e-commerce businesses to employ high-quality online reviews for sustainable growth.

[1] College of Economics and Management, Beijing University of Technology, Beijing 100124, China. [2] School of Economics and Management, Wenzhou University of Technology, Wenzhou 325035, China. [3] Odette School of Business, University of Windsor, Windsor, ON N9E 4Z4, Canada.
✉email: wangqiang@wzut.edu.cn

Introduction

Online consumer reviews are crucial in the age of the platform economy, a new form of economy that uses digital technologies and internet platforms to coordinate and organize resources (Vana and Lambrecht, 2021; Yu et al. 2022). For consumers, online reviews can provide valuable information for purchase decisions (Lei et al. 2021; Li et al. 2019). For e-commerce businesses, online reviews can help better understand consumers' concerns to improve products or services (Anderson and Simester, 2014; Q. Wang et al. 2022a, 2022b). As a result, online reviews have become an important information source for consumers and e-commerce businesses (Lamb et al. 2020; Zuo et al. 2022). According to a public survey, 92% of consumers actually use online reviews as references in their online shopping, and 90% of these consumers say that positive reviews make them more likely to use a product in purchase decisions (Zhang et al. 2022).

However, due to the lack of strict scrutiny on online reviews, a large number of deceptive online reviews have been generated and used for profit-seeking, and deceptive reviews have become a major problem in the era of the platform economy (Pang et al. 2022; Zhuang et al. 2018). Here, deceptive online reviews are online reviews that are inconsistent with a true evaluation of the product or service (Wu et al. 2020). These deceptive reviews often lead to bad online shopping experiences (Jaziri, 2019; Lamb et al. 2020), cause economic loss to online consumers, and consequently damage the reputation of involved businesses and further the platform economy as a whole (Zhuang et al. 2018). For instance, the Daily Mail investigation found that rogue firms are selling deceptive reviews on Amazon.com to online retailers which put millions of Amazon.com consumers at risk with potential bad purchase decisions. As deceptive online reviews emerge as a pervasive issue in today's platform economy, the study of deceptive reviews has attracted increasing attention from industry and academia.

Extant research on deceptive online reviews concentrates on the underlying motives of deceptive reviews and related identification methods. Many studies have confirmed that the underlying causes for manipulating online reviews are either vendor-oriented for financial gains and competitive advantage or consumer-oriented such as for the release of emotion (Wu et al. 2020), self-promoted brand management (Salehi-Esfahani and Ozturk, 2018), or social status enhancing (Anderson and Simester, 2014). At the same time, more research is designed to identify deceptive online reviews and a series of computing techniques have been developed to detect deceptive online reviews by combining natural language processing and machine learning (Kumar et al. 2018; Zhang et al. 2018). This line of research contends that since deceptive online reviews are manufactured by reviewers with fictitious opinions deliberately written for their purposes, deceptive reviews may contain inconsistency in language compared with genuine reviews that are based on real experiences (Banerjee and Chua, 2017; Chatterjee et al. 2021; Gentina et al. 2021).

While it is well-known that being able to use language characteristics to identify deceptive reviews is beneficial for all stakeholders (Mayzlin et al. 2014), the linguistic manifestations of deceptive online reviews under different motives have not been well studied (Barbado et al. 2019; Chatterjee et al. 2021). Understanding the linguistic manifestations of deceptive reviews is crucial for e-commerce stakeholders. For consumers, it helps create a clearer profile of deceptive online reviews. Consumers could write authentic reviews with high credibility, rather than being perceived as fraudulent reviewers because they may accidentally use the linguistic features of deceptive reviews. For platform enterprises, they could use review tips to guide consumers to post credible online reviews based on the knowledge of the linguistic manifestations of deceptive reviews. Moreover, platform businesses can differentiate the reviews with different motivations and thus conduct more strict scrutiny on the reviews with the possibly more harmful motivation of fraudulent promulgators to improve their e-commerce ecosystems (Mayzlin et al. 2014). In addition, some studies have argued that the linguistic characteristics of deceptive online reviews may vary depending on the underlying motives (Wu, 2019; Wu et al. 2020). Thus, to understand this pervasive issue and gain deeper insight into the linguistic manifestations of deceptive online reviews, this paper intends to examine two important research questions: *(1) what are the linguistic manifestations of deceptive online reviews? (2) How do the linguistic manifestations of deceptive online reviews differ under different motives?*

To help bridge the research gap and address these research questions, this study conducts empirical research to explore specific linguistic manifestations of deceptive online reviews under different motives. First, we develop a series of hypotheses on the linguistic manifestations of deceptive reviews with different motives based on the reality monitoring theory. Second, we collect the deceptive online reviews and extract their linguistic manifestations using the Linguistic Inquiry and Word Count (LIWC) tool (Chung and Pennebaker, 2011). The linguistic manifestation includes linguistic characteristics and psychological characteristics. Third, negative binomial regression is adopted to analyze the specific linguistic manifestations of deceptive reviews whereby the significant differences in linguistic manifestations of deceptive online reviews are identified. Within the context of the platform economy, this study is the first few of its kind to explore linguistic manifestations of deceptive online reviews (Chatterjee et al. 2021; Plotkina et al. 2020; Zhuang et al. 2018). The results of this study will be able to shed light on a better understanding of deceptive online reviews and provide important insights to help improve the practice of online review management in e-commerce businesses.

The rest of the paper is organized as follows. Section "Literature review" presents the literature review to construct a conceptual framework. Section "Hypothesis development" develops hypotheses on the linguistic manifestations of deceptive online reviews under different motives. Section "Methods" reports research methods and the data of deceptive online reviews collected from Amazon.com. Section "Results" employs negative binomial regression to analyze the linguistic manifestations of the collected deceptive online reviews. In addition, we also validate the important role of linguistic manifestations of deceptive online reviews in improving consumers' trust perception and purchase intention. Section "Discussion and conclusions" discusses research findings, the theoretical and managerial implications, limitations, and future research directions.

Literature review

Motives for deceptive online reviews. The commercial value embodied in online reviews comes with a fast emergence of deceptive online reviews in the era of the platform economy (Barbado et al. 2019; Chatterjee et al. 2021; Plotkina et al. 2020). In general, there is a dearth of frameworks for deceptive online review motives in the e-commerce context. The existing work on deceptive online reviews has examined the motivational antecedents of deceptive reviews (Hussain et al. 2018; Wu et al. 2020). Generally speaking, the motivation of deceptive online reviews can be divided into external motivation and internal motivation (Hussain et al. 2018). Deceptive reviews induced by external motivation refer to the manipulation of online reviews by vendors

Table 1 Motives for deceptive online reviews.

Motivation	Definition	Example practice
Emotional catharsis	The motive that drives reviews to post deceptive online reviews for the purpose of emotional release	Online reviewers post excessively negative reviews to express their dissatisfaction with products or services.
Perfunctory response	The motive that drives reviewers to post reviews of little relevance or useless for other customers.	Reviewers repeatedly copy a small number of words used in their online reviews.
Financial incentives	The motive that drives reviewers to post deceptive reviews to receive rewards from online vendors.	Online reviewers post deceptive positive reviews to obtain cashback from vendors.
Paid posters	The motive that drives paid reviewers to post deceptive reviews to help a particular vendor gain competitive advantages and promote product sales.	paid posters are hired by online vendors to post positive reviews for these vendors' products or negative reviews for the vendor's competitors.

for pecuniary motivation, and these deceptive reviews are often posted by paid posters (Kumar et al. 2019) for financial benefits or competitive advantage (Lee et al. 2018). Here, paid posters refer to deceptive reviewers who are paid by the vendors to post fake online reviews according to the vendors' preferences (Ananthakrishnan et al. 2020). In the increasingly competitive market environment, more e-commerce businesses are worried that other businesses will manipulate online reviews (Gössling et al. 2018).

Consumers could also post deceptive reviews to obtain rewards from vendors and to satisfy their psychological needs – internal motivation (Hussain et al. 2018). The reward mechanism is an important motivation for consumers to post reviews (Qiao et al. 2020; Yu et al. 2022). A consumer survey shows that financial rewards drive consumers to post more deceptive online reviews (Wu et al. 2020). As far as psychological needs are concerned, Anderson and Simester (2014) contend that sometimes deceptive online reviews are posted to satisfy consumers' non-monetary needs such as respect from the group or the release of anger resulting from bad experiences. Online users sometimes create multiple virtual identities to post deceptive online reviews or use fake identities to post misleading information in virtual communities to gain attention from others (Wang et al. 2019). Previous studies proposed that the need for social interaction, the desire for economic incentives, and advice-seeking were significant motivators for consumers to write online reviews (Kapoor et al. 2021; Vana and Lambrecht, 2021). The studies on electronic word-of-mouth communication in social media further argued that consumers engaged in writing online reviews for different purposes, such as product involvement, information involvement, or self-involvement (H. Wang et al. 2022a, 2022b).

According to the motivation theory for word-of-mouth communication (Dichter, 1966), consumers' subconscious motives can explain their word-of-mouth communication motives and further purchase decisions. Many scholars employ this theory to examine online reviews and classify the motivations for posting online reviews into four categories (Öğüta and Cezara, 2012), including the motive for product involvement, the motive for information involvement, the motive for self-involvement, and the motive for other involvement. More specifically, the motive for product involvement refers to a consumer's desire to post online reviews based on their direct product experiences, often extreme experiences. Considering that this motive provides a channel for stress and frustration release when consumers have an extremely positive or negative experience in online shopping (Allard et al. 2020), we call this motive as emotional catharsis in writing deceptive online reviews in this study, which means that reviewers are influenced by extreme product experiences and thus often post deceptive online reviews for the purpose of emotional catharsis.

The motive for information involvement refers to consumers' online reviews to spread information through various channels (Qiao et al. 2020), including purposely constructing deceptive reviews to generate benefits. The motive for financial incentives in writing deceptive reviews is related to the information involvement motivation, and it refers to consumers' motive to post deceptive reviews as one way of information spreading to receive rewards from online vendors. The motive for self-involvement or self-enhancement refers to reviewers' psychological needs to gain attention or respect from others to improve their image among the group (Ke et al. 2020; Wang et al. 2019). Driven by these psychological needs, consumers could demonstrate conformity behaviors by posting online reviews to gain attention for themselves but giving no sensible information or valuable advice on target products or services (Tunc et al. 2021), and these reviews are often perfunctory and deceptive. In this regard, a perfunctory response is one motive in writing online reviews due to self-involvement motivation, and it implies that reviewers post useless or deceptive reviews as they see online reviews are meaningless but to gain attention. This type of motive is called perfunctory response in this study.

The motive for other involvement refers to the concern of helping other consumers make better purchase decisions using online reviews (Allard et al. 2020; Ke et al. 2020). Online vendors may use this to manipulate consumer reviews by hiring paid posters to post more positive information on their products to influence consumers' purchase decisions. Thus, we call this motive as paid posters, which refer to online vendors' efforts to gain competitive advantages and promote product sales by hiring paid posters. Altogether, this study proposes four motives for deceptive online reviews, including emotional catharsis, perfunctory response, financial incentives, and paid posters for deceptive reviews to examine their linguistic manifestation. Table 1 shows the definitions of the proposed four motives for deceptive online reviews.

Linguistic manifestations of deceptive online reviews. The definition of deceptive online reviews or deceptive reviews varies among scholars. For instance, Ott et al. (2011) suggest that deceptive reviews are those untruthful online opinions on products or services posted by online reviewers to obtain benefits or defame competitors. Wu et al. (2020) define deceptive reviews as online reviews posted by consumers, online vendors, or platforms that are inconsistent with truthful reviews, including false, bogus, and deceptive reviews. In marketing, scholars focus on the influence of deceptive online reviews on consumer decision-making behavior, and the determining attribute of deceptive reviews is whether they would mislead consumers or not. Based on the definition of Wu et al. (2020), we define deceptive online reviews as online reviews that are inconsistent with a true evaluation of the product or service.

Research has shown that people's basic thoughts, emotions, and motivations can be understood by counting and classifying the words people use to communicate with others (Dong and Lian, 2021). Some studies on fraud detection have provided support for the effectiveness of using linguistic cues to identify deceptive language, and fraudulent reviewers often adopt a series of strategies to control the information in conversations to prevent lies from being exposed (Ananthakrishnan et al. 2020). However, it is less known whether the use of general linguistic cues to detect specific deceptive language will be successful for deceptive reviews with different motives because of the motivational impairment effect (Zhou et al. 2023). The motivational impairment effect refers to that liars with different motives use different ways to control their deceptive language. Extant studies have explored the characteristics of deceptive language under different motives and found that the linguistic characteristics used by reviewers in deceptive online reviews can reveal their mental, emotional, and cognitive states (Kumar et al. 2018; Luca and Zervas, 2016).

The changes in the linguistic features and psychological characteristics in the contents of the deceptive reviews are thus different from truthful reviews (Zhang et al. 2022). Consequently, the characteristics of the language, emotions, and psychology of deceptive reviews under different motives are also quite different, which provides a good research opportunity to explore the language features of deceptive reviews (Martinez-Torres and Toral, 2019; Zhang et al. 2018). Previous research has identified several linguistic cues for deceptive reviews, such as affective, cognitive, social, and perceptual cues in face-to-face scenarios (Li et al. 2020). However, there is relatively little research to explore the linguistic and psychological characteristics of deceptive reviews on virtual platforms when these reviews are with different motives (Chatterjee et al. 2021). It is thus essential to explore the linguistic manifestations of deceptive online reviews under different motives to better identify deceptive reviews to facilitate the growth of e-commerce businesses (Salminen et al. 2022).

Reality monitoring theory. The reality monitoring theory is developed from cognitive psychological research on human memory, and it argues that there is a qualitative difference between the memory of real events and the memory of imaginary events (Mac Giolla et al. 2019). The memory of real events is obtained through the perceptual process, so it has three main characteristics: perceptual information (i.e., hear, sight, taste, smell, and touch), spatial details, and temporal details. In contrast, the memory of virtual events is derived from internal cognitive resources and thus has more cognitive operations information, such as thinking and inference. Therefore, the memory of real events has a different manifestation than that of the memory of imaginary events.

Sporer (1997) defined eight criteria for identifying deceptive language based on the reality monitoring theory, including clarity, sensory information, spatial information, time information, affective information, constructability of the story, realism, and cognitive operation. Among them, clarity and constructability are rarely used by researchers in empirical studies. Specifically, clarity denotes that the language used is vivid, and constructability refers to the language using dialogue and scene setting to highlight important information about the event. These two criteria are usually used in story descriptions, but online reviews contain information about consumers' objective descriptions of products or services. Therefore, these two criteria are not suitable for the study of linguistic manifestations of deceptive online reviews. Sensory information contains visual information, audio information, and sensory information, and this set of information represents *perceptual cues*. Spatial information contains information about places or the spatial location of people. Time information contains cues about the occurrence time of an event or a clear description of the order in which the event occurs. Both spatial information and time information represent *detail cues* in language. In addition, affective information contains information about a person's feelings about an event. Realism means the statements are reliable, reasonable, and relevant. Cognitive operation means that the statement contains a description of a person's thinking and inference. Affective information, realism, and cognitive operation represent *affective cues*, *relevance cues*, and *cognitive cues* respectively in human language. In this study, we use perceptual cues, detail cues, affective cues, relevance cues, and cognitive cues to explore the linguistic manifestations of deceptive online reviews under different motives.

Hypothesis development

Emotional catharsis. Human behavior would be affected by emotion, and consumers would be affected by their emotions when they post online reviews. Emotional consumers may post unreal or biased reviews to vent their emotions because of emotional catharsis. When consumers are satisfied with the purchased products, they may post exaggerated positive reviews to express their shopping experiences. Thus, this type of online review would overpraise the products. Conversely, when consumers feel that the purchased product is bad, they may post excessively negative reviews to express their dissatisfaction. In addition, consumers may also give unrealistically low ratings because online vendors fail to meet certain requirements, such as gift-giving or promised cashback. Therefore, under the motive of emotional catharsis, consumers often post reviews that do not contain an evaluation of the quality of goods and services but are simply emotional expressions that only reveal their level of satisfaction with the goods or services. There are two kinds of emotions expressed under emotional catharsis: positive emotional expressions that overly praise the product and service and negative emotion expressions that vent their dissatisfaction, which both lead to extremely emotional online reviews.

As discussed in the reality monitoring theory, affective information is more likely to be found in deceptive language. Researchers have reached a consensus that deceptive language contains more affective cues (Kumar et al. 2019; Zhang et al. 2022). Moreover, fraudulent reviewers are more likely to use positive and negative emotional expressions than people who post truthful reviews, and positive or negative affective words are used more in deceptive reviews to mislead consumers (Li et al. 2020). Other studies have also obtained a similar finding on the positive relationship between affective cues and deceptive reviews. For instance, interpersonal deception theory explains the characteristics of deceptive language, suggesting that affective information is positively related to deceptive language (Petrescu et al. 2023). Scientific content analysis technology develops standards for detecting deceptive language in ten aspects such as pronoun use, word changes, and emotional description (Mac Giolla et al. 2019), and further points out that deceptive language is abundant with affective information. For example, Zhang et al. (2016) report that there are significant differences in affective clues between truthful and deceptive reviews. We admit that deceptive reviewers who seek emotional catharsis through online reviews may also use objective language to describe their experiences and the authentic reviewers may also use emotional words to describe their feelings (as suggested by one of the anonymous reviewers). However, compared with deceptive reviewers, authentic reviewers are more prone to use objective language to describe the product quality than to use emotional catharsis to describe their feelings.

By considering the psychological, linguistic, and empirical factors, it is valid to link affective cues to deceptive reviews under the motive of emotional catharsis. First, as a psychological process, emotional catharsis is often characterized by the release of repressed emotions and the desire to express one's feelings.

Reviewers who engage in emotional catharsis through deceptive reviews may be inclined to use affective language as a means of conveying their emotional experiences, whether positive or negative. Second, empirical research in the fields of linguistics and psychology has verified that emotional states tend to manifest through linguistic features. For instance, feelings of excitement, disappointment, and satisfaction are often conveyed through the intensity of language and the presence of emotional adjectives. By drawing upon this existing knowledge, we posit that deceptive reviews under the motive of emotional catharsis are more likely to contain affective cues. Third, deceptive reviewers motivated by emotional catharsis may differ from other deceptive reviewers in their underlying motives. While some deceptive reviewers write to deceive potential consumers or to gain financial incentives, those seeking emotional catharsis may prioritize self-expression and emotional release. As a result, they are more likely to use affective cues to convey their emotional experiences, regardless of the actual product quality. Hence, it is expected in this study that:

H1: *Affective cues are positively related to deceptive reviews for emotional catharsis.*

Perfunctory response. Many consumers are not good at writing reviews and even consider writing online reviews is a waste of time. Therefore, many consumers are likely to respond perfunctorily when they have to post online reviews for some reasons such as poor quality or bad experiences with the platform. Under the motive of perfunctory response, the content of a review would contain a very small number of words (such as "very good", "not bad" and "pretty good", etc.) when consumers are in a hurry or choose to perfunctorily respond to review requests. Sometimes they may plagiarize these words to meet the review word count requirements set by online vendors, which can be considered as the reviewer's self-image and self-relationship protection behavior. For instance, reviewers repeatedly copy a small number of words used in their reviews to make the reviews look long and authentic (Zhang et al. 2022).

According to the reality monitoring theory, deceptive reviews under the motive of perfunctory response tend to have little detail cues. For instance, deceptive language contains less information which can be an indicator to measure the deceptiveness of language expression (Yin et al. 2021). Following this logic, researchers can measure the richness of language information by the diversity of sentences, such as the distribution probability of prepositions, conjunctions, and adjectives in sentences (Li et al. 2022). Other researchers point out that the contents of deceptive language would contain fewer adjectives, prepositions, and comparative words (Ho and Hancock, 2019), and online reviews with this simple structure would most likely be deceptive ones (Shan et al. 2021). Furthermore, the lying behavior pattern based on the interpersonal deception theory states that liars are more verbal, use fewer words and sentences, and liars are less likely to be negative in conversation to avoid being exposed to negative emotions (Yin et al. 2021). Therefore, the general structure of the sentences used in deceptive reviews under the motive of perfunctory response tends to be quite simple, and the textual contents of the reviews may be less informative, leading to a lack of details in deceptive reviews.

H2: *Detail cues are negatively related to deceptive reviews for perfunctory purposes.*

Financial incentives. In the face of fierce competition, businesses might take proactive action to obtain consumers' positive reviews to increase sales. A reward strategy is a common method to pay consumers for their positive reviews (Qiao et al. 2020). In some extreme cases, online vendors even ask online buyers directly (by telephone calls or instant messages) to modify their reviews with cashback compensation to improve product ratings. If complied and implemented, consumers could post deceptive reviews that do not match the facts of the products or services (Shan et al. 2021). Research has shown that incentives have a significant positive impact on deceptive online reviews, and a large number of consumers would post deceptive reviews to obtain review rewards from vendors (Wu et al. 2020).

Under the financial incentives, consumers post deceptive reviews to obtain rewards by touting the virtues of the product and posting exaggerated positive reviews. Meanwhile, online vendors try to increase the number of positive reviews by persuading consumers to make positive deceptive reviews through review rewards. With this type of review, the review language would be filled with product information and experience information if reviewers post real reviews after a purchase (Liu et al. 2021). However, as reviewers are motivated by financial incentives and often boast their claimed product experiences with positive words, the content of review language often lacks a professional valence of products or even is irrelevant to products with little or no useful information for purchase reference. As a result, consumers usually use fewer honest, personal, and disclosing text in the virtual community to make the review sentences ambiguous, as has been found in the research on deceptive reviews (Zhang et al. 2016). In addition, research on deceptive online reviews shows that deceptive reviews are mostly fictional descriptions and have less or no relevance to products or services (Huang and Liang, 2021).

The negative relationship between relevance cues and deceptive reviews under the motive of financial incentives can be attributed to the fundamental drivers of deceptive behavior. Reviews created to obtain financial incentives often prioritize the achievement of monetary rewards over the provision of relevant and helpful information to potential consumers. In the case of financial incentives, reviewers may deliberately omit relevant product details and objective assessments to maximize their chances of obtaining incentives. Consequently, they may focus on fulfilling the minimum criteria necessary to qualify for the incentive, and write shorter, less detailed, and less relevant reviews. This strategic behavior aligns with the motive of financial incentives and contributes to the negative relationship between relevance cues and deceptive reviews under the motive of financial incentives. Therefore, the deceptive language under the financial incentives often lacks relevance cues.

H3: *Relevance cues are negatively related to deceptive reviews for financial incentives.*

Paid posters. Along with the intensifying competition within the platform economy, self-boasting behaviors or malicious defamation among competitors have begun to widespread (Cao, 2020). Some vendors could employ paid posters to make fake reviews to boost their stores' sales volume and improve their ranking to make profits and obtain competitive advantages. As a result, a large number of deceptive reviews could appear on various platforms. It is a widespread and growing phenomenon for online vendors to manipulate online product reviews by employing paid posters. These deceptive reviews posted by paid posters are usually unauthentic and exaggerated. Meanwhile, online vendors may also employ paid posters to attack and defame competitors to improve their competitive advantage (Mayzlin et al. 2014).

The reality monitoring theory points out that liars' memory comes from internal cognitive resources, and it will have more information about cognitive operations in deceptive language. Fraudulent reviewers use more cognitive operations in deceptive reviews to make their arguments or statements appear more convincing, even though they have no purchase experience with the product at all. Therefore, language cues involving cognitive processes (such as "cause", "know", "ought" and "think") are more likely to be involved in deceptive language, and this information has been used as language clues for detecting deception in many studies (Kumar et al. 2019; Zhang et al. 2022). Deceptive reviews posted by paid posters contain more information about cognitive operations, including certainty words, insight words, causation words, and discrepancy words. Certainty words (i.e., always, never) show fraudulent praise and disparagement of a product or service. Insight words (i.e., think, know) are to mislead consumers by highlighting fraudulent opinions in reviews. Causation words (e.g., because, effect) are to support the reason for giving positive or negative reviews so that consumers would be more convinced. Discrepancy words (i.e., should, would) reveal the fake persuasion about why consumers should or should not purchase the product. Deceptive reviews posted by the paid posters are often derived from internal cognitive resources because they don't have real experiences with the product or service, and thus reviewers have to use more cognitive expressions to fabricate an imaginary story (Zhang et al. 2016). Compared with authentic reviews, the deceptive reviews posted by paid posters contain more cognitive cues (Shan et al. 2021). Specifically, deceptive reviews tend to have more cognitive information to deceive readers when vendors intend to promote their goods or defame competitors' reputations (Ansari and Gupta, 2021).

The positive relationship between cognitive cues and deceptive reviews under the motive of paid posters can be attributed to the cognitive demands associated with creating deceptive content. Financial incentives may lead to a reduction in the emphasis on relevance cues due to a focus on obtaining rewards, while paid posters strategically utilize cognitive cues to enhance the believability of their deceptive reviews. Paid posters often create reviews that require careful planning and a high degree of cognitive effort to appear genuine to both readers and automated review detection algorithm. To avoid detection, paid posters may employ cognitive cues (i.e. complex sentence structures, diverse vocabulary, and logical reasoning) to make their deceptive reviews appear more convincing. This deliberate use of cognitive cues helps create the illusion of authenticity and expertise, thus serving the purpose of misleading potential consumers. Therefore, it is hypothesized that.

H4: *Cognitive cues are positively related to deceptive reviews by the paid posters*.

In addition, since language cues in perceptual processes can be combined to distinguish truthful language from deceptive language, many studies have verified the role of perceptual information in predicting deceptive language (Zhang et al. 2016). Under the motive of emotional catharsis, consumers merely express their satisfaction or dissatisfaction when consumers vent their emotions in a review, and they would not describe more perceptual details about the product or service (Q. Wang et al. 2022a, 2022b). Under the motive of perfunctory response, deceptive reviews tend to contain fewer perceptual process words (such as "look", "heard" and "feel") compared with truthful reviews (Zhang et al. 2022). The deceptive reviews with a perfunctory response would contain less detailed information compared with other reviews, resulting in a lack of description of perceptual information. Under the financial incentives, reviewers would not express detailed perceptual expressions in reviews because of their exaggerated experiences of the reviewed product or service. It is thus hard to find perceptual information in reward-based deceptive reviews (Li et al. 2020). The truthful reviews reflect the real after-use experience of consumers with the product or service, but the paid posters generally do not buy or experience the goods being reviewed and they can merely post reviews by imagination. These would also lead to less perceptual information in deceptive reviews (Kumar et al. 2019). In this study, it is thus expected that all deceptive online reviews would have little or no perceptual information.

The negative relationship between perceptual cues and all deceptive online reviews can be attributed to the strategic choices made by deceptive reviewers to preserve authenticity and maintain deceptive consistency. To preserve authenticity and avoid suspicion, deceptive reviewers often create reviews that appear authentic and genuine to potential consumers. In this regard, they may strategically avoid perceptual cues because these cues may raise suspicion among readers or automated review detection systems. To maintain deceptive consistency, deceptive reviewers may maintain a consistent tone and style across their deceptive reviews. By limiting perceptual cues, which may require additional creativity and effort, they can achieve a more uniform and less conspicuous deceptive writing style. Therefore, we hypothesize that all deceptive online reviews lack perceptual cues in their contents.

H5: *Perceptual cues are negatively related to all deceptive online reviews*.

Methods

Procedure. In this study, we first collect a set of online reviews available from Amazon.com and then identify both deceptive online reviews and authentic reviews by tracking the changes in online reviews on this platform. Second, we conduct data annotation on online review motives which include all deceptive reviews and possible motives so that participants can classify all the deceptive reviews into different groups based on their motives through the data annotation task. Third, we adopt the Linguistic Inquiry and Word Count (LIWC) tool to extract linguistic manifestations of the deceptive reviews and then adopt the negative binomial regression to examine specific linguistic manifestations in the deceptive reviews under different motives. Fourth, the usefulness of these linguistic manifestations of deceptive reviews under different motives for better online information management in marketing is then tested with empirical data.

Data collection. Amazon.com has its own internal filtering algorithms to identify deceptive reviews and suspicious reviews will be filtered out (i.e., deleted) from the platform. If consumers believe their genuine reviews are deleted, they can appeal to Amazon.com and submit evidence to prove the reviews are truthful and genuine. In our study, we periodically examine the reviews of target products on Amazon.com and through comparison with previously posted reviews, the deleted online reviews that are filtered out by the platform of Amazon.com are collected as deceptive online reviews for our study. These deceptive reviews were collected from July 1, 2019, to December 31, 2019. We collected the target product reviews in the first three months and then tracked the suspected deceptive reviews in the next three months. Reviews that are reposted on the platform after consumers' appeals are removed from our dataset of deceptive reviews.

To increase the representativeness, our deceptive reviews dataset contains product reviews from 20 stores of various product categories such as clothing, cell phones, headphones, laptops, other electronics, and more. Specifically, to prevent the linguistic manifestation of deceptive reviews from being overrepresented by online reviews of a single product in the LIWC analysis, we selected 10 product categories that were widely used in previous research about online reviews (Hussain et al. 2018;

Table 2 Descriptive statistics of annotation results.

Motivation	Mean	Std. Err.	Min	Max
Emotional catharsis (Luca and Zervas, 2016; Wu et al. 2020)	43.152	2.381	3	189
Perfunctory response (Barbado et al. 2019; Shan et al. 2021)	52.034	3.682	2	176
Financial incentives (Banerjee, 2022; Pang et al. 2022)	68.295	3.105	1	164
Paid posters (Ananthakrishnan et al. 2020; Kumar et al. 2019)	58.322	2.659	19	179

Kumar et al. 2019; Q. Wang et al. 2022), including experience products (i.e., clothing, headphones) and search products (i.e., laptops, cell phones). Each product category contained 2 stores, thus product reviews from 20 stores of products were collected. In the first three months, we obtained 837 product reviews that were filtered out by Amazon. In the next three months, we tracked 12 product reviews reposted on the platform, which were reconsidered as truthful reviews and removed from our dataset of deceptive reviews. During the data collection period, we also collected the reviews that were not filtered out by Amazon.com and selected the top five reviews based on the voted helpfulness for each targeted product. The resulting 100 genuine reviews are used for the validation experiment (Section "Validation of the results"). In addition, deceptive reviews collected from the Amazon platform are all in English, and annotators were recruited from a public university in China to complete the annotation task. We use the translate-to-translate method to ensure the consistency of the Chinese and English reviews. Specifically, we first translated the deceptive reviews into Chinese and then translated the reviews back to English using reverse translation technology. The Chinese version of the deceptive reviews was ultimately determined by comparing and correcting the differences in the translated contents.

Following previous studies (Jha and Shah, 2021; Ma et al. 2017), we used the data annotation method to obtain the total number of annotations for each motive of deceptive reviews. Annotators labeled the types of motivation for deceptive reviews, including emotional catharsis, perfunctory response, financial incentive, and paid posters. Following the step of the data annotation method (Jha and Shah, 2021), we conducted a pre-annotation to determine the number of deceptive reviews in the annotation task before the formal annotation task. In the pre-annotation phase, we selected 30 consumers from a public university in China who had rich experience in posting online reviews to conduct the pre-annotation. The annotation time for each participant was recorded during the pre-annotation, and the mean value of annotation time for each review was 20 sec. According to the suggestion of Ma et al. (2017), the annotation time for each batch was controlled from 5 to 10 min to ensure the quality of the data annotation. According to this criterion, setting 30 deceptive reviews in a batch could not only ensure the quality of data annotation but also maximize the number of annotations obtained from a single participant. Therefore, we randomly selected 300 deceptive reviews from the collected reviews and divided these deceptive reviews into 10 batches. Each batch contained 30 deceptive reviews and was assigned 50 different participants for labeling.

In the annotation task, annotators were asked to choose the possible motivations of each deceptive review. Each participant just labeled two batches of deceptive reviews to prevent the motives of deceptive reviews from being overrepresented by single participants. A deceptive review might be produced under more than one type of motivation thus participants can annotate a deceptive review with multiple motivation labels. For a deceptive review with multiple motivation annotations, we counted the total number of annotations for each motive and used it as the dependent variable to run statistical models in Section "Choice of statistical models". In addition, we added the option "I don't think this is a deceptive review" to avoid the suspected deceptive review dataset containing authentic reviews that are actively deleted by consumers. During the data annotation task, we counted the number of annotations for each motive of each deceptive review.

We recruited five hundred consumers (217 males and 283 females) from a public university in China to complete the annotation task, and they were paid \$1. These participants were between 20 and 37 years old ($M = 26$), and everyone had more than 3 years of experience on average in posting online reviews ($M = 3.4$). The responses of 48 participants were found biased because their answers were the same for all deceptive reviews. We excluded their responses from the analysis. In addition, among the 300 potential deceptive reviews, 36 reviews are not considered deceptive by more than 80% of the respondents and thus these reviews are removed from our deceptive review dataset, resulting in 264 deceptive reviews for further analysis. The new dataset with 264 deceptive reviews also consisted of deceptive reviews of 20 products to prevent experimental results from being overrepresented by deceptive reviews of a single product. Table 2 shows the descriptive statistics of annotation results of 264 deceptive reviews. Note that this research does not categorize deceptive reviews based on motivation annotation results, and we just count the total number of annotations for each motive in 264 deceptive reviews.

Measures. Natural language processing (NLP) is a technology developed through the integration of linguistic theory and computing technology that can quantitatively analyze textual contents (Yi and Oh, 2022). This technology is widely used in the field of lie recognition, and the most commonly used software system in this field is the Linguistic Inquiry and Word Count (LIWC) tool. Prior studies have used the LIWC tool to calculate the percentage of specific language features in deceptive language texts, and it has produced a high level of accuracy for different types of deceptive languages (Liu et al. 2019; Xu and Zhang, 2018). Most research on linguistic analysis of deceptive reviews uses the LIWC tool to calculate the linguistic features (such as shorter words (Zhang et al. 2016), pronouns (Plotkina et al. 2020), and information richness (Zhang et al. 2022)) and psychological features (such as emotions (Yin et al. 2021), perceptual information (Ansari and Gupta, 2021), and cognitive burden (Wu et al. 2020)). These empirical studies suggest that the LIWC is a powerful tool to identify the linguistic manifestations of deceptive reviews.

In this study, we examine several important variables, including *Authentic, Total function words, Affective processes, Cognitive processes*, and *Perceptual processes*. Among them, "*Authentic*" is the relevance of language to the subject, which indicates the degree to which the language used is related to the language topic. It represents the content relevance in the hypotheses and its low score suggests an uncorrelated, irrelevant form of expression, and thus it is used to assess relevance clues. The summary variable "*total function*" measures the information richness of the language, and it is an indicator of the quantity of details in the review text sample. When the language content is full of details, it will have a high score, which means the language contains a wealth of information. Therefore, this summary

Table 3 Variable notations and measures.

LIWC Category	Notation	Measure	Corresponding variable
Authentic	*Authentic*	The authenticity of a review as calculated by LIWC	Relevance cues
Total function words	*Function*	Percentages of total function words in a review as calculated by LIWC	Detail cues
Affective processes	*Affect*	Percentages of an affective process word in a review as calculated by LIWC	Affective cues
Cognitive processes	*Cogproc*	Percentages of cognitive process words in a review as calculated by LIWC	Cognitive cues
Perceptual processes	*Percept*	Percentages of a perceptual process word in a review as calculated by LIWC	Perceptual cues

variable can be used to measure whether the deceptive reviews have detail cues. *Affective processes* reflect people's emotions in language expression. LIWC uses positive emotion, negative emotion, anxiety, anger, and sadness to measure *Affective processes*. The positive emotion dictionary in LIWC contains 620 words (such as "love", "nice", and "sweet") and the negative emotion dictionary contains 744 words (such as "hurt", "ugly", and "nasty"). The rate of *Cognitive process* words (such as "cause", "know", and "ought") in a review text sample shows how the writer is processing and interpreting information to mentally organize their circumstance. The variable of *Perceptual processes* is to assess the connection with the content about people's personal feelings in language expression, related to "see", "hear", and "touch".

These LIWC features can be a great measure to assess the linguistic manifestations of deceptive online reviews under various motives. Therefore, this study uses the LIWC text analysis tool to analyze the language characteristics of deceptive reviews with different motives. The LIWC tool categorizes the words as part-of-speech based on word measurement and calculates the proportion of words in the text that express the psychological characteristics of language organizers, such as insight, cognition, emotion, and social processes. We used LIWC 2015 to conduct the language analysis on deceptive reviews. The extracted features are shown in Table 3.

Choice of statistical models. When constructing the model to test the research hypotheses, for each deceptive review, we used the LIWC extracted features as the independent variables and the total number of annotations for each motive in the data annotation as the dependent variable. In addition, review length and whether the reviewer was verified to have purchased the product (verified purchase) are used as control variables. The five independent variables are constructed to verify the research hypotheses and investigate the linguistic manifestations of deceptive reviews under different motives. In the collected annotation data, the number of annotations for each motive is a discrete count of non-negative integer values, which does not meet the requirements of data homoscedasticity and normal distribution in the OLS linear regression model. Instead, the counting model is usually used to process discrete count data.

The counting model includes Poisson regression, negative binomial regression, Zero-inflated Poisson regression (ZIP), and Zero-inflated negative binomial regression (ZING). The premise of choosing Poisson regression is that the mean and variance of the dependent variable are equal. However, the variance of the dependent variable is often larger than the mean in actual data. As a generalized linear model in which the dependent variable is a count of the number of times an event occurs, negative binomial regression is preferred when the phenomenon of "over dispersion" occurs independent variable. If the dependent variable contains a large number of zero values, Poisson regression, and negative binomial regression are not good choices to estimate the model. In this case, ZIP or ZING should be used for model construction. Researchers usually use "Vuong statistic" (Vuong, 1989) as the criterion to choose the regression model. If the "Vuong statistic" is a large positive value, we should choose ZIP or ZING for regression. Otherwise, if the "Vuong statistic" is a large negative value, we should select Poisson regression or negative binomial regression for model construction.

Based on the descriptive statistics shown in Table 2, the mean of the emotional catharsis motivation is 43.15, and the standard error is 2.38. The means of other motives are also not equal to the variance. It is obvious that the dependent variables of the samples have the problem of "over dispersion". For this reason, we cannot use the Poisson regression and the ZIP model. Besides, the minimum values of all dependent variables are greater than zero and do not include zero values. Thus, we cannot use the ZIP model. Furthermore, we use the ZING model to verify the "Vuong statistic" and the result shows that all the z statistics of the Vuong test are negative and much less than -1.96 ($p < 0.001$). Thus, the ZING model is not a good choice for our data. Considering "over dispersion" with no zero value in the variable of motives, we argue that the negative binomial regression is the most appropriate for the empirical analysis in this study.

Results

Experiential results. We analyzed the linguistic features of deceptive reviews under corresponding motives to verify the research hypotheses. Before constructing the text regression model, we perform a correlation analysis between the dependent and independent variables. The Pearson correlation coefficient measures the correlation between the variables, and Table 4 shows the Pearson correlation between the relevant variables. The results of the variable correlation test show a significant correlation between each motive of deceptive reviews and linguistic manifestations of deceptive reviews, which provides a basis for further construction of the regression model between deceptive review cues and review manipulation motives. In addition, independent variables are not correlated with each other, and their correlation coefficients are less than 0.8, which does not cause the problem of multicollinearity between independent variables.

Table 5 shows the results derived from the model estimation using the negative binomial regression. The four models test the significance of the selected review features under different motives. We also used Poisson regression and ZING to run the four models to measure the goodness-of-fit of the model. The Akaike information criterion (AIC) for the four negative binomial regression models is lower than the AIC for the ZING model and Poisson regression model. Taking model 1 as an example, the AIC for the negative binomial regression model is 488.05 and it is lower than the AIC for the ZING model (574.64) and Passion model (1498.66). To this end, the negative binomial regression model proves to be the most appropriate among all the counting models.

As shown in Model 1, perceptual cues are negatively related to emotion-based deceptive reviews ($\beta = -0.085$, $p < 0.01$). Similarly, the deceptive reviews under the motivate of perfunctory response also lack the perception process words ($\beta = -0.104$, $p < 0.01$), as in Model 2. The results of Model 3 and Model 4 show similar relationships between deceptive reviews and perception cues, with

Table 4 Pearson correlation of variables.

Variables	1	2	3	4	5	6	7	8	9
1 Emotional catharsis	1								
2 Perfunctory response	−0.499***	1							
3 Financial incentives	−0.722***	0.107*	1						
4 Paid posters	−0.025*	−0.416**	−0.236**	1					
5 Relevance cues	0.272**	−0.152*	−0.240**	0.134*	1				
6 Detail cues	0.184**	−0.329**	−0.022*	0.138*	0.229**	1			
7 Affective cues	−0.328**	0.481**	0.031	0.112*	−0.261**	−0.148**	1		
8 Cognitive cues	0.114*	0.076*	−0.151*	−0.060	0.285**	−0.030*	−0.052*	1	
9 Perceptual cues	−0.119*	−0.147*	−0.143*	−0.046	−0.062	−0.080*	0.007	0.203**	1

Note: ***$p < 0.01$. **$p < 0.05$. *$p < 0.1$.

Table 5 The results of model estimation.

Variable	Model 1		Model 2		Model 3		Model 4	
	Emotional Catharsis		***Perfunctory Response***		***Financial Incentives***		***Paid Posters***	
	Coefficient	**Robust S.E.**	**Coefficient**	**Robust S.E.**	**Coefficient**	**Robust S.E.**	**Coefficient**	**Robust S.E.**
Relevance cues	−0.002	0.004	0.005	0.006	**−0.504*** **	0.042	−0.004	0.002
Detail cues	0.024	0.015	**−0.194*** **	0.048	−0.002	0.008	0.001	0.005
Affective cues	**0.225*** **	0.059	0.011	0.005	0.003	0.005	0.003	0.003
Cognitive cues	0.046	0.027	−0.020	0.018	0.053	0.018	**0.205*** **	0.048
Perceptual cues	**−0.085** **	0.033	**−0.104** **	0.049	**−0.215*** **	0.412	**−0.191*** **	0.063
Review length	−0.101**	0.048	−0.386***	0.064	0.124**	0.516	0.106***	0.039
Verified purchase	−0.084**	0.038	0.409***	0.054	0.137***	0.048	−0.222***	0.031

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

deceptive reviews for financial incentives at $\beta = -0.215$, $p < 0.001$, and deceptive reviews from paid posters at $\beta = -0.191$, $p < 0.001$. Overall, the percentage of perceptual cue words is lower than 9% in more than 80% of the 264 deceptive reviews (the mean value of perceptual cues in authentic reviews is 10.21%), and over 40% of these reviews do not contain any perceptual process words (*Percept* score is zero), which indicates that there is no description of the perception information of products or services in these deceptive reviews. This result suggests that there are few perception process words in deceptive reviews, and the description of perceptual cues is insufficient, which thus provides support for Hypothesis 5. In other words, the empirical data on Amazon.com support our prediction that all deceptive reviews lack perceptual cues.

As expected, Model 1 shows that the relationship between affective cues and emotion-based deceptive reviews is significant ($\beta = 0.225$, $p < 0.001$). Under the motive of emotional catharsis, reviewers use either positive emotional words to express affection and appreciation of the target product or negative emotional words to express dissatisfaction with the target product, and thus affective cues are positively related to emotion-based deceptive reviews. Hypothesis 1 is thus supported. Model 2 shows that detail cues are negatively related to deceptive reviews under the perfunctory response ($\beta = -0.194$, $p < 0.001$), which indicates that there are few function words in the deceptive reviews under the motive of perfunctory response, and these reviews are short of detailed information. The result thus provides support for Hypothesis 2, which states that deceptive reviews with perfunctory responses are negatively related to detail cues. In addition, fraudulent promulgators would write deceptive reviews with less information when they are motivated by emotional catharsis and perfunctory responses, resulting in short review lengths. Consequently, review length is negatively related to deceptive reviews under the motives of emotional catharsis and perfunctory response.

The result of Model 3 also supports a significant relationship between relevance cues and deceptive reviews for financial incentives ($\beta = -0.504$, $p < 0.001$). When reviewers are motivated by the financial rewards to post reviews, they just meet the minimum requirements for the review set by the vendors, such as the number of words and sharing the photo of the target product. The textual contents of these reviews lack objective evaluation of the target product and sometimes are irrelevant to the product, which leads to deceptive reviews of little or no reference value for other potential consumers. Therefore, Hypothesis 3 is supported, that is, the deceptive reviews for financial incentives lack relevant information, and relevance cues are negatively related to financially driven deceptive reviews.

The result of Model 4 shows a significant and positive relationship between cognitive information and deceptive reviews from the paid posters ($\beta = 0.205$, $p < 0.001$). The purpose of paid posters is to mislead consumers by fabricating an imaginary story in the reviews. However since the paid posters have not purchased and used the products, it is very difficult for them to describe product details and after-use experience in deceptive reviews. Therefore, deceptive reviews posted by the paid posters would contain more cognitive cues as a result of the cognitive operations to make their reviews look more convincing. The result again provides support for Hypothesis 4, that is, the deceptive reviews from paid posters contain more descriptions of cognitive expressions, and thus are positively related to cognitive cues. Moreover, review length is positively related to deceptive reviews under the motives of financial incentives and paid posters. This is because fraudulent promulgators would write longer reviews to make deceptive reviews look like authentic ones, and these longer reviews can also make them more inconspicuous in online review fraud.

For deceptive reviews labeled as "verified purchase," we observed a significant positive impact on perfunctory responses

Table 6 Linguistic manifestations differences between deceptive and authentic reviews.

Comparisons	Relevance cues	Detail cues	Affective cues	Cognitive cues	Perceptual cues
Deceptive reviews under emotional catharsis vs. authentic reviews			7.32**		−7.05**
Deceptive reviews under perfunctory response vs. authentic reviews		−22.36***			−7.46**
Deceptive reviews under financial incentives vs. authentic reviews	−23.31***				−6.58**
Deceptive reviews under paid posters vs. authentic reviews				18.28**	−3.71*

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

and financial incentives. This finding suggests that consumers who purchased the product were more likely to engage in perfunctory responses, possibly influenced by their lack of tendency to write detailed reviews. Furthermore, the presence of financial incentives seemed to play a role in encouraging deceptive reviews among this group. Conversely, deceptive reviews labeled as "verified purchase" exhibited a negative impact on emotional catharsis and the presence of paid posters. This implies that authentic consumers were less inclined to express emotional catharsis in their reviews. Additionally, the presence of paid posters appeared to be less prevalent among reviews from this group, possibly indicating that such tactics were more commonly employed by those who did not actually purchase the product.

Validation of the results. The data annotation method obtains the total number of annotations for each motive of deceptive reviews through the review motives annotation task. To verify the accuracy of the data annotation method, we conducted the second-period review motives annotation task based on the categorization outcome of motivation types. Different from the first data annotation task, participants were required to select whether the deceptive review r was posted under motive m. Specifically, we first categorized the 264 deceptive reviews by their motive types with the criterion that the probability of the review r being labeled as the motive m exceeds 66.7% (i.e. more than two-thirds of the participants regard that the review r is posted under the motivation m). Here, a deceptive review could be categorized into multiple motive types because a deceptive review might be annotated as multiple motive labels. Then, we calculated the percentage of participants who agreed that the deceptive review r was posted under motive m. The results show that for each review r of all 264 reviews, more than 86.2% of the participants regard that it is posted due to motive m. Therefore, we conclude that the data annotation method is accurate, and the data annotation process does not pose a serious problem in data analysis and the findings.

To provide further support for the major findings of the linguistic manifestations of deceptive online reviews under different motives, we conducted a one-way analysis of variance (ANOVA) test on the difference in the linguistic manifestations of deceptive reviews under different motives and authentic reviews. First, we categorized the 264 deceptive reviews by their motive types, with the criterion that more than two-thirds of the participants labeled the motive of the review r as the motive m. Second, we used LIWC to extract linguistic cues (shown in Table 3) of deceptive reviews under different motives as well as authentic reviews. Here, authentic reviews are 100 reviews collected during the data collection. Third, we ran the ANOVA to test the difference in linguistic manifestations between deceptive reviews and authentic reviews. Table 6 shows the linguistic manifestations comparison between deceptive reviews under different motivations and authentic reviews. The coefficients represent the difference in the mean value of linguistic cues extracted by LIWC between deceptive reviews and authentic reviews.

Results in Table 6 show that affective cues of deceptive reviews under emotional catharsis are significantly more than those of authentic reviews (16.82 vs. 9.50, diff. = 7.32, $p < 0.01$), providing solid support for the finding that affective cues are positively related to deceptive reviews for emotional catharsis. Moreover, the detail cues of deceptive reviews under perfunctory responses are less than those of authentic reviews (31.40 vs. 53.76, diff. = −22.36, $p < 0.001$). In this regard, the result could further support the finding that detail cues are negatively related to deceptive reviews for perfunctory purposes. The difference in relevance cues of deceptive reviews under financial incentives and authentic reviews showed that the difference in relevance cues of deceptive reviews and authentic reviews is statistically significant ($p < 0.001$), with the mean of relevance cues being 24.97 and 48.28 (diff. = −23.31, $p < 0.001$), respectively. Deceptive reviews under paid posters have more cognitive cues than authentic reviews (30.72 vs. 12.44, diff. = 18.28, $p < 0.01$), which indicates that cognitive cues are positively related to deceptive reviews by paid posters. As expected, the percentage of cognitive process words in deceptive reviews is lower than that in authentic reviews. Thus, all deceptive online reviews lack perceptual cues in their contents.

Discussion and conclusions

Research findings. Online reviews are vital for the platform economy, and extant studies have explored the motives of deceptive online reviews and the linguistic feature between deceptive reviews and authentic reviews (Li et al. 2020; Liu et al. 2019), yet the linguistic manifestations of deceptive online reviews under different motives have not been well studied (Chatterjee et al. 2021). It is thus essential to better understand and then guide consumers to post high-quality online reviews to facilitate the development of e-commerce businesses in the era of the platform economy. We conduct an empirical study on linguistic and psychological features of deceptive online reviews with different motives. The results show that the linguistic manifestations of deceptive online reviews vary along with their motives. This study would add value to the research on deceptive reviews and the practice of online information management for e-commerce businesses (Plotkina et al. 2020; Zhuang et al. 2018).

This study can make important contributions to the knowledge of deceptive online reviews in two ways. First, this study focuses on linguistic characteristics and psychological characteristics of deceptive online reviews and identifies different linguistic manifestations of deceptive reviews under different motives. This finding is consistent with Li et al. (2020), who report that spammers would vary their writing styles across different reviews under different review motives. Based on the reality monitoring theory, this study examined perceptual cues, affective cues, detail cues, relevance cues, and cognitive cues of deceptive online reviews with different motives with empirical data supporting our proposed relationships. This study thus broadens the application of the reality monitoring theory in e-commerce business by providing a more holistic understanding of the motives and linguistic manifestations of online deceptive reviews (H. Wang et al. 2022; Wu et al. 2020).

Second, this study explains the usefulness of linguistic manifestations of deceptive reviews under different motives for better online information management in online marketing – an extension to current research that is often focused on how review content features can help identify deceptive reviews (Kumar et al. 2019; Zhang et al. 2016). Apart from developing deceptive review detection algorithms, the knowledge of linguistic manifestations of deceptive reviews is also helpful in combating deceptive reviews (Banerjee and Chua, 2021; Yang and Zhang, 2022). Based on the findings of linguistic manifestations of deceptive reviews under different motives, platform firms could provide review tips to guide consumers to avoid the linguistic features of deceptive reviews and to contribute high-quality online reviews for other consumers to make informed decisions.

Theoretical implications. From the theoretical perspective, while many studies have examined deceptive reviews as a pervasive issue in the platform economy and its potential damage to e-commerce businesses (Plotkina et al. 2020; Zhuang et al. 2018), relatively few studies have explored the underlying motives for individual consumers' deceptive reviews as well as the linguistic manifestations of deceptive reviews under different motives. In this study, we propose there are four different motives for posting deceptive online reviews based on the previous research, including emotional catharsis, perfunctory response, financial incentives, and paid posters, and then empirically validate the significant linguistic differences of deceptive online reviews with different motives. This study is thus able to provide important insights for better understanding the linguistic manifestations of deceptive reviews under different motives and shed light on how to develop a more integrated theory on deceptive reviews and further on knowledge management in the increasingly digitalized world (Chen et al. 2021), an emerging phenomenon facing all the scholars in e-commerce businesses in the era of the platform economy.

Second, we extend the reality monitoring theory to explain the linguistic manifestations of deceptive online reviews. To the best of our knowledge, this study is the first to apply the reality monitoring theory to explore the linguistic manifestations of deceptive reviews under different motivations. This theory has been applied in linguistic research on cognitive psychology (Dijkstra and Fleming, 2023) and deceptive language (Mac Giolla et al. 2019). This study not only extends it to the analysis of the linguistic manifestations of deceptive reviews but also examines the differences in the linguistic characteristics and psychological characteristics of deceptive reviews under different motives. We pay greater attention to building the connection between the reality monitoring theory and linguistic manifestations of deceptive reviews rather than just text analysis. Therefore, this study extends the current literature on deceptive online reviews from a theoretical perspective.

Managerial implications. Our study can also have important practical implications. First, we provide consumers with a relatively clearer profile of deceptive online reviews under different motives to help them understand deceptive online reviews. While past studies have identified distinctive characteristics or cues that can be used to differentiate between deceptive reviews and authentic reviews, no study has examined these characteristics by dividing deceptive reviews into different motives. The findings of this study thus provide a more nuanced understanding of deceptive reviews under different motives to help develop more accurate distinctions. Consumers can try to avoid using the linguistic features of deceptive reviews in creating high-quality authentic online reviews if they have more knowledge about the linguistic manifestations of deceptive reviews. Consumers could shape their perceived authenticity of online reviews based on the knowledge of linguistic manifestations of deceptive reviews. In this regard, deceptive reviews would be a futile strategy when consumers gain a deeper understanding of the linguistic manifestations of deceptive reviews (Banerjee and Chua, 2021). Even though adding deceptive reviews may make the product sound more attractive, consumers would suspect the authenticity of and discount the value of deceptive reviews, consequently reducing their purchase willingness. It is thus better for both consumers and e-commerce businesses to develop a trusting relationship and for e-commerce businesses to achieve more sustainable and healthy growth when deceptive reviews are reduced or removed (Mayzlin et al. 2014).

Second, this study provides significant management implications for e-commerce businesses that hope to guide consumers to post high-quality online reviews. For online platforms, one of the key challenges is how to guide consumers to contribute high-quality online reviews because these reviews are key to developing the value and sustainability of e-commerce businesses (Yu et al. 2022). Reviewers' misuse of linguistic features of deceptive reviews may cause unintended biases that ultimately affect the credibility of reviews. Thus, e-commerce businesses could consider using review tips to guide consumers to post highly credible online reviews. For instance, e-commerce businesses could guide reviewers to avoid using excessive language features that are irrelevant to the target product when they encourage consumers to contribute online reviews by providing financial incentives. When consumers post negative reviews due to their dissatisfaction with products or services, e-commerce businesses should guide consumers to describe the shortcomings of goods or services in their reviews rather than just using overly negative linguistic expressions. Otherwise, these reviews will be mistaken as deceptive reviews by consumers. Therefore, e-commerce businesses could increase the value and sustainability of e-commerce businesses and facilitate the establishment of effective online customer information management systems.

Third, the results of this study can help e-commerce businesses differentiate deceptive reviews with different motives and thus conduct strict scrutiny on reviews with the possibility of identifying and deleting more harmful reviews such as the ones for emotional catharsis. This may help solve the problem that has often frustrated e-commerce businesses: without knowing the nuance of deceptive reviews' impact on purchase decisions, e-commerce businesses or other online vendors have to spend more resources to inspect all the reviews to identify deceptive reviews. Although e-commerce businesses can use internal filtering algorithms to identify and filter out deceptive reviews through automated algorithms, real-time detection of deceptive reviews is not yet possible. On the one hand, the system of Amazon is not already successful in removing the deceptive reviews and the internal filter algorithm of Amazon cannot spot all the deceptive reviews on the platform with its accuracy lower than 100 percent. For this reason, a series of third-party algorithms and Apps such as FakeSpot (Wu et al. 2021), ReviewMeta (Choi et al. 2019), and the Review Index (Choi et al. 2019) are developed outside the e-commerce platforms to help online shoppers clear up deceptive reviews from different perspectives. On the other hand, the removal of deceptive reviews on Amazon has taken place retroactively rather than proactively. That is, even if some deceptive reviews would be spotted by the internal algorithm of Amazon eventually, they could be shown in the review list for at least one week and during this time, these deceptive reviews could also mislead online shoppers to make an unwise decision.

Limitations and future research. Our research has some limitations and caution should be exercised in applying the findings. First, although our study has proposed and then empirically tested some linguistic and textual features of deceptive reviews, it is still challenging to determine whether an online review is deceptive based on these linguistic manifestations alone (Plotkina et al. 2020). Other factors need to be considered to accurately identify deceptive reviews. Therefore, our study can provide important clues to help understand deceptive online reviews rather than provide a guaranteed approach to identifying deceptive reviews. In addition, the proposed motives are not an exhaustive list of possible motives for deceptive online reviews. Future research could explore other antecedents of deceptive reviews to better understand and further help identify deceptive reviews. Second, the independent variables in our research are limited within the scope of features produced by LIWC2015. In addition, because deceptive reviews generated by computer bots are easy to identify, this research does not consider the significant number of deceptive reviews that are auto-generated by computer bots. Future research could consider more language styles of deceptive reviews and incorporate more deceptive language cues into the model to improve the language features of deceptive reviews (Kumar et al. 2019). Third, the sentiment intensity of deceptive online reviews would differ significantly with different motives, and this study does not examine the relationship between positive or negative emotion intensity and deceptive reviews. Future research could analyze and identify the specific association between review sentiment intensity and the truthfulness of online reviews. Fourth, although the LIWC tool could calculate the linguistic manifestations of deceptive reviews, this study does not consider the effect of word position in the linguistic manifestations of deceptive reviews. Future research could also explore the ordering effect of words to better understand the linguistic manifestations of deceptive online reviews.

Data availability

The dataset analyzed during the current study is not publicly available due to confidentiality and privacy. Data collected from private vendors may contain sensitive information about their operations and customers. Making such data public could breach confidentiality agreements or privacy regulations. However, the dataset is available from the corresponding author on reasonable request.

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Author contributions
WZ: Writing-review & editing, Conceptualization, Validation. QW: Data curation, Writing-original draft, Investigation. JL: Conceptualization, Funding acquisition. ZM: Methodology, Supervision, Proofread. GB: Supervision, Proofread. RP: Supervision, Funding acquisition.

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This article does not contain any studies with human participants performed by any of the authors.

Additional information
Correspondence and requests for materials should be addressed to Qiang Wang.

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