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Not all consumer-generated images are attractive and persuasive: A heuristic cue perspective

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ABSTRACT

This study explored how the features of consumer-generated images (CGIs) influence consumers' attention and purchase intention in both browsing and buying stages of online shopping, as well as the mediation of these effects. We consider the common features of image reviews (e.g. brightness, clarity, product displaying proportion and consistency) as heuristic cues evaluated by consumers. We posit that image brightness, clarity and product displaying proportion are product irrelevant cues associated with CGI attractiveness in the browsing stage, whereas product consistency is a product relevant cue associated with CGI attractiveness and purchase intention during the buying stage. Eye-tracking experiments with 127 undergraduates using Parka products support our hypotheses. The results indicate a positive correlation between the quality of product-irrelevant cues and CGI attractiveness in browsing, and a similar positive association with product-relevant cues during buying. The results also show that both product relevant and irrelevant cues are positively associated with consumers' purchase intention, mediated by eliciting emotional arousal rather than visual attention. This study extends the literature by shifting the focus from assessing the overall aesthetic quality of CGIs to the importance of specific features in different online shopping stages. The study provides important implications for e-commerce platforms to strategically encourage users to submit CGIs that maintain consistency with the merchant-provided images and exhibit high image quality attributes such as brightness and clarity. Future research should explore CGIs across different product types to understand their varying roles.

1. Introduction

Consumer-generated images (CGIs) in e-commerce refer to image reviews created and shared by consumers themselves to showcase products they purchased. Nowadays, CGIs are increasingly prevalent in e-commerce and are being regarded as indispensable references in evaluating the quality of products by consumers (Curran & Doyle, 2011). However, while CGIs offer a visually compelling way to showcase merchandise, there is a pressing need to comprehend how consumers interact with and respond to these virtual representations. This understanding is crucial for businesses seeking to optimize their online sales strategies and enhance the overall shopping experience for consumers. However, current understanding of factors that influence the attractiveness (e.g. visual elements that draw consumers' attention) and persuasiveness (e.g. visual elements that facilitate consumers' buying behavior) of CGIs is still limited. A more thorough investigation of the characteristics of CGIs and related influence on shopping behavior would benefit both ecommerce platforms and consumers themselves.

In light of the growing prevalence of CGIs as crucial components of online reviews, research on the informational value of CGIs has been relatively scarce. Prior studies have predominantly focused on the attributes of text-based reviews, such as review length, sentiment, emotional expression, helpfulness (e.g. Chua & Banerjee, 2015; Lee et al., 2021; Lei et al., 2021; Sahoo et al., 2018). Recently, however, there is a growing recognition of the impact of visual information online. Their findings suggest that CGIs serve as more vivid stimuli that can better capture consumers' attention and influence their behavioral intention compared to traditional text-based review (e.g. Childers & Houston, 1984; Peracchio et al., 2005; Wu et al., 2008; Yin et al., 2021). Particularly for experiential goods, which rely heavily on personal taste and subjective attributes, CGIs have been suggested to aid consumers in evaluating products more effectively and enhancing the perceived

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helpfulness of reviews (Filieri et al., 2018; Osterbrink et al., 2020). Despite the importance, the majority of work in this domain has focused on comparing the impacts of different review formats (e.g. video, image and text), but rarely discussed the characteristics of CGIs itself (Curran & Doyle, 2011; Xu, 2018). It is still unclear what constitute a "helpful" CGI that can capture consumers' attention and facilitate their purchases. To fill this gap, the present research focuses on the heuristic cues of CGIs and examines how both product relevant and irrelevant cues of CGIs influence consumers' attention and purchase intention.

Specifically, heuristic cues refer to the most salient features from the environment that requires minimal cognitive effort to process (Ferran & Watts, 2008). Particularly in the realm of image reviews, CGIs impose higher cognitive demands compared to text-based reviews (Ferran & Watts, 2008). This cognitive burden compels consumers to rely on heuristic cues embedded within CGIs to facilitate their decision-making process (Ozanne et al., 2019). Broadly, heuristic cues in CGIs can be categorized into two types: product-relevant and irrelevant cues (Ha & Lennon, 2010a, b). Product relevant cues include those that are related to the appearance of product itself such as the consistency of CGI with merchant-provided images. Product irrelevant cues include those that are only related to the quality of images rather than the specific product, such as image clarity, brightness and product displaying proportion. Prior research has shown that consumers have different information processing inertia when they face product relevant and irrelevant cues during online shopping (Eroglu et al., 2001; Ha & Lennon, 2010a, b). Hence, it is important to understand the role of different types of heuristic cues of CGIs in attracting consumers' attention and facilitating purchase.

Additionally, consumer exhibit distinct behaviors during the browsing and buying stages, with heightened motivation for careful decision-making and increased attention to product features during the buying stage (Li & Hitt, 2008). Consequently, it is imperative to discern the relative significance of product-relevant and irrelevant cues in attracting consumers and facilitating purchases during the browsing and buying stages, respectively. Moreover, drawing on the literature of image processing, images can help facilitate consumers' decision making through either attracting visual attention or eliciting emotional arousal. Hence, we further examine the underlying mechanism that CGI's cue quality might be persuasive in facilitating purchase intention.

In an effort to bridge the identified research gaps, this research employs a combination of eye-tracking experiment and questionnaires, focusing on both the browsing and buying stages of online shopping. The aim is to delve into the nuanced impact of heuristic cues of CGIs on consumers' attention and purchase intention. Specifically, three research questions are proposed.

(1) How does the quality of product relevant and irrelevant cues influence the attractiveness of CGIs during the browsing and buying stage?
(2) How does the quality of the product relevant and irrelevant cues influence the purchase intention of consumers?
(3) What is the underlying mechanism that mediates the association between CGI cue quality and consumer purchase intention?

Critically, we seek to address a few ambiguities in the research on CGIs. First, few prior research differentiated factors that influence the attractiveness of CGIs in the browsing and buying stages. As the browsing and buying stages refer to different levels of situational involvement in the shopping process, consumers are shown to engage in different behaviors in the two stages (Ha & Lennon, 2010). During the browsing stage, consumers often exhibit exploratory behavior, casually perusing various products without a strong commitment to purchase. At this stage, they may be more inclined to engage in information gathering, comparing different options, and assessing product features and prices. In contrast, the buying stage marks a transition from exploration to commitment, where consumers are more motivated to make a purchase decision. At this stage, consumers are better motivated to make a careful decision and may pay greater attention to product features in the buying stages. Hence, we posit that product relevant and irrelevant heuristic cues of CGIs might affect differently in drawing consumers' attention in the browsing and buying stages.

A second ambiguity in the previous work stems from the relationship between attractive cues and persuasive cues of CGIs. Attractive cues of CGIs capture consumers' attention and thus enhancing the importance of the focal CGI (Arbouw et al., 2019). Persuasive cues refer to the features of CGIs that are persuasive in changing consumers' mental states and facilitating buying behavior (Lei et al., 2021; Xu, 2018). While a common assumption in prior research and practice is that more attractive reviews are often perceived as more persuasive in facilitating purchases (Elder & Krishna, 2012; Lurie & Mason, 2007; Meyvis et al., 2012), however, as consumers process image information differently while they are in different levels of situational involvement and rely on different types of cues in the shopping progress, we posit that the tendency of simply discussing CGI helpfulness without distinguishing the attractive and persuasive CGI features will lead to a lack of understanding on when and how CGIs excel. In this regard, it is worthy examining whether attractive CGIs at the browsing stage are also persuasive in facilitating purchases at the buying stage.

Further, prior research on CGIs has mostly focused on examining the direct impact of visual elements on consumer behaviors, such as image complexity, texts and objects within images (Chen et al., 2019; Clow et al., 2006; Poor et al., 2013; Small & Verrochi, 2009), but the underlying mechanisms of the link between CGI features and behavioral outcomes in different shopping stages have rarely been investigated. However, this topic merit deeper understanding as it explains why CGIs affect shopping behaviors differently. In so doing, this study further contributes to extant literature by presenting the mechanisms through which heuristic cues of CGIs affect consumers' decision making.

Methodologically, we adopt eye-tracking approach in measuring consumers' reactions towards various CGIs. While prior research has mostly used surveys to capture the influence of visual information on shopping behaviors, Eye-tracking offers a unique and objective method for analyzing visual attention and engagement, allowing us to precisely track participants' gaze patterns as they interact with CGIs. This methodology provides valuable insights into how consumers allocate attention to different elements within CGIs. By leveraging the advantages of eye-tracking technology, including its high temporal and spatial resolution, we aim to uncover nuanced patterns of attention and response to attractive and persuasive cues embedded within CGIs. Our findings contribute to the burgeoning literature on consumer behavior in e-commerce contexts and offer practical implications for optimizing CGI design to enhance consumer engagement and facilitate purchase decisions.

The reminder of this paper is organized as follows. The subsequent section presents the theoretical framework and hypotheses. Following this, two experimental studies are presented to test these hypotheses. Study 1 simulates the browsing stage of online shopping, where the attractiveness of CGIs is assessed through participants' eye movement behavior while perusing a variety of CGIs with product relevant and irrelevant heuristic cues. Study 2 replicates the buying stage of online shopping, measuring CGI attractiveness through eye movement behavior, as well as participants' emotional arousal and purchase intentions via questionnaires. Next, we present the experimental results and analyses. Finally, the paper discusses the theoretical contributions and practical implications of the research and the study limitations and concludes.

2. Theoretical background and hypotheses

2.1. heuristic cues of consumer-generated images(CGIs)

The significance of online reviews has been widely emphasized by prior research. Online reviews can not only help reduce information asymmetry between merchants and consumers, but also assist consumers in making purchase decisions online (Babić Rosario, Sotgiu, De Valck, & Bijmolt, 2016; Lei et al., 2021; Mudambi & Schuff, 2010; Sidnam-Mauch & Bighash, 2021). Despite the importance, prior studies on online reviews have mostly focused on the impact of textual reviews on sales. For examples, prior research has examined the effects of various textual review attributes like length, sentiment, emotional expression, and another stream of research on online reviews focused on the influence of follow-on reviews and reviewer characteristics (see Table 1 for a sample of literature on text reviews). In general, most of the prior studies have used textual online reviews as the study context by default, very few have shed light on the effects of CGI comments on sales. However, the prevalence of CGIs in e-commerce platforms (e.g. Amazon, Ebay, Taobao) calls for a thorough understanding on how and when CGIs can affect sales.

Recently, a growing number of studies turn to discussing richer forms of online reviews such as image and video reviews (see Table 1 for a sample of literature on image reviews). For example, Xu et al. (2015) compared the impact of different review formats (video, image and text) on sales. Curran and Doyle (2011) showed that people are more likely to remember pictures and videos than text. However, these studies have mostly compared the significance between visual and textual review formats on sales, yet rarely discussed the effects of the characteristics of CGI itself. While few in number, Guan et al. (2023b) discussed the influence of aesthetic quality of CGIs, but their focus is on CGIs' impact on consumer expectations and post-purchase satisfaction. As such, the understanding of the impact of CGIs on consumers' purchase intention is still limited. Further, prior research on CGIs' characteristics has mainly focused on the effects of image content like the emotion expressions in picture (Small & Verrochi, 2009), image of unhealthy (vs. healthy) food (Poor et al., 2013) and image of a group of people with a product (Chen et al., 2019). However, these findings cannot be directly applied to image reviews directly as the content of image review varies significantly depending on the product category. Hence, to fill the gap, the present study takes the common characteristics of image reviews (e.g. brightness, clarity, product displaying proportion and consistency) as heuristic cues evaluated by consumers and examines their impacts on consumer behaviors.

According to attribute substitution theory (Kahneman & Frederick, 2002), consumers generally tend to rely on those heuristic cues presented in CGIs to simplify their decision-making process. Heuristic cues refer to the most distinctive features from the environment that requires little cognitive workload to process (Ferran & Watts, 2008). They serve as cognitive shortcuts that significantly influence consumer decision-making processes, particularly in the context of online shopping, where individuals face numerous choices and information overload is prevalent. Prior research has leveraged attribute substitution theory to understand various facets of online consumer behavior. For instance, Levin et al. (2003) investigated how consumers' dependence on easily accessible attributes such as product reviews and ratings could lead to attribute substitution. Additionally, Zinko et al. (2021) explored how the design and presentation of online product attributes can influence consumers' propensity for attribute substitution, thereby impacting their purchase decisions. Moreover, research indicates that consumers are more inclined to make purchase decision when they perceive the heuristic cues as satisfactory, underscoring the importance of these cues in driving consumer behavior (Kahneman & Frederick, 2002; Yin et al., 2021).

We posit that heuristic cues are especially important for CGIs. That is, the process of visual information requires greater cognitive capacity compared to textual information (Ferran & Watts, 2008). Such cognitive load will activate consumers' use of heuristic cues presented in CGIs to aid their decision-making process (Ozanne et al., 2019). Further, we posit that the heuristic cues of CGIs can generally be divided into two types-product relevant and product irrelevant cues (Ha & Lennon, 2010a, b). Product relevant cues include those that are related the appearance of product itself such as the consistency of CGI with merchant-provided images. We specifically choose consistency as a proxy for product relevant cues due to its pivotal role in establishing trust and authenticity in the online shopping environment (Zhang et al., 2022). This standard is widely relied upon by consumers to assess the

Table 1
Sample of literature on online reviews.

Category	Feature	Define/measure	Representative Study
Text reviews	Length	Total number of words in the review	Chevalier & Mayzlin, 2006; Fink et al., 2018;
	Emotion	The emotional expression of the text review, such as positive, negative, anxiety, happy	Archak et al., 2011; Chong et al., 2016; Li et al., 2019; Ansari & Gupta, 2021; Yin et al., 2021
	Style	Whether the style of review content is formal or informal	Guo & Zhou, 2017
	Follow-on reviews	The presence of follow-on reviews	Shi et al., 2018; Xu et al., 2015; Yan et al., 2015
	Reviewer characteristics	Reviewer rank, identity disclosure, reviewer friend number, reviewer experience	Forman et al., 2008; Huang et al., 2015; Sahoo et al., 2018; Xia et al., 2021; Xu et al., 2017; Zhou & Duan, 2016
Comparison with this study: While many previous studies have focused on textual online reviews as the default study context, only a few have examined the effects of CGI comments on sales. This study aims to investigate how the features of CGIs attract consumers' attention during online shopping and subsequently influence their purchase intention.			
Image reviews (CGIs)	Review formats	Different review formats (video, image and text)	Xu et al., 2015; Curran & Doyle, 2011
	Aesthetic quality	Aesthetic perception of images by consumers	Guan et al., 2023; Bilal et al., 2021
	Emotion	Emotional attributes carried by the photo content	Small & Verrochi, 2009; Li et al., 2023
	Product type	Image of unhealthy (vs. healthy) food, image of search (vs. experience) good	Poor et al., 2013; Sun et al., 2019
	Photo-text consistency	Content consistency, emotional consistency	Ceylan et al., 2023; Zhang et al. (2022)
	Content	Number of people in CGI	Chen, et al. (2019)
Comparison with this study: ① Unlike most studies that assess the aesthetic quality of CGIs through surveys or general discussions, our study focuses on specific features of CGIs. We categorize these features into product relevance and irrelevance, providing more generalizability and actionable practical implications; ② While many studies discuss the impact of CGIs on consumer behavior without distinguishing between browsing and buying stages, our study explicitly examines the role of product-relevant and irrelevant cues at different stages of the shopping journey; While previous studies often discuss the helpfulness of CGI features without differentiating between their roles in attractiveness and persuasiveness, our study aims to distinguish between these two aspects; ④ Prior research on CGIs has mostly focused on examining the direct impact of visual elements on consumer behaviors, this study further investigates the mechanisms through which heuristic cues of CGIs affect consumers' decision making.			

reliability of the product representation and its alignment with their expectations. Notably, consistency between CGIs and merchant-provided images can be directly observed through CGIs, offering a tangible indicator of product authenticity compared to other product-related cues like product quality. Conversely, product irrelevant cues are characterized by factors unrelated to the specific attributes of the product but rather pertain to image quality, such as clarity, brightness, and product displaying proportion. In this context, we also classify product displaying proportion as an irrelevant cue, as it aligns with factors that do not directly impact the appearance of the product but rather reflect image quality from a compositional standpoint. While cues like brightness, clarity, and product displaying proportion may not directly pertain to the product itself, they still hold substantial influence over consumers' perceptions and decision-making. Brightness and clarity contribute to the overall aesthetic appeal of CGIs, whereas the proportion of product display within the CGI can shape consumers' perceptions of product prominence and importance.

Prior research has shown that consumers have different information processing inertia when they face product relevant and irrelevant cues during online shopping (Eroglu et al., 2001; Ha & Lennon, 2010). Hence, the present study will examine the effects of product relevant and irrelevant cues separately and develop hypotheses on how these two types of heuristic cues might influence consumers' attention on CGIs and their purchase intention.

2.2. CGIs and attractiveness

Nowadays, consumers are often surrounded by an overwhelming amount of CGIs while shopping online (Curran & Doyle, 2011). This way, a prerequisite for a helpful review comment is the extent to which the focal CGI can draw consumers' attention in the first place (Fiore et al., 2005; Menon & Kahn, 2002; Ozanne et al., 2019; Wu et al., 2008). According to the Elaboration Likelihood Model (ELM), there are two relatively distinct routes while people process information (Dröge, 1989; Petty & Cacioppo, 1986). The first, known as the "central route", entails deep cognitive processing. It involves deliberate and effortful cognitive activity, focusing on relevant information to evaluate and elaborate decisions. Individuals scrutinize the quality and relevance of the presented information, leading to robust and enduring attitude changes. In contrast, the second route, known as the "peripheral route", involves superficial processing. Here, individuals prioritize peripheral and easy-to-evaluate information, requiring less cognitive effort. Thus, attitudes formed through the peripheral route tend to be more transient and susceptible to change (Cyr et al., 2018; Lien, 2011).

Prior research has shown that an individual's choice of central or peripheral route depends on the likelihood of elaboration, that is, the importance of the decision to be made and their situational involvement (Greenwald & Leavitt, 1984; Hawkins & Hoch, 1992). In this regard, we posit that consumers may activate different routes of processing information while in the browsing stage and the buying stage respectively. Ha & Lennon, 2010a, b found that consumers have lower situational involvement during browsing compared to buying, when they have a purchase goal. When consumers need to make purchase decisions, they are motivated to activate the central route of information processing and make a careful decision based on information quality (Zaichkowsky, 1986). Hence, while consumers may indeed encounter and process both relevant and irrelevant cues at both the browsing and the buying stages, we argue that they may shift their attentional priorities across shopping stages due to different levels of situational involvement. Specifically, during the browsing stage, as consumers are low in situational involvement, they tend to prioritize the evaluation of easily assessable cues, including those that are irrelevant to the product. Moreover, consumers often engage in exploratory behavior during the browsing stage, where their attention is primarily focused on visually stimulating or attention-grabbing cues, regardless of their relevance to the product itself. As such, we posit that CGIs featuring higher quality product irrelevant cues, such as image clarity, image brightness, and product displaying proportion, are more effective in capturing consumers' attention during the browsing stage. In contrast, as consumers are high in situational involvement during the buying stage, they tend to activate the central route of information processing. They engage in heightened scrutiny and consider decision-making criteria more carefully as they approach making purchase decisions. At this stage, consumers become more goal-oriented and attentive to cues directly related to the product itself, rather than being swayed by visually stimulating but irrelevant cues. Thus, emphasizing the quality of relevant cues becomes paramount in influencing consumers' attention during the buying stage. So, we further posit that CGIs with higher-quality product relevant cues, such as the consistency of image reviews with merchant-provided images, are positively associated with the attractiveness of CGIs during the buying stage.

H1. During the browsing stage, CGIs featuring higher-quality product irrelevant cues, such as image clarity (H1a), image brightness (H1b) and product displaying proportion (H1c), are positively associated with the attractiveness of CGIs.

H2. During the buying stage, CGIs featuring higher-quality product relevant cues, such as the consistency of image review with merchant-provided images, are positively associated with the attractiveness of CGIs.

2.3. CGIs and purchase intention

Attribute substitution theory shows that people tend to use heuristic cues to simplify the complex decision making process (Kahneman & Frederick, 2002). Draw on attribute substitution theory, we argue that heuristic cues are especially important and being widely utilized by consumers while they process CGIs. Due to the overwhelm volume of CGIs and complex visual information in CGIs, high cognitive demand is often required to process CGIs before making purchase decisions (Ferran & Watts, 2008). Such cognitive load can activate the use of heuristic cues by consumers (Ozanne et al., 2019), and consumers are highly likely to purchase the product if they feel the heuristic cues are sufficient to support their purchasing decision (Fu et al., 2020; Kahneman, 2011; Kahneman & Frederick, 2002; Lei et al., 2021). Specifically, product relevant cues (e.g. consistency of image review with merchant-provided images) provide consumers with pertinent information about the product. This information helps consumers evaluate the product's utility and determine whether it meets their specific needs and requirements. Likewise, product irrelevant cues, such as image brightness or clarity, may trigger consumers' emotional responses or aesthetic preferences, which in turn may influence their purchase intention (Li et al., 2023). Consequently, we hypothesize that high quality of both product relevant and irrelevant cues of CGIs is important in enhancing consumers' purchase intention.

H3. The quality of both product relevant and irrelevant cues of CGIs is positively associated with consumer purchase intention.

To further gain a better understanding on why and how CGIs' cue quality might be persuasive in facilitating purchase intention, we identify two major underlying mechanisms from literatures of image processing – visual attention perspective and perception perspective – to explain the relationship between image reviews' cue quality and persuasiveness in enhancing purchase intentions (Chen et al., 2017; Guan et al., 2023a; Orquin et al., 2021). Indeed, visual attention and perception perspectives are pivotal dimensions in image processing literature because they provide valuable insights into how individuals process, interpret, and respond to visual stimuli. These perspectives serve as integral dimensions that are shown to profoundly influence human cognition, behavior, and subjective experiences when interacting with visual stimuli (Orquin et al., 2021).

One potential explanation lies in the effects of visual attention. Prior research has shown that attention serves as a crucial intermediary, converting visual information perception into behavioral responses, with substantial evidence indicating a close association between these processes (Janiszewski, 1998; LaBerge, 1995; Pieters et al., 2007; Pieters & Wedel, 2004; Zhang et al., 2009). Visual attention, typically measured by gaze duration, reflects consumers' focus on specific elements within visual stimuli (Lin et al., 2014; Russo & Leclerc, 1994). Prior research has consistently revealed that options presented for a longer duration tend to have a higher likelihood of being chosen (Bird et al., 2012). Similarly, studies have demonstrated a higher likelihood of choosing the more salient option (Peschel et al., 2019). Recent investigations by Ji et al. (2023) highlight the significance of visual attention in online consumer behavior, particularly within the realm of ecommerce livestreaming. By analyzing eye-tracking data alongside online shopping behaviors, these researchers observed a positive correlation between attention directed towards products showcased in livestreams and purchase intention. Additionally, Weilbächer et al. (2021) found that consumers often rely on memory to retrieve product information while making purchase decision. This way, higher visual attention can by helpful in enhancing purchase intentions by making the retrieval of the product information easier. Hence, we propose that CGIs with high quality cues can be persuasive in enhancing purchase intention because these CGIs can better capture consumers' visual attention.

H4. The positive association between CGIs' cue quality and consumer purchase intention is mediated by consumer visual attention on these cues.

Alternatively, emotional arousal denotes the degree to which individuals experience excitement, stimulation, and positivity within a given context (Russell, 1980). In the realm of consumer behavior, emotional arousal induced by high-quality visual cues is characterized by feelings of contentment, happiness, and satisfaction, consequently enhancing their purchase intention (Meng et al., 2021). According to the Stimulus (S) – Organism (O) – Response (R) paradigm (Mehrabian & Russell, 1974), pleasure environmental stimuli can evoke individuals' emotional arousal and thus enhancing satisfaction (Eroglu et al., 2001; Spies et al., 1997) and purchase intention (Babin & Babin, 2001; Fiore et al., 2005; Hu et al., 2016; Wu et al., 2008). Hence, we also propose that high quality cue of CGIs can be persuasive in enhancing consumers' purchase intention because high quality cues are often more pleasurable visual stimuli that can evoke emotional arousal of consumers, which ultimately affect consumers' purchase intention.

H5. The positive association between CGIs' cue quality and consumer purchase intention is mediated by consumers' emotional arousal.

To test the proposed hypotheses, we conducted two laboratory studies using a combination of eye-tracking experiments and questionnaires. Study 1 aimed to test hypothesis 1 by manipulating the browsing stage of online shopping. Participants were presented with a selection of CGIs featuring different heuristic cues, and their eye movement behavior was tracked to measure the attractiveness of the CGIs. To test hypothesis 2 to 5, study 2 manipulated the buying stage of online shopping. Participants were informed of their intention to purchase a parka, and the attractiveness of CGIs was assessed by tracking their eye movement behavior. Additionally, emotional arousal and purchase intention were measured using questionnaires administered to participants following the buying tasks.

3. Methodology

A laboratory experiment was conducted to systematically study the effects of CGIs cues. To simulate the characteristics of real CGIs in popular e-commerce platforms like Taobao, we conducted quantitative analysis on the image comments crawled from Taobao and prepared experimental materials.

3.1. Participants, exclusion and sampling

The study recruited a total of 131 undergraduate students (61 males, 70 females, aged from 18 to 25) through advertisements posted on the university's internal forum in China. This university specializes in science and engineering, with students mainly majoring in software, information services, communication, management, and other related fields (please refer to Appendix A.4 for detailed demographic information of the sample). The study was conducted following ethical standards and guidelines set forth by the Institutional Review Board and Ethics Committee of the University.

Drawing from previous studies utilizing the eye-tracking technique (Lee et al., 2019), we suspect a small to medium effect size. Consequently, a priori power analysis for F-testing between means with $\alpha = 0.05$, with a power of 80% and an estimated effect size of 0.20 indicated that a sample size of 34 was required.

To ensure the accuracy of our research findings, we conducted a data cleaning process consisting of the following steps: Firstly, we checked for missing values in the dataset and considered removing participants with a substantial number of missing values. Secondly, we identified and addressed outliers by analyzing the scatterplot distribution of the data and using the 3-SD method in statistics. Participants with response times shorter than the average are regarded as outliers. Lastly, we excluded participants who didn't meet the research requirements based on experiential attributes, such as online shopping experience. Specifically, participants with limited online shopping experience were excluded from the analysis. In study 1, two participants were excluded due to a lack of online shopping experience, and two others were removed for not passing the eye movement calibration test,[1] Hence, data from 127 participants were included in the data analysis for study 1. For study 2, the same participant pool was utilized, however, two participants withdrew from the study after completing study 1, resulting in 125 participants for study 2.

Before the experiment, all participants were required to sign an informed consent form, after which they completed a survey on their personal information like gender, age, and years of online shopping experience, whether they would look at the CGIs while shopping online and whether they perceive CGIs as helpful (please refer to Appendix A.2 for the survey), demographic information shows more than 68% of the participants have more than 4 years of online shopping experience, and most of the participants think watching CGIs are helpful for purchasing decisions (mean = 4.49 out of 7 points likelihood). Then participants actively engaged in both study 1 (browsing stage) and study 2 (buying stage). In study 1, each student experienced all experimental conditions, whereas in study 2, students were randomly assigned to one of four conditions. Each participant was rewarded two dollars upon completion of the experiment.

3.2. Experimental materials

The current study employed images as stimuli material, incorporating three types of materials: CGI material (Fig. 1), merchant-provided material (Fig. 2), pairwise material (Fig. 3). We use CGI material with different Clarity, Brightness, and product displaying proportion to represent three types of irrelevant cues. Relevant cues (i.e. consistency) were manipulated by presenting pairwise material, consisting of merchant provided images paired with CGIs. Considering that both men and women would like to purchase parka on ecommerce platform, we finally chose CGIs on parka as our experiment materials that are vary in consistency level with merchant-provided images. The specific details of

[1] Calibration test is designed for ensuring that the eye-tracking device accurately tracks the participant's eye movements, thus ensuring the reliability and accuracy of the experimental data(Hung & Wang, 2021). More details of calibration process were presented in Appendix B.

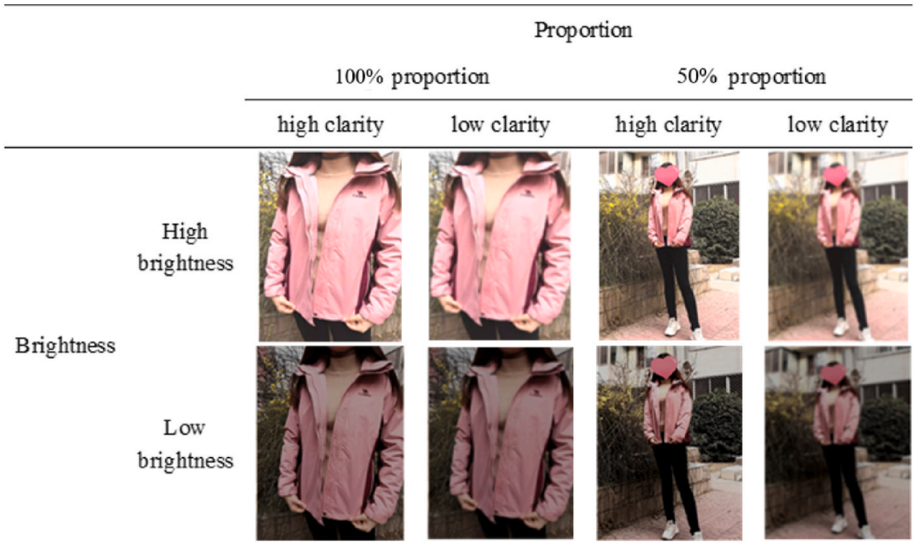

Fig. 1. An example of CGI materials with different irrelevant cues (i.e. proportion, brightness and clarity) used in the experiment.

Fig. 2. Merchant-provided image.

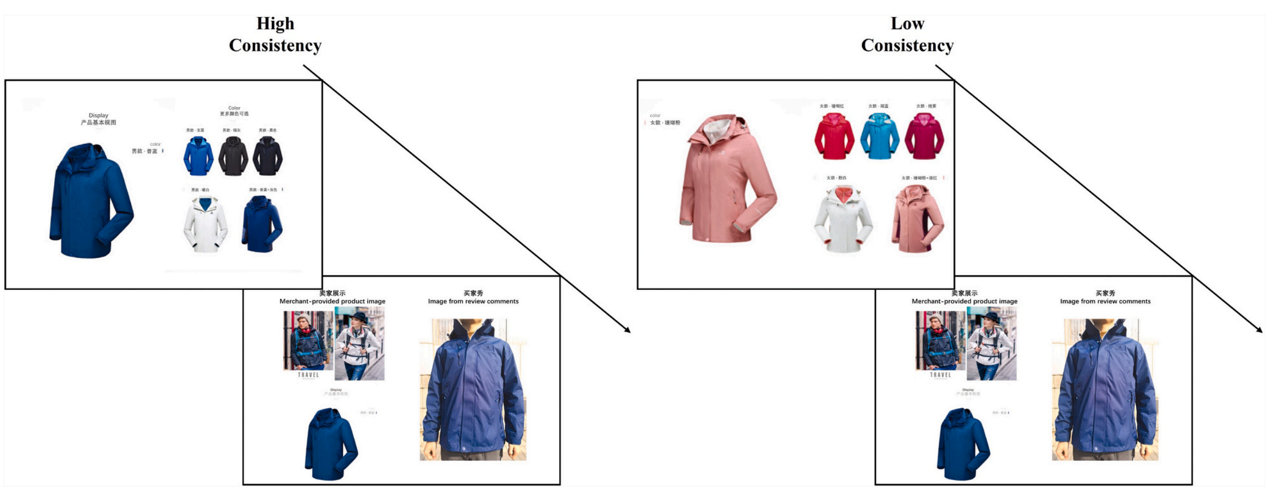

Fig. 3. Pairwise material and the manipulation of 2 levels in consistency.

each cue's manipulation are as follow:

Clarity. To ensure the level of clarity and brightness manipulation is consistent with the distribution of these two features of online CGIs, we crawled around 3500 CGIs of parka product, and analyzed the clarity and brightness of these CGIs accordingly.

As the clarity of images is usually subjective, we adopt the approach of calculating image clarity by using gray value in the image (Pech-Pacheco et al., 2000; Sept.3-7). Specifically, we calculate the Laplace mask of gray value and then calculate its standard deviation. That is, the more blurred the image, the fewer its edges. Generally, prior research regards the image as clear when the standard deviation is greater than or equal to 100.

Hence, we take the image standard deviation (SD) of 100 as the cutting off point and categorize all the CGIs to two groups. Specifically, for CGIs that are generally low in clarity (SD < 100), the lowest SD value is 1.64, the largest SD value is 99.96, and the median value is 51.44. For

CGIs that are generally high in clarity (SD > 100), the lowest SD value is 100.0577, the largest SD value is 114.64, and the median value is 272.71. In this regard, we take the median value in each group as the criteria for CGIs with high or low clarity. That is, when the SD value is lower than 51.44, we regard the CGI as being low in clarity. When the SD value is higher than 272.80, we regard the CGI as being high in clarity. This way, we not only make sure that our experiment materials are indeed high or low in clarity, but we also make sure the level of clarity is consistent with the distribution of clarity of CGIs of ecommerce platforms.

Brightness. The brightness of an image is also a subject feature. Prior research shows that image brightness can be assessed by using the average pixel brightness (Ibrahim & Kong, 2007). We use the Image Stat module in Python to calculate the average pixel brightness. The distribution of the average pixel brightness of the CGI sets show that the minimum value of the average pixel brightness is 22.08, the maximum value is 201.25, the median value is 112.05. Hence, we regard the CGIs with the average pixel brightness larger than 112.05 as high in brightness, otherwise, low in brightness.

Product displaying proportion. In CGI, the size of the product displayed in the image will form a proportion to the whole image. When the proportion of the product in the CGI is about 50%, we considered the product displaying proportion as moderate, and when the proportion of the product in the CGI is about 100%, we considered it as having large product displaying proportion.

Consistency of CGI with merchant-provided images. We choose the CGI of the merchant displayed product as CGIs with high consistency, and we use a similar product's CGI as the experimental material with low consistency.

According to the above criteria, we calculate the related index of each CGI (e.g. clarity SD, average pixel brightness). Then, we calculate the value of clarity and brightness of the selected CGIs, and use Photoshop to adjust the clarity, brightness and product displaying proportion levels to generate CGI materials that satisfy the above manipulation criteria (see Fig. 1).

Manipulation checks of CGI materials. We conduct manipulation check on these four grouping variables. 214 participants (Male = 63) were recruited on Credemo for manipulation check. They are firstly invited to view the merchant-provided images (see Fig. 2), and then they are randomly assigned one of the images of our experiment material, and are asked to rate the clarity, brightness, product displaying proportion, consistency of CGI with merchant-provided images using the four questions as shown in Appendix table A1. We conducted ANCOVA analysis to check whether the manipulation has succeeded. We take one of the four grouping variables in turn as dependent variables, and controlled the other three grouping variables and participants' age and gender. The result shows that the p values of all the four grouping variables are all smaller than 0.001, indicating the success of manipulation for each condition. Also, when using age and gender as categorical variables the rating difference between age and gender is not significant ($ps > 0.05$), indicating that participants' differences in age and gender will not interfere with the rating consequence.

Pairwise materials. The pairwise image of merchant provided image and CGI, this kind of material was used for indicate the level of consistency, the snapshot for 2 levels of consistency are as Fig. 3.

3.3. Measurement

We investigated our hypotheses with two studies using a combination of eye-tracking experiment and questionnaire.

Eye-tracking measurement. We employed Tobii X120 eye tracker with a sampling rate of 120 Hz to track the eye movements of each participating student during browsing and purchasing activities. Each participant sat approximately 70 cm in front of the eye tracker while browsing or purchasing. Calibration was performed after entering the participant's experimental ID to ensure a difference of less than 0.5° in their eye offset. Eye movement data analysis was performed using Tobii Studio 3.1.6 software. In this study, four areas of interest (AOIs) were defined based on the heuristic cues targeted by the research. Accordingly, we primarily exported three types of metrics: fixation heatmaps, fixation duration, and fixation counts, the definition are in Table 2.

Questionnaires. The measurement conducted through questionnaires was divided into two parts. The first part consisted of a demographic questionnaire and inquiries about prior experience with online shopping and viewing CGIs as potential covariates, administered before the eye-tracking study (refer to Appendix A.2 for the survey). The second part was utilized during the buying stage to measure participants' emotional arousal and purchase intention of each product presented (refer to Appendix A.3 for the survey).

3.4. Design and procedure overview

Given that buying behavior often follows browsing in real-life contexts, we conducted two studies within a single workflow. The research team thoroughly explained the experiment process and precautions to all participants. Participants were informed that they were intended to make a future purchase of the displayed product for either themselves or their significant other. Additionally, they were encouraged to browse the page information in accordance with their own browsing habits during the experiment, without any time constraints (see details in Fig. 4).

Browsing stage. Participants were first shown the merchant-provided product page (see Fig. 2). Then, they would see a browsing page. In browsing stage, we capture the eye movement behavior of participants while they were browsing a group of CGIs with different heuristic cues. We applied a repeated measure within-subject design to minimize the effects of individual preferences and differences among study participants (Choudhury, 2009; Suh & Lee, 2005). Based on our research interests, we designed 2 (clarity: high vs. low) x 2 (brightness: high vs. low) x 2 (product displaying proportion: 50% vs. 100%) x 2 (consistency with merchant-provided images) = 16 unique combinations of CGIs. This comprehensive design ensures that we can capture the eye movement of participants on all 16 unique combinations of CGIs. Additionally, each feature can be evaluated twice to better capture their reactions to each CGI.

To ensure that each CGI is displayed in a proper size as in ecommerce platforms, each page contains eight CGIs as shown in Fig. 1. The eight CGIs in each page are all from a same product that have the same level of consistency with the merchant-provided image, and they only vary on the other three features (2 (clarity: high vs. low) x 2 (brightness: high vs. low) x 2 (product displaying proportion: 50% vs. 100%)). The participants will see four pages of CGIs in total, and two pages display CGIs that are consistent with merchant-provided image, and the other two pages display CGIs that are not consistent with merchant-provided image. Indeed, by displaying eight CGIs on one page, it not only conforms with the display format of CGIs online at consumer browsing stage, but also avoids potential measurement bias resulted from participants' view of too many pages of CGIs separately.

Buying stage. After completing the browsing stage, all the participates were informed that they would be presented with CGIs of the products shortlisted in the prior browsing stage. They were instructed to

Table 2
Definition of each eye-tracking measurement.

Eye-tracking measurement	Definition
Fixation duration (fixation time, FT)	the time spent viewing an AOI
Fixation heatmaps	Different color depths describe the degree of attention of the participant. The red-colored areas represent the hottest ones with longest fixation time.
Fixation count	the fixation counts within an AOI

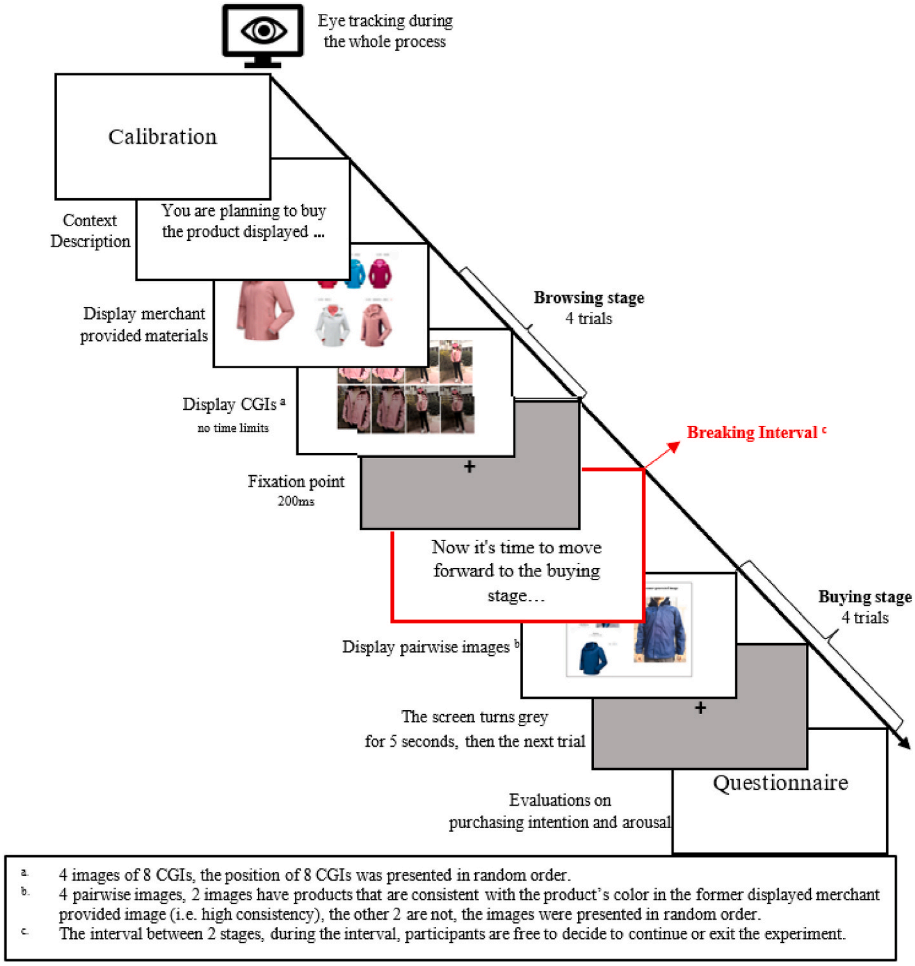

Fig. 4. Trial flow of eye-tracking task.

decide whether they would like to buy these products at this stage. Participants were given the freedom to browse the page information according to their individual buying habits during the experiment, without any time constraints. During this stage, participants viewed four pairwise images. To align with typical shopping behavior, wherein individuals evaluate one product in detail at a time during the buying stage, we presented participants with one CGI at a time. We tracked participants' eye movements and measured their emotional arousal and purchase intention for each product. This procedure comprised four trials, each consisting of a pairwise image, a 5-s gray screen (intended to eliminate the influence of the previous image on the participants), and a subsequent questionnaire.

4. Study 1: browsing stage

In study 1, we employed eye-tracking heatmaps to investigate the features that capture participants' attention during the browsing stage. The objective was to validate Hypothesis 1, positing that consumers are more likely to be attracted by images with higher levels of irrelevant cues (i.e. high level of clarity, brighter, larger product displaying proportion) during the browsing phase. To accomplish this, we first collect the heatmaps of the CGIs, then we use fixation time on AOIs as a measure of attractiveness. Given the utilization of a repeated measure within-subject design, we employed a repeated measures ANOVA as the statistical method.

4.1. Variables

4.1.1. Dependent variable

Attractiveness. Prior eye-tracking research has widely used the fixation time spent on the areas of interest (AOIs) to explain the cognitive activities and visual attention of the participants (Fu et al., 2020). In the present study, we also use the fixation time on each CGI, which measures the amount of attention drawn by each CGI, to reflect the extent of CGI attractiveness. The range of fixation time spent on each CGI is 0 ms–7240.15 ms, and the average fixation time is 872.17 ms, the standard deviation of the fixation time on each CGI is 833.26 ms.

4.1.2. Independent variable

Independent variables are the 4 heuristic cues former mentioned. Each of them has two levels: high and low.

4.2. Data analysis and results

4.2.1. Heatmap results

Fig. 5 presents the heat map at the browsing stage. Different color depths describe the degree of attention of the participant. The red-colored areas represent the hottest ones with longest fixation time. The heat map shows that consumers pay more attention to CGIs that are high in clarity, brightness and have proper product displaying proportion regardless of the consistency of the CGI with merchant-provided image.

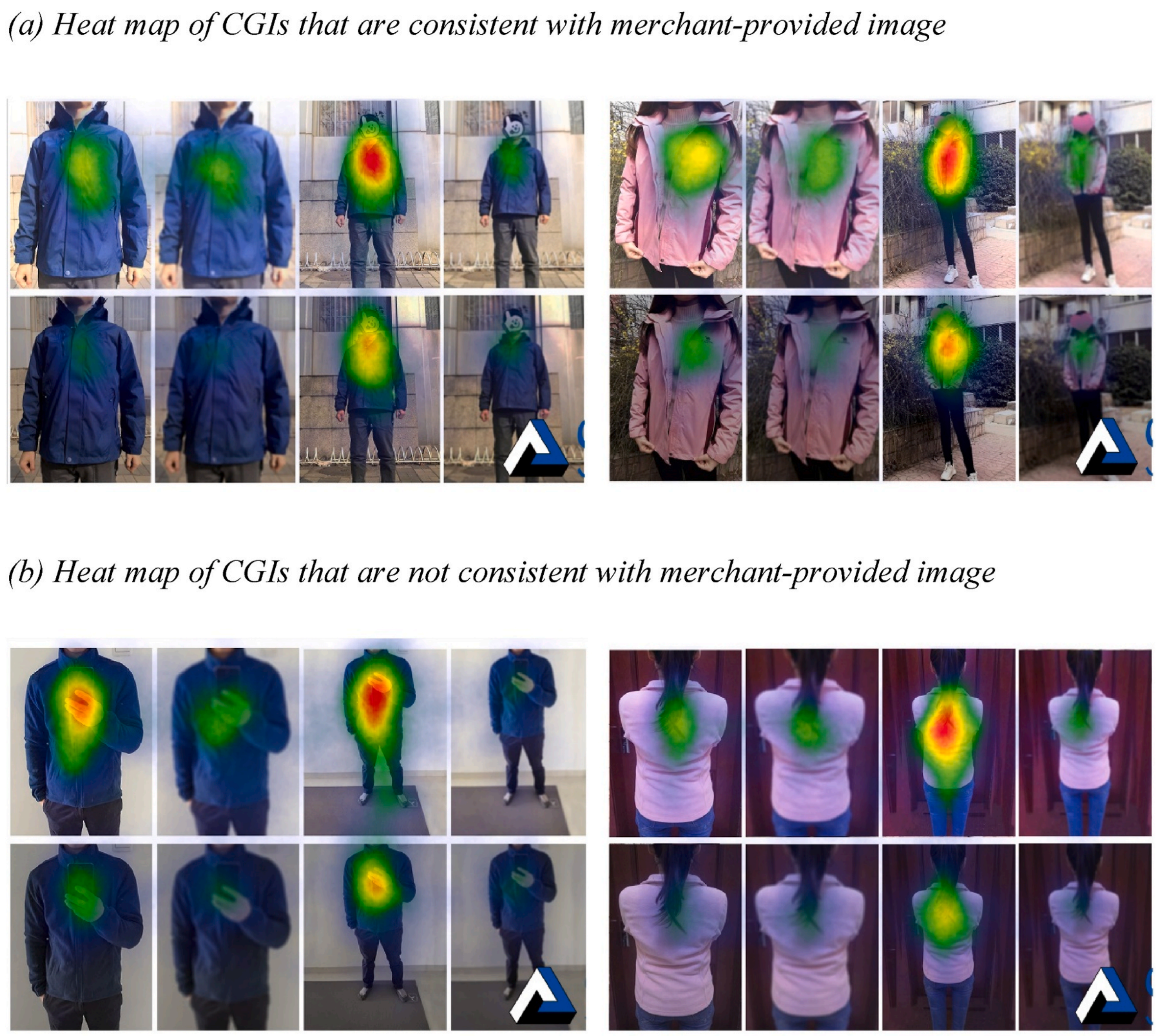

Fig. 5. Heat map.

(a) Heat map of CGIs that are consistent with merchant-provided image
(b)Heat map of CGIs that are not consistent with merchant-provided image

4.2.2. Repeated-measure ANOVA results

All data were analyzed with SPSS 25.0, The Kolmogorov-Smirnov test indicated a slight positive skew of our data. Hence, a square root transformation was applied for calibration. Subsequent tests showed that the transformed data followed a normal distribution, satisfying and the assumptions of homogeneity of variance and homoscedasticity of ANOVA analysis. Then, repeated-measure ANOVA was conducted using the calibrated data.

The results revealed that CGI attractiveness significantly differed across product irrelevant cues. Specifically, the two levels (high vs. low) of image clarity ($F(1, 126) = 169.08$, $p = 0.00$, $\eta p^2 = 0.57$, $f = 1.15$), image brightness ($F(1, 126) = 116.35$, $p = 0.00$, $\eta p^2 = 0.48$, $f = 0.96$), and product displaying proportion ($F(1, 126) = 18.80$, $p = 0.00$, $\eta p^2 = 0.13$, $f = 0.38$), all demonstrated large effect according to cohen's standard (Cohen, 1977). But the CGI attractiveness does not differ significantly across product relevant cues—whether the CGI is consistent with merchant-provided image ($F (1, 126) = 3.65$, $p = 0.058$, $\eta p^2 = 0.028$, $f = 0.17$). Please refer to Appendix A.5 for detailed results of repeated ANOVA, presenting main effects and interaction effects of all variables in study 1.

As illustrated in Fig. 6, Bonferroni pairwise comparisons revealed that CGIs with high clarity attract significantly longer fixation duration than those with low clarity (M = 1145.09ms vs. M = 599.25ms, SEdiff = 41.98, p = 0.00). Similarly, CGIs with high image brightness attract significantly longer fixation duration than those with low brightness (M

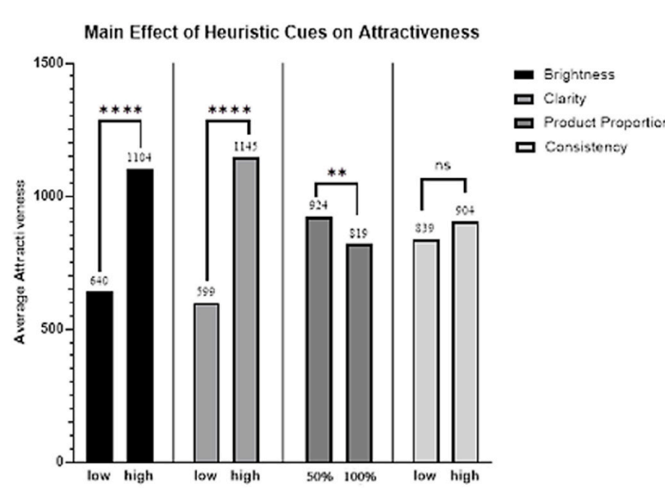

Fig. 6. Bar graph of Bonferroni pairwise comparisons.

= 1104.29ms vs. M = 640.04ms, SEdiff = 43.04, p = 0.00). Additionally, CGIs with proper (50%) product displaying proportion attract significantly longer fixation duration than those with high (100%) product displaying proportion (M = 924.47ms vs. M = 819.86ms, SEdiff = 24.13, p = 0.00). These results are visually depicted in Fig. 6.

The results of study 1 support hypothesis 1. CGIs were found to be more attractive when clarity and brightness were higher, and when the product proportion was proper (i.e. 50%). At the same time, we observed that the effect of consistency is not statistically significant, and its effect size is also small. Therefore, there is no need for further discussion on power, indicating that the effect of proportion is not statistically significant and lacks practical significance as well.

5. Study 2: buying stage

In study 2, we will further investigate participants' eye movement behavior and purchase intention during the buying stage. Study 2 has three purposes: (a) To verify that consumers exhibit higher purchase intentions for products with a higher level of relevant cue (i.e., high Consistency) in CGIs during the buying stage. To achieve this, a mixed-design ANCOVA of purchase intention is conducted. (b) Conducting correlation analyses to demonstrate the positive correlation between four heuristic cues and purchase intention. (c) Employing Process to validate the hypothesized intermediate model of hypothesis 3 and 4.

5.1. Variables

5.1.1. Dependent variables

Attractiveness. In this stage, we also use the fixation time on each CGI, which measures the amount of attention drawn by each CGI, to reflect the extent of CGI attractiveness. The range of fixation time spent on each CGI in this stage is 0 ms–13,183 ms, and the average fixation time is 2332.40 ms, the standard deviation of the fixation time on each CGI is 1569.49 ms.

Purchase intention. We measured purchase intention by using three items (see Appendix A. 3) from Boulding (Boulding et al., 1993). The Cronbach α is 0.916, indicating that the items are good in reliability.

5.1.2. Independent variables

The independent variables include consistency of merchant-consumer generated images, clarity, brightness and product displaying proportion. As we have 16 sets of CGIs according to our research interests (2 (clarity: high vs. low) x 2 (brightness: high vs. low) x 2 (product displaying proportion: 50% vs. 100%) x 2 (consistency with merchant-provided images)), we divide these 16 sets of CGIs into four groups (please refer to Appendix A. 6 for details of the groups divide). Each participant will be randomly assigned to one group in Table 1 and will need to evaluate their purchase intention four times, corresponding to the four CGIs, respectively.

5.1.3. Mediators

Attention. Given that the collection of eye movement data includes images from both merchants and CGIs, we employ the proportion of relative fixation points within the area of interest as a measure of attention to the displayed CGIs. This approach helps mitigate the influence of merchant-provided images in the experimental materials. The formula is defined as: Attention = Total number of fixation points in the area of interest/Number of fixation points in the whole page. The results show that the mean value of attention is 0.41, and the standard deviation of attention is 0.18.

Arousal. Following Mehrabian (1974), we asked participants to rate their feelings of viewing the CGIs based on the following dimensions using 7-point Likert scale (refer to Appendix A.3 for the survey questions). The *Cronbach* α is 0.896, indicating that the items are good in reliability.

5.1.4. Control variables

We introduced gender, helpfulness (the extent to which viewing buyer reviews was perceived helpful to make purchase decisions), shopping frequency (experience of online shopping), and the experience of viewing image comments as potential covariates. We did not introduce age as control variable because all the participants were in the same interval of 18–25. The survey questions of these variables can be found in Appendix A.2.

5.2. Data analysis and results

We first conducted the Kolmogorov-Smirnov test to make sure that our data distribution satisfies the assumption of normality. The result indicated a slight positive skew of our data. A square root transformation was applied for calibration. Subsequent tests showed that the transformed data followed a normal distribution and the assumptions of homogeneity of variance and homoscedasticity. A mixed-design ANCOVA was conducted using the calibrated data.

5.2.1. ANCOVA results

We conducted an ANCOVA to explore the effects of product irrelevant cues (e.g. clarity, brightness, product displaying proportion) and relevant cues (e.g. consistency with merchant-provided image) on the attractiveness of CGIs at the buying stage (H2).

A mixed-design ANCOVA was conducted using the calibrated data. Results revealed that CGI attractiveness differed significantly across the two levels (high vs. low) of consistency with merchant-provided image ($F(1, 121) = 5.32$, $p = 0.023$, $\eta p^2 = 0.042$, $f = 0.23$), and image clarity ($F(1, 121) = 6.44$, $p = 0.012$, $\eta p^2 = 0.051$, $f = 0.25$), indicate a small to medium effect according to Cohen's convention (Cohen, 1977). But the product irrelevant cues— brightness and product displaying proportion— are not significantly different in attracting consumers' attention on the CGIs (Brightness: $F(1, 121) = 1.01$, $p = 0.317$, $\eta p^2 = 0.008$, $f = 0.09$; Product displaying proportion: $F(1, 121) = 0.19$, $p = 0.67$, $\eta p^2 = 0.002$, $f = 0.05$).

As illustrated in Fig. 7, Bonferroni pairwise comparisons revealed that CGIs that are consistent with merchant-provided image attract significantly longer fixation duration than those not consistent with merchant-provided image (M = 2550.12ms vs. M = 2075.19ms, SEdiff = 205.87, $p = 0.023$). Moreover, CGIs with high clarity attract significantly longer fixation duration than those with low clarity (M = 2573.93ms vs. M = 2051.38ms, SEdiff = 205.87, $p = 0.012$).

But the fixation duration does not differ significantly between CGIs with high vs. low brightness (M = 2365.53ms vs. M = 2259.77ms, SEdiff = 105.76, $p = 0.32$) and product displaying proportion (M =

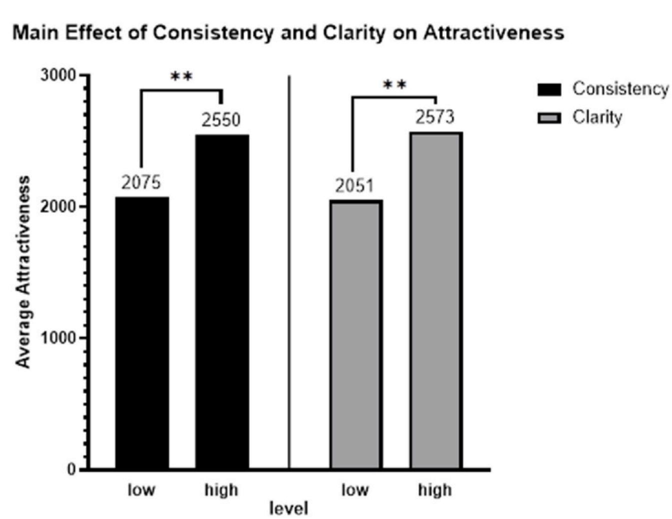

Fig. 7. The main effect of consistency and clarity on attractiveness.

2334.83ms vs. M = 2290.47ms, SEdiff = 102.25, $p = 0.67$). Therefore, hypothesis 2 is partially supported, indicating that consumers are more easily attracted by CGIs with higher-quality product-relevant cues (e.g. the consistency of CGI with merchant-provided images) at the buying stage.

The results also reveal that although most product irrelevant cues (e.g. high brightness and proper product displaying proportion) are not useful in attracting attention at the buying stage, image clarity is an important product irrelevant cue in attracting attention at both the browsing and buying stage.

5.2.2. Correlation results

Since we have both continuous data and categorical data, we first change the continuous data into four sequential categories, then a Spearman correlation was employed. Table 3 shows the descriptive statistics and bivariate correlations among all the variables in study 2. Attention and emotional arousal are positively related to consumers' purchase intention (attention: $r = 0.088$, $p = 0.01$; arousal: $r = 0.594$, $p = 0.00$). Moreover, most heuristic cues of CGIs are shown to be significantly correlated with consumers' purchase intention (Clarity: $r = 0.217$, $p = 0.00$; Brightness: $r = 0.12$, $p = 0.01$; Consistency with merchant-provided image: $r = 0.301$, $p = 0.00$), but product displaying proportion is not significantly correlated with consumers' purchase intention ($r = -0.047$, $p = 0.38$).

5.2.3. Linear regression result

We further conducted a linear regression analysis to examine the impact of both product relevant and irrelevant cues of CGIs on consumer purchase intention (H3). Here, we choose to use a multiple linear regression model to analyze the relationship between the variables. Additionally, validation results affirm that our data meet all assumptions necessary for linear regression. We developed two empirical models shown below in accordance to our proposed hypothesis, model 1 only contains all the potential covariates:

$$\text{Purchase Intention} = \gamma_0+\gamma_1\text{Gender}+\gamma_2\text{Preceived Helpfulness}+\gamma_3\text{Shopping Frequency}+\gamma_4\text{View Image Comments} +\varepsilon. \quad (1)$$

After testing model 1, our plan is to validate our hypothesis with model 2, which incorporates four heuristic cues:

$$\text{Purchase Intention} = \gamma_0+\gamma_1\text{Gender}+\gamma_2\text{Preceived Helpfulness}+\gamma_3\text{Shopping Frequency}+\gamma_4\text{View Image Comments}+\gamma_5\text{clarity}+\gamma_6\text{brightness}+\gamma_7\text{Product displaying Proportion}+\gamma_8\text{Consistency}+\varepsilon. \quad (2)$$

Before implementing linear regression, a check on the data revealed that the Durbin-Watson test result is 1.693, indicating conformity with the independence of residuals. The VIF values, ranging between 1 and 1.2, suggest the absence of multicollinearity issues. The residual histogram indicates that the linear regression meets the normality assumption. However, upon examining the residual scatter plot, it was observed that the variance of the study data is not homogeneous. Consequently, weighted least squares will be utilized to estimate the regression coefficients in subsequent analyses. As each participant rated four types of CGIs in each experiment group, to account for the possibility that the regression residuals are not independent within each participant, we specified the residuals as clustered under each participant (Liu et al., 2021).

Table 4 presents the results of Model 2 from the linear regression analysis. The coefficients estimation table can be found in Appendix A.7. Supporting H3, CGIs with higher clarity (b = 0.189, se = 0.036 t[124] = 3.68, $p = 0.00$, 95%CI[0.27, 0.91]), higher brightness (b = 0.122, se = 0.035, t[124] = 3.41, $p = 0.001$, 95%CI[0.14, 0.53]) and higher consistency with merchant-provided image (b = 0.284, se = 0.035, t[124] = 4.93, $p = 0.00$, 95%CI[0.48, 1.12]) are associated with higher purchase intention from consumers. But the results also reveal that whether the product has proper displaying proportion in the CGI does not have significant impact on purchase intention (b = −0.045, se = 0.035, t[124] = −1.19, $p = 0.24$, 95%CI[-0.29, 0.07]). Hence, H3 is partially supported. Fig. 8 visually illustrates the relative impact of each regression coefficient.

5.2.4. Result of mediation test

As a final step, we used the PROCESS macro model number 4 to test the mediation path (Hayes, 2012). The results show that the effect of high image clarity on purchase intention is mediated by consumers' emotional arousal (*ab* = 0.437, *se* = 0.082, 95% CI[0.282, 0.602]), but is

Table 4
Linear regression results for full sample (N = 125).

	DV:Purchase Intention	
	Model 1	Model 2
Constant(γ_0)	1.604(0.172)[a]	1.301(0.164)
Gender(γ_1)	−0.039(0.038)	−0.24(0.036)
Perceived Helpfulness(γ_2)	0.127**(0.020)	0.105*(0.019)
Shopping Frequency(γ_3)	0.006(0.029)	0.032(0.027)
View Image Comments(γ_4)	−0.135**(0.038)	−0.114*(0.035)
Clarity(γ_5)		0.189***(0.036)
Brightness(γ_6)		0.122**(0.035)
Product Displaying Proportion(γ_7)		−0.045(0.035)
Consistency(γ_8)		0.284***(0.035)
adjusted R^2	0.014(small)	0.152(medium)

*p < 0.05; **p < 0.01; ***p < 0.001.
Adjusted R2 is nearly the same as effect size f2, and the conventions of f2 here is: small effect f2 = 0.02, medium effect f2 = 0.15, large effect f2 = 0.35, according to G*power (Faul, Erdfelder, Lang, & Buchner, 2007).
[a] . Inside the brackets shows the standard error, left side of the bracket is the standardized coefficients.

Table 3
Descriptive statistics and spearman correlation table.

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11
1	Purchase intention	2.82	1.41	1.000										
2	Attention	0.41	0.18	0.088*	1.000									
3	Emotional Arousal	3.19	1.22	0.594**	0.072	1.000								
4	Gender	–	–	−0.031	−0.070	−0.046	1.000							
5	Helpfulness	5.50	1.00	0.136**	0.072	0.124**	−0.108*	1.000						
6	Frequency	3.34	0.65	0.011	−0.006	−0.035	−0.198**	0.099*	1.000					
7	View CGIs[a]	2.62	0.53	−0.030	0.063	−0.048	−0.158**	0.321**	0.084	1.000				
8	Clarity	–	–	0.217**	0.251**	0.147**	−0.040	0.225**	−0.129**	0.044	1.000			
9	Brightness	–	–	0.120**	0.170**	−0.345**	0.000[b]	0.000	0.000	0.000	0.000	1.000		
10	Proportion	–	–	−0.047	−0.036	−0.130**	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
11	Consistency	–	–	0.301**	0.182**	0.060	−0.005	−0.033	0.006	−0.072	0.104*	0.000	0.000	1.000

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
[a] View CGIs means the covariate of experience of viewing image comments.
[b] The correlation is zero, because in study 2, brightness and proportion were in within-group setting.

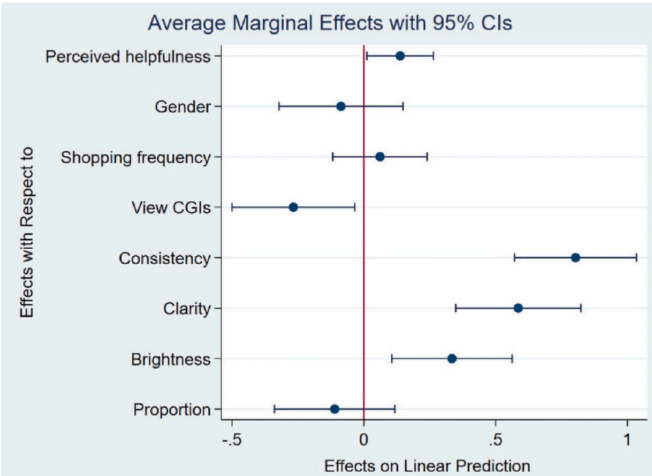

Fig. 8. Respective effects on linear prediction.

not mediated by consumer visual attention on the CGI ($ab = 0.017$, $se = 0.014$, 95% CI[-0.005, 0.053]). The effect of high image brightness on purchase intention is only mediated by consumers' emotional arousal ($ab = 0.337$, $se = 0.079$, 95% CI[0.187, 0.496]), but is not mediated by consumer visual attention on the CGI ($ab = -0.042$, $se = 0.032$, 95% CI [-0.108, 0.020]), the details of total, direct and indirect effect were presented in Table 5.

Finally, the effect of the consistency with merchant-provided image on purchase intention is also mediated by consumers' emotional arousal ($ab = 0.341$, $se = 0.079$, 95% CI[0.191, 0.501]), which shows support to the mediation of emotional arousal (H5), but is not mediated by consumer visual attention on the CGI ($ab = 0.007$, $se = 0.008$, 95% CI [-0.003, 0.033]) do not support when attention serve as the mediation (H4), the indirect effect accounting 67% of the total effect (Wen et al., 2016). Indicating that the impact of relevant and irrelevant cues of CGIs on consumers' purchase intention is only mediated by consumers' emotional arousal**,** the coefficient paths are as *Fig. 9*.

The mediation results reveal that the impact of CGI clarity on purchase intention is fully mediated by emotional arousal. In other words, the clarity attribute of CGIs does not directly affect purchase intention but rather influences it through the arousal of consumers' emotions. Additionally, we have verified that the clarity of CGIs indeed correlates with changes in consumers' attention. However, there is no significant correlation between attention and purchase intention. Therefore, the hypothesis proposing attention as a mediating mechanism has not been supported.

Finally, we summarized all the hypothesis testing results and their corresponding effect sizes in tabular form (see Table 6). We found that during the browsing stage, consumers are indeed more easily attracted by higher quality irrelevant cues, while in the buying stage, consumers are more easily attracted by CGIs that are consistent with the merchant-provided images. Regarding hypothesis (H3), which posited a positive relationship between the four heuristic cues of CGIs and purchase

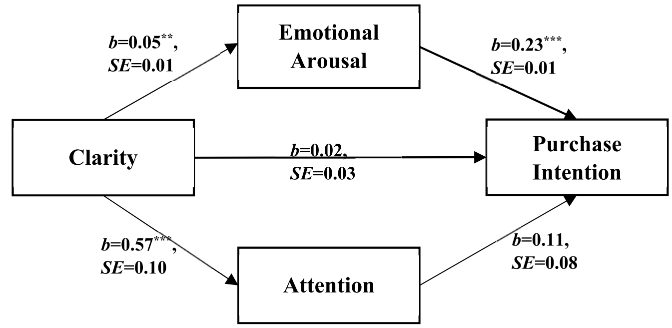

Fig. 9. Unstandardized Path Coefficients for Mediation. (*p < 0.05; **p < 0.01; ***p < 0.001).

intention, we only partially confirmed it. Specifically, the association between product proportion and purchase intention was found to be statistically insignificant. Lastly, in the verification of the mediating effects, we found that the mediating effect of visual attention was not significant, while the mediating effect of emotional arousal was significant. Therefore, we reject H4 and confirm H5.

5.3. Robustness check

To verify the robustness of the research findings, we employed the sub-participants approach to replicate the results.

Robustness Across Gender. We segmented the output regression results by gender. Here, an intriguing observation emerged: among female participants, the results indicate that, except for proportion, all the other important cues—clarity, consistency, and brightness—significantly influence purchase intention. Additionally, view image comments also show a significant impact. However, male participants exhibit different regression outcomes. Among the four cues, only consistency influences purchase intention for them. Moreover, factors such as helpfulness and shopping frequency significantly affect male purchase intention. This suggests that male purchasing behavior is notably influenced by rational factors, whereas females tend to prioritize aesthetic aspects when viewing product images. Concurrently, when reported by gender, the model's explanatory power increases (adjusted R^2 rises from 0.15 to 0.21), details of the sub-participants regression model please see in Appendix A.5.

Robustness Across Different Method of Parameter Estimation. In the main body of this study, parameter estimation is mostly performed using the least squares method. To validate the robustness of the research findings, we chose to replicate the statistical process using maximum likelihood estimation. We found that the research results remained consistent with the main findings.

Robustness Across Different Regression Methods. To verify the rationality of our model selection and the robustness of the model results, we simultaneously utilized the stepwise regression method. After incorporating relevant variables into the model, the most important three variables for Purchase Intention were identified as Consistency, Clarity, and Brightness. At this point, the adjusted R^2 of the model was

Table 5
Total, direct and indirect effects.

	Purchase Intention outcomes as criteria					
	b	*SE*	*t*	LLCI	ULCI	*β*
Total Effect	0.16	0.0360	4.417	0.0000	0.0882	0.38
Direct Effect	0.02	0.0275	0.861	0.3895	−0.0304	0.06
Total Indirect Effect	0.14	0.0252	–	0.0870	0.1851	0.32
Indirect Effect 1: Clarity→Emotional Arousal→Purchase Intention	0.13	0.0247	–	0.0833	0.1798	0.31
Indirect Effect 2: Clarity→Attention→Purchase Intention	0.01	0.0041	–	−0.0024	0.0139	0.01

Table 6
Results of hypothesis testing.

Hypothesis		statement	Consequence			Effect Size[a]
			supported	rejected	partial supported	
Hypothesis 1	H1a	During the browsing stage, CGIs featuring higher image clarity are positively associated with the attractiveness of CGIs	√****			huge
	H1b	During the browsing stage, CGIs featuring higher image brightness are positively associated with the attractiveness of CGIs	√****			big
	H1c	During the browsing stage, CGIs featuring proper product displaying proportion are positively associated with the attractiveness of CGIs	√**			medium
Hypothesis 2		During the buying stage, CGIs featuring higher-quality product relevant cues, such as the consistency of image review with merchant-provided images, are positively associated with the attractiveness of CGIs.	√**			medium
Hypothesis 3		The quality of both product relevant and irrelevant cues of CGIs is positively associated with consumer purchase intention.			√**	Small to medium
Hypothesis 4		The positive association between CGIs' cue quality and consumer purchase intention is mediated by consumer visual attention on these cues.		✓		n/a
Hypothesis 5		The positive association between CGIs' cue quality and consumer purchase intention is mediated by consumers' emotional arousal.	√***			67%

[a] The effect size's convention is different, since we use the different statistical method (e.g. f, f^2, the calculation of effect size in mediation test is $P_M = ab/c$).

0.15, with a corresponding effect size f^2 of 0.18, indicating a medium effect. (detailed model see Appendix A.9).

6. General discussion

The objective of this research was to investigate the nuanced impact of heuristic cues of CGIs on consumers' attention and purchase intention. Specifically, we sought to address the following inquiries: (a) How does the quality of product relevant and irrelevant cues influence the attractiveness of CGIs during the browsing and buying stage? (b) How does the quality of the product relevant and irrelevant cues influence the purchase intention of consumers? (c) What is the underlying mechanism that mediates the association between CGI cue quality and consumer purchase intention? To address these questions, we conducted two laboratory studies using a combination of eye-tracking experiments and questionnaires. Participants were informed of their task to either browse (study 1) or purchase (study 2) a parka, with the attractiveness of CGIs evaluated through tracking their eye movement behavior. Additionally, emotional arousal and purchase intention were measured using questionnaires administered to participants following the buying tasks.

6.1. Effects of heuristic cues on attractiveness of CGIs

Our experimental results suggest that consumers' behavioral responses toward product relevant and irrelevant cues of CGIs are different in the browsing and the buying stages. During the browsing stage, CGIs featuring higher-quality product irrelevant cues, such as image clarity, brightness and product displaying proportion, exhibit a positive association with CGI attractiveness. This suggests that consumers are more easily attracted by CGIs that exhibit superior clarity, brightness, and proper product displaying proportion. However, during the buying stage, CGIs featuring higher-quality product relevant cues, such as the consistency of image review with merchant-provided images, demonstrate a positive association with CGI attractiveness. This finding suggests that consumers prioritize CGIs that align closely with the images provided by the merchant.

The results provide support for hypotheses H1 and H2, indicating that while consumers encounter and process both relevant and irrelevant cues at both stages, they may shift their attentional priorities due to varying levels of situational involvement. During the browsing stage, consumers tend to engage in exploratory behavior, primarily focusing on visually stimulating or attention-grabbing cues, irrespective of their relevance to the product. In contrast, during the buying stage characterized by high situational involvement, consumers adopt a more central route of information processing. They scrutinize decision-making criteria more meticulously and prioritize cues directly related to the product itself, rather than being influenced by visually stimulating yet irrelevant cues.

6.2. Effects of heuristic cues on persuasiveness of CGIs

Persuasive CGIs are those that effectively alter consumers' mental states and facilitate purchasing behavior (Lei et al., 2021; Xu, 2018). Our findings show that most product relevant (consistency with merchant-provided images) and irrelevant cues (image clarity and brightness) are positively associated with consumers' purchase intention, with the exception of product displaying proportion, thus providing partial support for H3.

These results underscore the importance of heuristic cues within CGIs, particularly given the overwhelming volume and complexity of visual information they present. Specifically, product relevant cues, such as consistency of image review with merchant-provided images, provide consumers with pertinent information about the product. This information aids consumers in evaluating the product's utility and determining its suitability for their needs and preferences. Likewise, product irrelevant cues, such as image brightness or clarity, may evoke emotional responses or aesthetic preferences among consumers due to the enhanced image quality, thereby influencing their purchase intention. However, the lack of significant association between product displaying proportion and purchase intention may prompt consideration of other factors or variables that could influence consumers' responses to CGIs. It's plausible that personal preferences, rather than image quality alone, contribute to the perceived importance of product displaying proportion. The subjective nature of product displaying proportion may render it less influential in shaping purchase intention. Hence, the results suggest that not all irrelevant cues are persuasive in increasing purchase intention, rather, it's those irrelevant cues related to image quality that are persuasive for consumers.

6.3. Mediation effects of emotional arousal

Further, the results show that the positive association between CGIs' cue quality and consumer purchase intention is mediated by the elicitation of consumers' emotional arousal, rather than by an increase in visual attention, thereby supporting H5 while rejecting H4. This underscores the significant role of emotional arousal in shaping purchase intention compared to visual attention.

While visual attention is pivotal for initially capturing consumers' interest, it does not necessarily guarantee an increase in purchase intention. Consumers may indeed focus on visually appealing cues within CGIs, but if these cues fail to evoke emotional responses or align with their needs and preferences, they may not translate into actual purchase behavior. In contrast, emotionally compelling cues have the potential to forge a stronger connection with consumers, leading to a more favorable evaluation of the product and a heightened likelihood of purchase. According to the Stimulus (S) – Organism (O) – Response (R) paradigm (Mehrabian & Russell, 1974), pleasure environmental stimuli can evoke individuals' emotional arousal and thus enhancing satisfaction (Eroglu et al., 2001; Spies et al., 1997) and purchase intention (Babin & Babin, 2001; Fiore et al., 2005; Hu et al., 2016; Wu et al., 2008). When CGIs incorporate emotionally compelling cues that resonate with consumers' desires and aspirations, they are more likely to elicit favorable evaluations of the product and increase the likelihood of purchase.

6.4. Implications

The findings of the present study have several important implications for both online review and information cue literatures. First, these results demonstrate the different roles of high-quality product relevant and irrelevant cues in constituting an attractive and persuasive CGI. Although prior research has shown that CGIs with higher aesthetic quality are positively associated with consumer expectations and post-purchase satisfaction (Bilal et al., 2021; Guan et al., 2023b), they assess the aesthetic quality of CGIs through surveys or general discussions, without examining specific heuristic cues of CGIs. Our study contributes to the literature by shifting the focus from assessing the overall aesthetic quality of CGIs to analyzing specific features. Through the categorization of these features into product relevance and irrelevance, we provide a more nuanced understanding of how the quality of heuristic cues in CGIs influences consumer behavior in online shopping contexts. This approach enhances the generalizability of our findings and provides actionable insights for practitioners aiming to optimize CGI design.

Second, as consumers are shown to exhibit distinct behaviors during the browsing and buying stages, with heightened motivation for careful decision-making and increased attention to product features during the buying stage(Ha & Lennon, 2010; Li & Hitt, 2008). By explicitly examining the role of product-relevant and irrelevant cues at different stages of the shopping journey, our study advances existing research that often overlooks this crucial distinction (Poor et al., 2013; Sun et al., 2019). Our findings offer a deeper understanding of how CGIs influence consumer behavior during both browsing and buying stages, providing valuable insights for developing tailored strategies to effectively engage consumers throughout their online shopping experience.

Third, our results also help facilitate a better understanding of the impact of visual elements on consumer behaviors. Prior research has underscored the direct influence of visual elements on consumers purchase intention (Chen et al., 2019; Clow et al., 2008; Poor et al., 2013; Small & Verrochi, 2009), but the underlying mechanisms of the link between visual elements features and behavioral outcomes have rarely been investigated. This way, by showing that the heuristic cues of CGIs can affect consumer purchase intention through eliciting emotional arousal rather than attracting more attention, this research further contributes to extant literature by presenting the mechanisms through which heuristic cues of CGIs affect consumers' behaviors.

Finally, the utilization of eye-tracking data in our study offered invaluable insights into the visual attention patterns of consumers. Unlike previous research, which often relied on surveys to capture the impacts of visual attention on shopping behaviors (Jiang & Benbasat, 2004; Kim & Lennon, 2008; Li et al., 2014; Wang, Li, & Chau, 2014), our study employed data from an eye-tracking experiment. This approach allowed us to directly examine consumers' reactions towards CGIs with different features, bypassing the need for self-reported data on attention. The observed visual attention patterns not only provide empirical support for our findings but also reinforce the validity of our results concerning the association between heuristic cues of CGIs and CGI attractiveness. Consequently, this research offers a deeper insight into the impact of CGI features on their attractiveness.

In light of our findings regarding the significant influence of heuristic cues within CGIs on consumer behavior, there are several actionable recommendations that e-commerce platforms and online merchants can implement to optimize their marketing strategies.

First, E-commerce platforms should strategically leverage heuristic cues, both product-relevant and irrelevant, to enhance the visual appeal and persuasive impact of their product displays. By prioritizing cues such as image clarity, brightness, and consistency with merchant-provided images, platforms can create a more immersive and engaging shopping experience for consumers. Furthermore, platforms should carefully consider the balance between product-relevant and irrelevant cues at different stages of the consumer journey, customizing their strategies to align consumer preferences and situational contexts.

Second, recognizing the pivotal role of CGIs in influencing purchase intention, e-commerce platforms should implement specific strategies for selecting and showcasing these images effectively. Platforms can encourage users to submit CGIs that maintain consistency with the merchant-provided images and exhibit high image quality attributes such as brightness and clarity. This approach serves to enhance the overall attractiveness and credibility of the product listings. Additionally, platforms can leverage algorithms or manual curation processes to prioritize CGIs that closely align with merchant-provided images and uphold high image quality standards, thereby ensuring consistency and authenticity in the product presentation.

Third, given the significant influence of emotional arousal on purchase intention, e-commerce platforms should prioritize the creation of emotionally engaging content that resonates with consumers' desires and aspirations. By incorporating visually compelling cues within CGIs that evoke positive emotions, platforms can capture consumers' attention and stimulate their interest in the products being showcased. By appealing to consumers' emotions, platforms can foster deeper connections and drive purchase decisions.

6.5. Limitations and future directions

While our study investigated several heuristic cues within CGIs, it's essential to acknowledge the limitations of this study that future research can further address.

First, a notable limitation of our research is the relatively small sample size, which may affect the generalizability of our findings. While our study provides valuable insights into consumer responses to CGIs, the small sample size could potentially introduce biases and limit the robustness of our conclusions. To mitigate this limitation, we employed rigorous sampling techniques and statistical analyses to ensure the validity and reliability of our results. However, it's important to acknowledge that the small sample size may still have influenced the outcomes to some extent. Future research endeavors could address this limitation by employing larger and more diverse sample sizes, encompassing a broader range of demographic and socio-economic backgrounds. Additionally, longitudinal studies could provide deeper insights into the temporal dynamics of consumer responses to CGIs, allowing for a more comprehensive understanding of the factors influencing purchase intention over time.

Second, we recognize the limitation related to the exclusive focus on CGIs in our study. There is a presence of other potentially relevant variables that were not examined. These variables, such as color, image composition, or the presence of text overlays, could have nuanced effects on consumer responses and outcomes. Future research should consider exploring these variables to gain a comprehensive understanding of their impact on consumer behavior and purchase intention in the e-commerce context. Additionally, while our study focused on emotional arousal as a mediator, it did not extensively explore the nuanced dimensions of emotions. Future research could delve deeper into specific emotional responses and their varying impacts on consumer behavior. Understanding how different emotions influence purchase intention could inform targeted marketing strategies and enhance consumer engagement.

Third, we acknowledge the primary focus on clothes and the selection of CGIs used as stimuli in this study may introduce potential bias and limit the generalizability of our findings. Future research could explore potential variations in the impact of heuristic cues for diverse product categories. Investigating how heuristic cues influence consumer behavior across products ranging from experience goods to search goods could provide valuable insights into the broader applicability of our findings. Moreover, employing more diverse and representative stimuli in future studies could mitigate potential biases and enhance the generalizability of the results.

Fourth, while our study focused on the main effects of heuristic cues and emotional arousal, we recognize the importance of considering potential moderating variables. Future research could explore how factors such as consumer expertise, product familiarity, platform features, design, or cultural difference moderate the influence of heuristic cues on consumer behavior. Understanding these moderators can provide valuable insights into tailoring marketing strategies to different consumer segments effectively.

Fifth, while eye-tracking data provided valuable insights into visual attention, it's crucial to emphasize its limitations in capturing the full spectrum of attention and cognitive processes in consumer responses. Future research should consider employing complementary methodologies, such as qualitative interviews, to provide a more comprehensive understanding of consumer behavior in response to heuristic cues within CGIs.

Finally, we also acknowledge the possibility that consumers' perceptions of image quality may be subjective. Future research should consider exploring individual differences in image quality perception and its impact on consumer responses. Recognizing that what is considered high-quality to one consumer may differ for another can inform strategies for optimizing visual content in e-commerce platforms.

7. Conclusions

This study delves into the impact of product relevant and irrelevant cues within CGIs on consumers' attention and purchase intention. Through two laboratory studies employing a combination of eye-tracking experiments and questionnaires, our findings reveal significant correlations between the quality of product irrelevant cues—such as clarity, brightness, and proper product displaying proportion—and the attractiveness of CGIs during the browsing stage. Conversely, product relevant cues, notably consistency with merchant-provided images, exhibit a positive association with CGI attractiveness during the buying stage. Moreover, our results emphasize the pivotal role of incorporating high-quality product relevant and irrelevant cues in CGIs to enhance purchase intention. Importantly, we identify that the underlying mechanism driving this effect lies in eliciting consumers' emotional arousal rather than mere visual attention. The findings underscore the importance of strategic cue incorporation in CGI design for effective consumer engagement.

CRediT authorship contribution statement

Yujie Zheng: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Baojun Ma:** Writing – review & editing, Resources, Project administration, Funding acquisition. **Xiwen Zhou:** Visualization, Investigation, Formal analysis, Data curation. **Benjiang Lu:** Validation, Supervision, Funding acquisition.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2024.108285.

Appendix A

Table
A1Manipulation check questions.

Variables	Items	Scales
Consistency with merchant-provided image	The product in this image review is consistent with merchant-provided image	1- Strongly disagree 7- Strongly agree
Clarity	This image review is clear	1- Strongly disagree 7- Strongly agree
Brightness	The color of this image review is bright	1- Strongly disagree 7- Strongly agree
Product displaying proportion	In this picture review, the product takes a large proportion of the whole picture	1- Strongly disagree 7- Strongly agree

Table A2
Demographic information.

Variables	Items	Scale
Gender	Your gender is?	A. Male; B. Female
Age	Your age is?	A. <18; B. 18–25; C. 26–35; D. >35
Years of online shopping experience	How many years have you been shopping online?	A. Less than 1 year; B. 1–2 years; C. 3–4 years; D. 5–6 years; E. More than 7 years
Usage of CGIs	Will you look at the image reviews while you are shopping online?	A. Every time; B. Some time; C. Rarely; D. Never
Perceived helpfulness	Image reviews are helpful while I shop online	1- Strongly disagree 7- Strongly agree

Table A3
Questionnaire used in buying stage.

Physical Properties: 1 = strongly disagree, 7 = couldn't agree more							
	1	2	3	4	5	6	7
The product in the consumer generated image is consistent with the product in merchant provided image.							
The consumer generated image is of high clarity							
The consumer generated image is bright and vivid							
The product takes up a big portion of the image							
Emotional Arousal: 1 = strongly disagree, 7 = couldn't agree more							
	1	2	3	4	5	6	7
I feel very boring							
I feel very calm							
I feel dull							
I feel very sleepy							
Purchase Intention: 1 = strongly disagree, 7 = couldn't agree more							
	1	2	3	4	5	6	7
I am very likely to purchase this product							
I would recommend others to purchase this item.							
I would recommend this product to someone seeking shopping advice from me.							

Table A4
Demographic Characteristics of The Sample Used for Complete Study.

Variable		N(%)	Mean(std)
Study1			
Gender	male	46.4	–
	female	53.6	–
Age	18–25	98.4	–
	26–35	1.6	–
Experience of online shopping	1–2 years	1.6	–
	2–3years	5.6	–
	3–4 years	24	–
	more than 4 years	68.8	–
Think CGIs are helpful in making purchase decisions	7 points of likelihood	–	4.496 (1.00)
Study2			
Experiment group	A1	28.8	–
	A2	21.6	–
	B1	23.2	–
	B2	26.4	–
Group-gender	A1-Male	44	
	A2-Male	44	
	B1-Male	48	
	B2-Male	48	

Table A5
Result table of repeated-ANOVA.

Variables	MS	F	p	ηp^2
consistency	2134703.46	3.652	0.058	0.028
clarity	151353752	169.075	0.000	0.573
proportion	5559871.93	18.797	0.000	0.130
brightness	109486886	116.355	0.000	0.480
consistency * clarity	231441.487	1.225	0.271	0.010
consistency * proportion	576787.304	2.999	0.086	0.023
clarity * proportion	105363690	214.023	0.000	0.629
consistency * clarity * proportion	31068.7819	0.137	0.712	0.001
consistency * brightness	404533.418	2.243	0.137	0.017
clarity * brightness	13304871.3	35.866	0.000	0.222
consistency * clarity * brightness	1225008.2	10.364	0.002	0.076
proportion * brightness	5222003.74	28.009	0.000	0.182
consistency * proportion * brightness	2219482.67	14.816	0.000	0.105
clarity * proportion * brightness	4592060.7	18.128	0.000	0.126
consistency * clarity * proportion * brightness	1157572.32	6.636	0.011	0.050

Table A6
Divide of the Experiment Groups.

Experiment Groups	A1				A2			
Grouping Variables	High Consistency	High Clarity	High Brightness	Product Displaying Proportion 100%	High Consistency	High Clarity	High Brightness	Product Displaying Proportion 100%
CGI 1	1	1	1	1	1	0	1	1
CGI 2	1	1	1	0	1	0	1	0
CGI 3	1	1	0	1	1	0	0	1
CGI 4	1	1	0	0	1	0	0	0
Experiment Groups	B1				B2			
Grouping Variables	High Consistency	High Clarity	High Brightness	Product Displaying Proportion100%	High Consistency	High Clarity	High Brightness	Product Displaying Proportion 100%
CGI 1	0	1	1	1	0	0	1	1
CGI 2	0	1	1	0	0	0	1	0
CGI 3	0	1	0	1	0	0	0	1
CGI 4	0	1	0	0	0	0	0	0

Table A7
Coefficients Estimation of Regression Model.

Model		B	Std. Error	t	p	95% Confidence Interval for B		ηp^2
						Lower Bound	Upper Bound	
B2	constant	3.427	1.071	3.200	0.002	1.307	5.548	0.079
	1[a]	−0.264	0.237	−1.111	0.269	−0.733	0.206	0.010
	2	−0.033	0.138	−0.239	0.811	−0.306	0.240	0.000
	3	−0.132	0.179	−0.738	0.462	−0.487	0.223	0.005
	4	0.045	0.220	0.203	0.840	−0.391	0.481	0.000
B1	constant	3.320	1.246	2.664	0.009	0.853	5.788	0.056
	1	−0.301	0.276	−1.092	0.277	−0.848	0.245	0.010
	2	0.110	0.161	0.684	0.495	−0.208	0.428	0.004
	3	0.077	0.208	0.368	0.714	−0.336	0.489	0.001
	4	−0.348	0.256	−1.357	0.177	−0.855	0.160	0.015
A2	constant	3.697	1.234	2.995	0.003	1.253	6.140	0.070
	1	0.007	0.273	0.025	0.980	−0.535	0.548	0.000
	2	0.042	0.159	0.265	0.791	−0.273	0.357	0.001
	3	−0.153	0.206	−0.741	0.460	−0.562	0.256	0.005
	4	−0.239	0.254	−0.942	0.348	−0.741	0.263	0.007
A1	constant	2.664	1.152	2.313	0.022	0.384	4.945	0.043
	1	0.004	0.255	0.017	0.987	−0.501	0.509	0.000
	2	−0.008	0.148	−0.051	0.959	−0.301	0.286	0.000
	3	0.241	0.193	1.253	0.213	−0.140	0.623	0.013
	4	−0.281	0.237	−1.186	0.238	−0.750	0.188	0.012

[a].1 = gender, 2 = online shopping experience, 3 = shopping frequency, 4 = view image comments.

Table A8
Sub-sample regression model.

	DV:Purchase Intention			
	Gender = Male		Gender = Female	
	Model 1	Model 2	Model 1	Model 2
Constant(γ_0)	0.809(0.232)[a]	0.748(0.229)	2.221(0.234)	1.626(0.228)
Perceived Helpfulness(γ_1)	0.083* (0.029)	0.145*(0.029)	0.061(0.027)	0.081(0.025)
Shopping Frequency(γ_2)	0.169* (0.040)	0.164** (0.038)	−0.092(0.043)	−0.052(0.040)
View Image Comments(γ_3)	−0.016(0.052)	−0.029(0.050)	−0.192**(0.058)	−0.124*(0.053)
Clarity(γ_4)		0.103(0.054)		0.221***(0.049)
Brightness(γ_5)		0.108(0.050)		0.134*(0.047)
Product Displaying Proportion(γ_6)		0.015(0.050)		−0.093(0.047)
Consistency(γ_7)		0.218*** (0.050)		0.323***(0.049)
adjusted R^2	0.05	0.152	0.04	0.216

*p < 0.05; **p < 0.01; ***p < 0.001.
[a]. Inside the brackets shows the standard error, left side of the bracket is the standardized coefficients.

Table A9
Step-wise regression model results [d]

model	R	adjusted R^2	SE	Changing in Statistics					Durbin Watson	VIF
				R^2	F	df 1	df 2	sig		
1	0.305[a]	0.091	1.35	0.093	51.070	1	498	0.000		1.000
2	0.376[b]	0.138	1.31	0.048	27.797	1	497	0.000		1.011
3	0.394[c]	0.150	1.30	0.014	8.230	1	496	0.004	1.705	1.000

a. Predictor variables: (constant), consistency.
b. Predictor variables: (constant), consistency, clarity.
c. Predictor variables: (constant), consistency, clarity, brightness.
d. Dependent variables: Purchase intention.

Appendix BSupplemental Materials

Appendix B.1. Eye-tracking calibration process

First, invokes the calibration routine in Tobii, the first screen shows a schematic image of the patient's eyes as shown below.

Participants should be approximately 50 cm from the screen with the "eyes" centered in the display. A warning will be displayed on the screen if they are too close or too far away. The system is capable of extracting eye position information through most spectacle prescriptions. The system operates under a wide range of ambient light conditions but for best results avoid direct light and aim for subdued lighting conditions if possible.

When the patient is correctly aligned, press any key to continue. A series of dots when then appear in different parts of the screen. The patients should be encouraged to keep their heads still and look toward each dot (in any order). When they fixate on the dot, it will spin and "pop".

This is repeated for four dots and the system will then report that calibration has been successful, This is repeated for four dots and the system will then report that calibration has been successful. If the calibration is unsuccessful the system will go back and retest some or all of the points.[Not Available in CrossRef].

Appendix B.2. Software & Extensions for Eye-tracking data recording and analysis

This study utilized Tobii Pro Lab for analyzing and processing eye-tracking data. The presentation of experimental materials was achieved through E-Prime 3.0, and the integration of material presentation and eye-tracking data recording was accomplished using the E-Prime Extension for Tobii Pro 3.2. The implementation of the experiment followed the instructions outlined in the User Manual for E-Prime Extension for Tobii Pro 3.2 (https://pstnet.com/wp-content/uploads/2019/05/EET_User_Guide_3.2.pdf).

Appendix B.3. Statistical process descriptions of study1 & study 2

Study 1

Before conducting the repeated ANOVA analysis, we assessed the normality of the data. Our findings revealed that the significance levels for all groups in Study One were less than 0.05, indicating that the data did not follow a normal distribution. To further investigate, we computed kurtosis and skewness measurements and observed that the skewness values for all groups were positive, suggesting a mild positive skewness ranging from 1 to 2 times the standard error. To address this skewness, we employed the square root transformation method and retested it for normality. The results showed that the data were now normally distributed, with only a few marginally significant outcomes. Overall, the data followed a normal distribution after correction.

We utilized fixation duration to reflect attractiveness and conducted a repeated-measures ANOVA on fixation duration. Upon obtaining the results, we found that the interaction effect between unrelated cues was significant. Hence, we proceeded with further simple effects analysis. Since clarity, proportion, and brightness were all factors with two levels, we employed paired-sample t-tests for the simple effects analysis.

Study 2

Before conducting statistical analysis on the data of Study 2, we also performed a normality analysis. Combining scatter plots with the Shapiro-Wilk test results, we found that the research data were essentially normally distributed.

Before conducting correlation analysis, we conducted a series of preprocessing steps on the data. As the other four variables used in the correlation analysis were ordinal, they could not be correlated with continuous variables directly. Therefore, continuous variables needed to be transformed into ordinal variables before calculating Spearman rank correlation coefficients. The variables purchase intention, attention, and arousal were divided into four ordinal levels based on percentiles: scores below the 25th percentile was assigned to Group 1, 25%–50% to Group 2, 50%–75% to Group 3, and above 75% to Group 4.

Before performing ANCOVA, we conducted tests for the normality, homogeneity of variance, and homogeneity of regression assumptions of the data. We found that our data met the assumptions for conducting ANCOVA.

Before implementing linear regression, a check on the data revealed that the Durbin-Watson test resulted in 1.693, indicating conformity with the independence of residuals. The VIF values, ranging between 1 and 1.2, suggest the absence of multicollinearity issues. The residual histogram indicates that the linear regression meets the normality assumption. However, upon examining the residual scatter plot, it was observed that the variance of the study data is not homogeneous. Consequently, weighted least squares will be utilized to estimate the regression coefficients in subsequent analyses.

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