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Users’ processing of online marketplace listings for high and low involvement goods

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A R T I C L E I N F O

Keywords:
Online marketplace
High and low involvement goods
Eye tracking

A B S T R A C T

Purpose: To understand how users of online marketplaces process market signals in their decision making and whether this depends on if the good is of high or low involvement.
Design/methodology/approach: The paper employs a mixed methods approach. Study 1 draws on an analysis of interviews with online marketplace users using hypothetical eBay purchases as stimuli, understanding how users conceptualize specific market signals and whether their importance varies depending on the type of purchase (high versus low involvement good). Study 2 tests hypotheses derived from signaling theory, using an eye tracking experiment.
Findings: Price and photographs act as “fast and frugal” signals for inclusion in consideration sets for low involvement purchases, but consumers deem them insufficient for high involvement purchases where high-cost signals that help establish seller credibility are far more salient. Users pay relatively greater attention to costly market signals, which are beyond sellers’ direct control, for high involvement goods.
Practical implications: The paper offers insights for sellers regarding the presentation of quality cues and strategies online marketplaces can employ to reduce information asymmetry.
Originality/value: Drawing on and extending signaling theory, the paper introduces and confirms hypotheses for understanding users’ attention to market signals when making purchase decisions on online marketplaces. It identifies how the degree of involvement of a product affects the processing of market signals.

1. Introduction

Online marketplaces bring together previously disconnected buyers and sellers, but the uncertainty caused by asymmetric information in an online environment can prolong and complicate the purchasing process. Consequently, consumers typically invest time into evaluating listings, from multiple online sellers, for the same product to reduce perceived risk. Given the rapid expansion of e-commerce, it is crucial to understand how consumers process market signals (cues) and their effect on purchase decisions (Lin and Kalwani, 2018; Yang, 2015; Venkatesh et al., 2022). For online marketplaces, understanding how different types of information and their presentation affect users’ decision remains an important practical challenge (Saura et al., 2021).

Extant research investigates the impact of increased uncertainty in purchasing products online compared to in-person exchanges and identifies factors that influence online purchasing decisions (Li et al., 2009). This includes research on strategies for reducing seller uncertainty in online marketplace auctions (Dimoka et al., 2012; Lu and Chen, 2021). For instance, Pavlou and Dimoka (2006) propose that sellers can reduce product uncertainty with a set of product information signals, including online product descriptions, third-party product certifications, posted prices, and intrinsic product characteristics. However, such signals are rather limited compared to the extensive set currently available on many online marketplaces, such as eBay. Moreover, much extant research considers specific cues in isolation (Li et al., 2015; Van Der Heide et al., 2013), rather than a holistic assessment of the relative

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salience of market signals currently available on online marketplaces, which is more relevant for practitioners. Consequently, 'future research should investigate the use of multiple signals (e.g., signaling strategies) because it is an important and common sales approach in e-marketplaces' (Li et al., 2015, p.718), as 'businesses and researchers still have much to learn regarding …online shopping' (Venkatesh et al., 2022, p.1590).

The paper addresses three crucial research questions. In the context of online marketplaces, consumers face an array of diverse market signals, which can assist them in making knowledgeable choices about products. However, some signals are likely to be more influential than others in shaping purchasing decisions (Frota Neto et al., 2016; Van Nguyen et al., 2020). Specifically, the more market signals that consumers consider, the more complex and cognitively taxing the decision-making process. Given that consumers favor simplicity in decision making, it is likely that they only consider a subset of all possible market signals when making purchases from online marketplaces (Darley et al., 2010). Given the multitude of market signals and the potential for consumers to trade off reductions in information asymmetry (through information acquisition and processing) for cognitive simplicity, our first research question is *what market signals are salient when consumers evaluate online marketplace listings for the same product (regardless of the degree of product involvement)?*

Empirical studies indicate that information asymmetry between sellers and buyers is magnified in online marketplaces due to buyers' inability to physically interact with products before purchasing (Li et al., 2015). In the consumer decision-making process, signals serve as informational cues used by consumers to infer product attributes or quality. Moreover, the perceived cost of a signal can influence the importance attributed to that signal during the inference process (Li et al., 2015). Nevertheless, the specific impact of signal cost on the evaluation and inference processes for high and low involvement goods remains underexplored. Specifically, the relationships between signal cost and high and low involvement goods remains under-theorized (Baier et al., 2022). While there exists an extensive body of literature investigating the effect of signal cost on consumer decision-making (e.g., Frota Neto et al., 2016; Van Nguyen et al., 2020), there is a need for further scrutiny into how these relationships may vary for high and low involvement goods. Hence, our second research question probes: *how does the processing of market signals differ when consumers make high-involvement purchases compared to low-involvement purchases*? To address this question, we evaluate two products characterized by low (iPhone charger) and high (iPhone) purchase involvement. Purchase involvement reflects the degree of personal importance or interest consumers assign to a product and the potential risks of poor decision-making (Beatty et al., 1988). Low-involvement products are usually inexpensive and pose minimal risk to the buyer. Conversely, high-involvement products are more complex, costly, and represent a greater risk to purchasers. In the latter case, buyers typically engage in extensive problem-solving, dedicating considerable time to compare different aspects of available options (Beatty and Smith, 1987). The level of purchase involvement affects information processing strategies, such as the depth of information search and the extent of signal consideration, but further research is needed to decipher these dynamics (Liu et al., 2019). Consequently, we hypothesize that the relationship between signal cost and consumer information processing may differ depending on the level of purchase involvement.

To comprehend users' processing of market signals, both practitioners and academics recommend the use of multiple methods, especially tracking eye movements to understand selective attention and information acquisition behavior (Wedel and Pieters, 2008; Kingsnorth, 2022). We employed eye-tracking in addition to interviews to explore consumers' conscious and unconscious visual attention, when evaluating webpages of both low- and high-involvement goods. To date, as far as we are aware, there have been no eye-tracking based research investigating consumer behavior in relation to low and high involvement goods. As presented in Table 1, we found only a few studies focusing on: reviews (Mikalef et al., 2021; Shi et al., 2020; Bigne et al., 2020; Jin et al., 2023), comparing consumer behavior for search and experience goods (Luan et al., 2016; Maslowska et al., 2020), and ratings (Guan and Lam, 2019). This literature confirms the usefulness of eye-tracking based research for studying consumers' online marketplace behavior as well as identifying the importance of understanding how behavior varies by product type.

Given limited prior research, there exists a unique opportunity to explore the connections between signal cost and high versus low involvement products. Signals vary in terms of the costs they impose on sellers. It is postulated that high-cost signals hold more value for buyers (Connelly et al., 2011), especially in a high purchase involvement situation. Our study investigates how consumers process and interpret signals of disparate costs in the context of high involvement products (e.g., iPhone) as opposed to low involvement products (e.g., iPhone charger). Our objective is to identify which signals - low versus high-cost signals - wield the most influence over consumers' decision-making processes when scrutinizing listings of identical products, differentiated by low versus high involvement purchases. Consequently, our third research question poses: *does the salience of high-cost signals intensify when consumers make high involvement purchases as opposed to their decision-making processes for low involvement purchases*?

While contributing to the academic literature, the study also has relevance for practitioners. Within the digital platform ecosystem, information asymmetry between stakeholders, such as developers and users, is a recognized as an important practical problem (Ahearne et al., 2022). For designers of digital platforms, it is imperative to comprehend how they should be designed enhance platform performance (Almunawar and Anshari, 2022). Similarly, for online retailers, it is essential to discern which market signals are most salient to potential buyers. This understanding can enable them to design their online marketplaces effectively (Venkatesh et al., 2022). Despite these important concerns, there is currently a lack of comprehensive evaluations of how the salience of market signals varies between high and low involvement purchase scenarios. To bridge this research gap and address the research questions, we present the results of two studies. The first study, qualitative in nature, employs interviews to capture users' conceptualizations of market signal salience, detailing how this varies between high and low involvement purchases. The second study utilizes eye tracking to test hypotheses generated from signaling theory.

2. Literature review and hypotheses development

Online marketplaces bring together a diverse set of sellers who typically are unknown to potential buyers. Consumers usually evaluate listings according to a variety of attributes to select an item that best suits their needs (de Langhe et al., 2016). However, the uncertainty caused by the online environment, buyers' lack of familiarity with sellers, and the volume of often conflicting information makes decisions potentially complex and cognitively demanding (Wang et al., 2024).

Signaling theory provides a basis for understanding how actors use cues (i.e., signals) to make judgements of quality when faced with limited information about an entity (Baier et al., 2022; Shah et al., 2023). It assumes that actors offering higher quality goods and services have an incentive to communicate (signal) this information to potential buyers, which reduces information asymmetry and allows the latter to make better-informed decisions (Connelly et al., 2011; Baier et al., 2022). In contrast, those offering lower quality goods prefer information asymmetry to persist, so that buyers cannot distinguish the inferior quality of their offerings, a feature that may lead ultimately to market failure (Akerlof, 1970). This problem relates to online marketplaces as they bring together a disparate set of buyers and sellers, who typically differ in the quality of their offerings. Prior to purchase, buyers have incomplete knowledge regarding the quality of the sellers' goods and their trustworthiness. If market signals are effective in allowing buyers

Table 1
Overview of previous eye-tracking based studies of online marketplace behavior.

Author	Objective/purpose	Methods	Key findings
Luan et al. (2016)	Investigation of consumers' online review search behaviour, considering the type of product reviewed	Eye-tracking	Consumers of search products seek attribute-based reviews, while consumers shopping for experience products tend to seek experience-based reviews
Guan and Lam (2019)	An examination of online product reviews with averages of product ratings given by reviewers	Eye-tracking	Consumers either confirm or disconfirm their expectancies about a product thanks to the average rating statistics
Maslowska et al. (2020)	Investigation of consumer reviews in the context of other elements on product pages for search and experience goods.	Eye-tracking	Although product-related information was crucial in consumer decision-making, consumers also spent time on review-related information. Differences between search and experience goods were observed.
Shi et al. (2020)	Examination of the relative effect of sales volume and the percentage of positive reviews	Eye-tracking	Consumers underestimate the rating of products with high sales volume relative to products with low sales volume. Nevertheless, the rating difference can be eliminated by presenting a percentage of positive reviews.
Bigne et al. (2020)	Analysis of conflicting online reviews (text and photos) using automatic processing patterns and conscious perceptions	Eye-tracking	The overall meaning of a sequence of online reviews is strongly influenced by the order of the positive and negative stimuli.
Mikalef et al. (2021)	Consumers' assessment of marketer-generated (MGC) as well as user-generated information (UGC)	Semi-structured interviews, Eye-tracking	Differences in terms of engagement, cognitive processing, and observation of consumers by the different types of content.
Brand and Reith (2022)	Examination of the credibility of online reviews (video vs. text) in relation to nationality, gender, and online shopping frequency	Survey, Eye-tracking	The results indicate that video reviews are only slightly better than textual reviews. Statistically significant differences between these two types of reviews were found in nationality, gender, and online shopping frequency.
Jin et al. (2023)	Investigation of consumers' perceived usefulness of overall and individual text-based reviews (OTRs vs. ITRs) for search vs. experience products, and information processing features.	Survey, Eye-tracking	OTRs show higher usefulness than ITRs, regardless of product type. ITRs are perceived to be more useful for experience products than for search products.

to distinguish between lower and higher quality sellers, they solve online marketplaces' information asymmetry problem, turning experience and credence qualities into quasi-search attributes that are known to the buyer prior to purchase (Perrini et al., 2010).

Extensive research on online marketplaces considers the effects of market signals on user behavior, focusing on aspects such as website characteristics, web design features, service feedback, and user ratings (Shah et al., 2023; de Langhe et al., 2016; Mavlanova et al., 2016; Mikalef et al., 2021; Maslowska et al., 2020). In addition, de Langhe et al. (2016) scrutinize the influence of online user ratings on consumer behavior, probing the accuracy with which these ratings depict the genuine quality of the goods or services in question. They raise critical questions concerning both actual validity (the correlation of ratings with quantifiable quality measures) and perceived validity (consumers beliefs in the credibility of these ratings). Similarly, Mavlanova et al. (2016) explore the roles of internal and external signals within online marketplaces. External signals entail market-driven or environmental elements such as customer reviews, competitor actions, or policy shifts. Internal signals, however, emerge from within the e-commerce platform itself, epitomized by sales figures, website traffic, or performance metrics. They find that both types of signal affect perceived trust, which in turn affects purchase intentions, but that perceived signal believability, regardless of whether internal or external, is paramount.

Numerous studies examine the impact of online marketplace signals on bidding behavior, both in terms of amounts and timings. For example, Li et al. (2009) explore the use of three categories of signals leveraged by eBay sellers: direct quality indicators, indirect indicators, and credibility cues. They find that direct and credibility indicators are the most influential. However, the study does not account for more recently added market signals, such as text-based reviews. Van Der Heide et al. (2013) expand on previous studies by considering the effects of reputation systems and product photography on eBay sales. They concluded that high-quality product photos and strong seller reputations increase bid frequency but do not necessarily translate into actual sales.

Signal costs represent the perceived transaction costs associated with a given signal (Connelly et al., 2011). For instance, high-cost signals like independent buyer recommendations are not easily fabricated by sellers and thus command greater credibility. In contrast, textual product descriptions constitute low-cost signals, as they can be easily manipulated by the seller (Palmieri and Rocci, 2023). From this perspective, low-cost signals may not effectively distinguish between high and low-quality offerings (Walczak et al., 2006), limiting their value in terms of facilitating informed decisions (Gneezy, 2023). Consequently, in the realm of online marketplaces, high-cost signals are expected to be more salient in the consumer decision-making process. Li et al. (2015) provide empirical evidence supporting this theory, demonstrating that auctions on eBay with user-generated photographs are more likely to lead to a sale than those with stock photographs. Therefore, it is anticipated that:

H1: Users of online marketplaces will pay greater attention to costly signals during purchase decisions.

In the vast and complex landscapes of online marketplaces, the act of searching and processing market signals is a task that requires both time and cognitive effort (Moraga-González et al., 2017). As expounded by Moraga-González et al. (2017), the principle of nonsequential search - an exploratory strategy where consumers are not bound to the first acceptable product they discover, but rather revisit previously inspected options - adds another layer of intricacy to this process. The cognitive investment inherent in this search methodology necessitates consumers to critically assess the costs and beenfits of the attention they allocate to market signals. Devoting greater attention to searching and processing market signals has the benefit of reducing the likelihood of making an inappropriate purchase, thus reducing purchase risks. However, the risks associated with purchase decisions is not uniformly distributed across all product categories. Low involvement goods, are typically inexpensive and pose limited risks to the buyer, thus requiring a relatively simple decision-making process (Brisoux and Cheron, 1990). In contrast, high involvement products - complex, expensive, and fraught with elevated buyer risk - demand an elevated degree of consumer vigilance in their market signal evaluation (Beatty and Smith, 1987). This discrepancy in risk profiles should affect the extent to which consumers are willing to bear search costs. The expectation being that, in the case of high involvement goods, consumers are predisposed to an extensive problem-solving process, evaluating market signals rigorously when making a purchase (Bettman et al., 1998). Consequently, consumers' evaluative strategies and attention to market signals varies, contingent on the level of purchase involvement of the goods under consideration. Therefore, we propose that:

H2: For high, as opposed to low, involvement goods, users of online marketplaces will pay greater attention to market signals

In the domain of online marketplaces, it is expected that consumers exhibit heightened attention towards market signals, especially when purchasing high involvement goods due to the amplified risks. High-cost signals play a particularly crucial role in these decisions as they serve as robust mechanisms for ameliorating the information asymmetry between sellers and buyers, thereby empowering consumers to make purchases that align well with their preferences (Connelly et al., 2011; Boulding and Kirmani, 1993; Dang and Viet, 2021). These high-cost signals, often involving considerable seller investment or risk (Spence, 1973; Cabral and Hortacsu, 2010), functioning as reliable indicators of genuine product quality, which is a key determinant of consumer choice for high involvement goods (Zeithaml, 1988; Erdem and Swait, 1998). On the other hand, low-cost signals, due to their ease of imitation and limited credibility (Kirmani and Rao, 2000), offer little in terms of enhancing users' ability to gauge the true quality of a product (Hoch and Ha, 1986). This may render them less influential or even irrelevant in the context of high involvement goods where quality judgments are critical (Byun et al., 2021). Consequently, consumers may discount or ignore these signals when evaluating such purchases (Resnick et al., 2006; Gneezy, 2023). Overall, the differential impact of signal cost on consumer decision-making in online marketplaces underscores the need for a nuanced understanding of how consumers navigate and interpret these cues in different product contexts. Consequently, we expect that:

H3: For high, as opposed to low, involvement goods, users of online marketplaces will pay relatively greater attention to costly market signals, which are beyond sellers' direct control

3. Study 1

3.1. Design and methods

To assess the salience of market signals in high and low purchase involvement decisions, Study 1 adopted a qualitative, interview-based approach. Informed by signaling theory, interview questions concerned (a) what market signals interviewees considered salient in their decision-making when evaluating listings of the same product and (b) how the importance of different market signals changed when consumers made high compared to low involvement purchases. Interviewees discussed whether high-cost signals were of greater importance in their decision-making process than low-cost signals. To stimulate discussion and improve external reliability, we presented each interviewee with a common set of actual listing results from eBay. These listings concerned a specific high involvement purchase (a new iPhone) and low involvement purchase (new, replacement iPhone charger). Interviewees also confronted cases where listings included a range of price points and, to explore in greater depth non-price related factors, search results displayed prices with limited variance. All products listed were new (not used or remanufactured).

Through the interviews, we examined the relative importance of thirteen market signals used on eBay. They are categorized into three groups: *product signals* (price, photograph, title, and number sold), *logistics* (postage cost, delivery time, auction vs. buy it now, eBay premium service, and payment method), and *seller signals* (seller rating / feedback score, reviews, location of seller, and seller start date). Some of these signals involve higher transaction costs and are less easily feigned (high-cost signals). In the case of eBay, some signals are displayed in the initial search listing results while others are only revealed to users after clicking on a specific item in the search listings.

The study adopted operational construct (theoretical) sampling, selecting cases that represent 'real-world examples (i.e., operational examples) of the constructs in which one is interested' (Patton, 2002, p.238–9). Consequently, to be included an interviewee had to have made multiple (5 +) purchases via eBay and be an eBay user for at least two years. This allowed all interviewees to discuss, based on experience, the salience of specific market signals. The sample comprised 20 young adults who, at the time of interview, had used eBay for 5.65 years on average. Table 2 profiles interviewees in terms of gender, age, and usage experience.

All interviewees received a participant information sheet explaining the research project and after agreeing to participate, interviewees signed a consent form. On average, each interview lasted for one hour. All interviews were audio-recorded (following interviewees' agreeing consent) and transcribed, permitting qualitative data analysis. We employed thematic analysis to identify, analyze, and report patterns (themes) within the data (Braun and Clarke, 2006). The inductive analysis followed the procedures recommended by Braun and Clarke (2006), namely: data familiarization, generation of initial codes, searching for themes, reviewing themes, and defining and naming themes.

3.2. Findings

The first aspect of the thematic analysis considered users' perceptions of the salience of the thirteen market signals available for eBay online marketplace listings when making purchase decisions. Interviewees deemed eleven of the thirteen market signals to be salient: price, photograph, title, number sold, postage cost, delivery time, eBay premium service badge, seller rating / feedback score, reviews, and location of seller. Table 3 summarizes the salient market signals, with illustrative quotations for high and low involvement goods. Users deemed two market signals available on eBay as irrelevant to judgments of quality: payment method, and seller start date.

Regarding the identification of salient signals, some are consistent with past evidence, but this study also identifies factors not previously

Table 2
Profile of Interviewees.

Participant ID	Sex	Age	Usage experience of eBay
P1	M	23	5 years
P2	M	21	7 years
P3	F	20	4 years
P4	F	20	5 years
P5	F	21	4 years
P6	F	21	4 years
P7	F	21	2 years
P8	F	19	8 years
P9	M	22	3 years
P10	M	22	7 years
P11	F	23	6 years
P12	F	22	5 years
P13	F	21	10 years
P14	M	21	3 years
P15	M	22	5 years
P16	M	22	8 years
P17	M	22	7 years
P18	M	22	4 years
P19	M	22	10 years
P20	F	20	6 years

Table 3
Salient market signals.

Category of Signals	Market signal	Illustrate quote relating to low involvement purchase	Illustrate quote relating to high involvement purchase
Product	Price	"it is just a cable and (…) so it doesn't actually really matter what it looks like. Then I guess I'd look at the price." (P11)	"I think because I'm spending a lot of money, I don't want to take any risks. I'd rather pay more for the product itself but be sure I'm going to get the one that I paid for." (P3)
	Photograph	"I wouldn't click on … cos I don't like the picture. Even though it says eBay premium service … I don't like it." (P8)	"Probably that one because that looks like someone has taken it in their own home and you know that they've actually got it." (P11)"I'm looking at it and I'm saying 'is this a legit seller?' based on the picture" (P10).
	Title	"I don't think I even really looked at the title." (P11)	"I have to know what it is and what condition it's in and everything. I think it's important for all that to be in the title." (P14)"Sometimes they put like 100 stars and put "genuine genuine genuine item" and I just think that is not genuine." (P12)
	Number sold	"Quite a lot have been sold so that shows that it's probably a good product." (P4)	"The fact that … has sold 1087 is drawing me towards it." (P3)
Logistics	Postage cost	"I'm not gonna pay that because percentage wise, it's a 30 % increase in the overall price of buying the charger." (P19)	"I also wasn't as bothered about postage charge and some of the other minor things when choosing the phone because it's more important for me to get a good product so those other things become less significant." (P8)
	Delivery time	"If it takes a while to come but it's a lot cheaper then I'm not too bothered. Unless I needed it like, tomorrow." (P20)	"The importance of delivery time just depends on the immediacy I need the item." (P19)
	Auction versus buy it now	"It is too time consuming. I'm not attentive enough to get there on time or whatever for an auction." (P9)	"I like buy it now so I know there's no competition with other buyers" (P20)
	eBay premium service	"eBay premium seller - I don't know what that means but that looks official." (P19)	"That is probably quite a big thing for me….It makes me feel a bit more comfortable when buying like (…) I dunno, it reduces the risk." (P14)
Seller	Seller rating / feedback score	"Photograph and price are what I look at first but it would definitely be the seller that I would make my final decision on." (P8)	"Even if I was in love with something and the seller had a bad rating that would be the deal breaker." (P20)
	Text reviews	"I probably wouldn't click on the profile and read all the reviews if I was just buying the charger. I'd just look at their like, rating and that's it. But if I was spending more money then I'd definitely spend more time looking into them and reading everything, yeah."(P7)	"If it was an expensive product though like if I was buying the phone, I'd click on the seller and probably actually read reviews from other buyers and just check everything looked okay." (P4)
	Location of seller	"Unless that meant it was gonna take like weeks for it to arrive I wouldn't really care no." (P9)	"For me it's not really about the time I don't really care how long it takes but the worry is like, it's going through customs, it's going abroad, it's doing all this, I don't want to have my little new phone going on a plane flying around, I just want it to get safely from the seller to me, you know?" (P10)

considered within the literature on online marketplace signals. Signals identified as salient in this study which have been previously identified as important include: price (Ba and Pavlou, 2002), photographs (Li et al., 2009; Van Der Heide et al., 2013), title / product description (Li et al., 2009), number sold (Resnick et al., 2006), postage cost (Van Der Heide et al., 2013), delivery time (Hoxmeier, 2000), seller rating (Dewan and Hsu, 2004; Manes and Tchetchik, 2018), feedback scores (Bolton et al., 2024), and reviews (Li et al., 2020; Manes and Tchetchik, 2018). We find photographs to be an important signal, with a preference for user-generated over stock photographs. This echoes findings that user generated photographs generate a greater likelihood of a sale (Li et al., 2015) as well as more bids and higher selling prices (Van Der Heide et al., 2013). As far as we are aware, previous research on online marketplaces does not consider the country of origin of the seller as a salient signal, which our interviewees regarded as important, especially regarding high involvement products. There is also a lack of specific previous research on the eBay premium service badge, which in our study interviewees took as an indicator of seller credibility albeit with very little understanding of what it implied.

A second stage of the analysis considered whether the salience of market signals varies depending on the type of purchase (high versus low purchasing involvement) and stages of decision-making (inclusion in a consideration set, then selection from within a consideration set). Fig. 1 synthesizes the findings to derive a process model. Regarding low involvement purchases, for inclusion within a consideration set, price is critical, due to low monetary risk, as well as the inspection of photographs. For high purchase involvement decisions, the first requirement is to establish seller credibility and for this, users evaluate high-cost

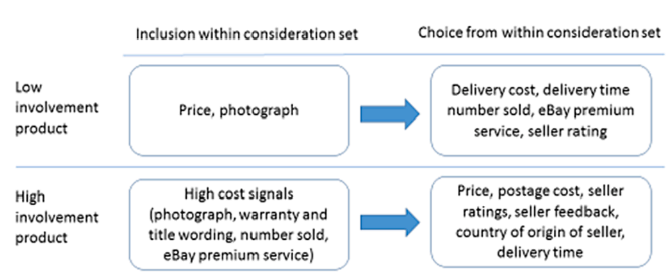

Fig. 1. Model of salient market signals for online marketplaces by degree of involvement and stage of decision-making.

signals. Consequently, in the high purchase involvement scenario, interviewees took longer to evaluate listings of the same product and identified more signals as relevant when drawing up a consideration set. For high involvement goods, after an initial screening of seller credibility to establish a consideration set, online marketplace users assess the seller in greater depth by reading recommendation reviews and reflecting on their location, as well as judging prices and logistics issues, before making a purchase. Regarding logistics cues, such as, free shipping, participants performed quick mental accounting to see if adding more products would increase the utility of the total cart. The examination of market signals thus became a lengthier and complex process when making high involvement purchases. Generally, users took more time examining these listings, paying attention to the title, reading the full description of the product, and paying attention to signals linked to recommendations from past users. This suggests that the importance of market signals depends on the degree of purchase involvement, as assessing seller credibility is more important when making a high involvement (riskier) purchase.

In contrast, for low purchase involvement situations, users deemed a small number of signals (e.g., price and photograph) as sufficient for initial screening. Such a limited range of cues allows for 'fast and frugal' decision-making (Gigerenzer et al., 1999) which users regard as appropriate for low involvement purchases. However, multiple high-cost signals are attractive in the case of high involvement purchases. Specifically, users value signals that establish seller credibility, as this is a necessary requirement for inclusion in the consideration sets for high involvement purchases.

In many cases, users' understanding of market signals is limited (e.g., eBay premium service) but what matters for decision-making is if consumers regard an indicator to be a reliable cue of seller credibility. Consumers generally deem seller ratings as dependable indicators of seller credibility. In the low involvement scenario, interviewees often used this as a sufficient indicator of seller credibility. On the other hand, before making a high involvement purchase, interviewees assessed the seller in greater depth, by reading free text reviews and discovering the location of the seller.

4. Study 2

While interviews provide rich data regarding users' conceptualization of decision-making processes (Kienzler and Kowalkowski, 2017), there is a danger of incomplete accounts and demand artefacts, whereby individuals provide answers perceived to be most socially acceptable. Moreover, assessing the allocation of visual attention with conventional methods provides feedback only on those processes which are part of conscious reflection, yet attentional processes do not solely depend on conscious control (Shipley, 2021). Consequently, it is beneficial to utilize more technically advanced methods to obtain more accurate results (Godfroid and Hui, 2020, Mikalef et al., 2021). An eye tracking study captures directly which market signals consumers look at first, for how long, and the order of scrutiny when evaluating listings, providing a more accurate picture of shoppers' information processing than self-reported methods (Ye et al., 2020). It is a valuable method to elucidate visual attention processing by consumers, measuring their interest in presented information, and how and where they search for specific items on the screen (Ye et al., 2020, Motoki et al., 2021). Study 2 thus tests the hypotheses, employing an eye tracking experiment. Prior to conducting Study 2, a pilot study with 8 subjects occurred, establishing the appropriateness of an iPhone and iPhone charger as high and low involvement goods respectively. Pilot study results are not reported. However, because they were in accordance with the expected outcomes, we proceeded to Study 2. Eye-tracking data are available from the authors on request.

4.1. Design and methods

4.1.1. Participants

In June 2020, we recruited 49 students by approaching them at Poznań University of Life Sciences in Poland, out of which 47 students were invited to pursue the experiment due to a satisfactory eye-tracking calibration. From this sample, three students had to be excluded from the study because the Ogama program crashed during the experiment. Consequently, 44 students were considered for the final analysis. When recruiting the subjects, participants responded to pre-selection questions, confirming that they purchased at least three goods via online marketplaces (e.g., Allegro or eBay) in the previous two years.

4.1.2. Experimental design

The eye-tracking study was performed on a 22-inch monitor with a panel eye tracker (GazePoint). Data recording occurred at a sampling rate of 60 Hz, that is about every 16 ms (ms). Prior to the experiment, participants read a participant information sheet and then if happy to proceed, signed an informed consent form and followed the calibration process for the eye-tracker. Participants received information on the study's purpose and that their tasks were twofold: *1)* choose between three products from a listings page, and *2)* choose whether to buy or not a particular product. After they made their choices, subjects completed a short questionnaire on a different laptop, which measured demographics and control variables (e.g., number of past online purchases and gender). The subjects could spend as much time as they wished to make their decisions. Consequently, we avoided any time pressure, which affects attention, specifically fixation durations and the number of fixations (Pieters and Warlop, 1999). Fixations are periods of relative stability in eye movements, in which visual information is extracted. In other words, they reveal the maintenance of a gaze on a particular point at a particular point in time. An average fixation duration corresponds to 200–300 ms (Duchowski, 2017).

During the experiment, subjects had to make purchase decisions regarding the same two types of goods as in Study 1: a high-involvement good (an iPhone) and a low-involvement good (an iPhone charger). Firstly, for each of these goods, they had to choose between three similar products, which differed in terms of prices on a listings page (Fig. 2). Secondly, they had to decide whether to buy or not one of the options, based on selected market signals, presented on the product page (Fig. 3). In the experiment it was expected that subjects would pay more attention to user-made pictures rather than catalogue pictures given that the former are more costly market signals.

All subjects participated in all conditions, meaning that they saw both high- and low-involvement goods in a randomized order (within-subjects design). It was decided to conduct a within-subject design due to difficulties recruiting participants caused by the Covid-19 outbreak. At that time, students learnt mainly online and only sporadically attended the University campus. During the experiment subjects wore face masks and plastic gloves to diminish the risk of contamination, in keeping with university and national public health protocols.

4.1.3. Results

In this section, we address the hypotheses stated at the beginning of this paper. Firstly, we analyzed the product listings. Secondly (and more deeply), we analyzed product pages, for which we identified relevant Areas of Interest (AOIs), presenting descriptive statistics. For analytical purposes, we divide the AOIs into three groups: product signals (1a - photograph/catalogue, 1b - photograph/user, 2 – title, 3 - product rating, 4 – price, 5 - product description), logistics signals (6 - price including delivery / delivery cost, time of delivery, return cost, location of a seller, 7 – "buy" and "not buy" buttons), and seller signals (8 - feedback score, 9 - seller rating, 10 – reviews). The AOI for pictures was divided into two sub-groups, namely user generated and catalogue images.

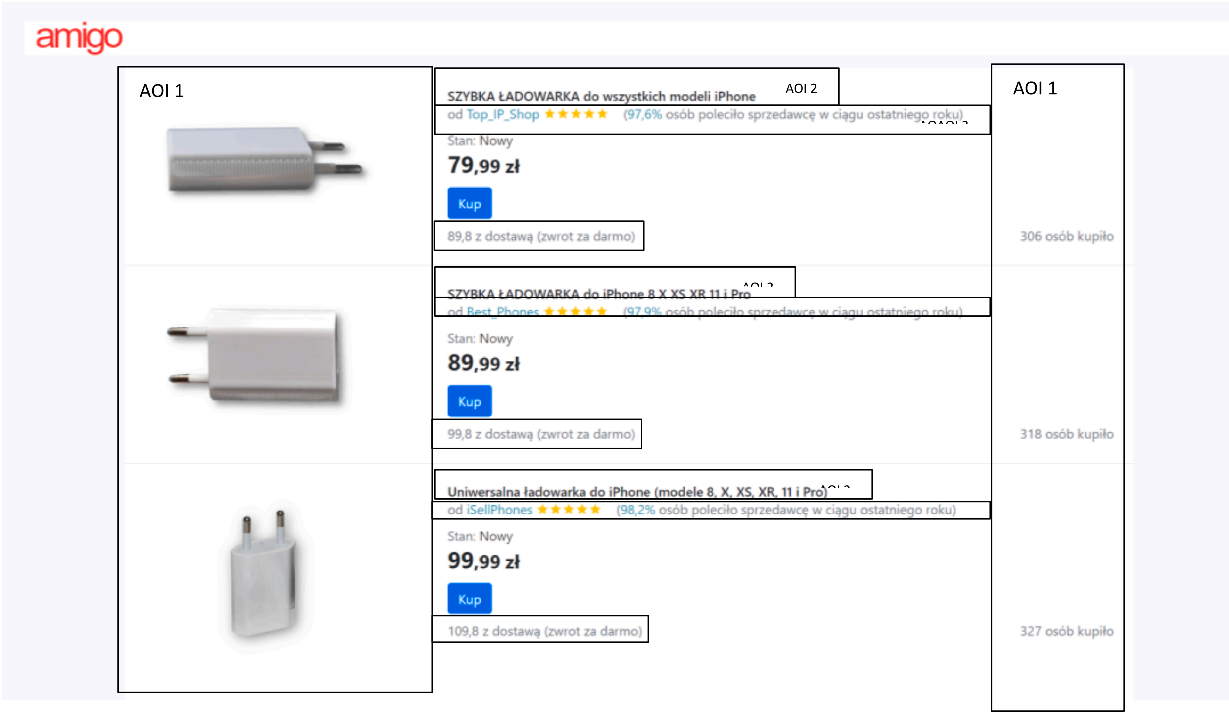

Fig. 2. Areas of Interest (AOI) for a listing page of a low involvement purchase: an iPhone charger. AOI product signals: 1 - photo, 2 - title, 3 – product rating, 4 – price; AOI logistics signals: 5 – buy button, 6 – logistics (price with delivery, return for free), 7 – who bought – where would you classify it?

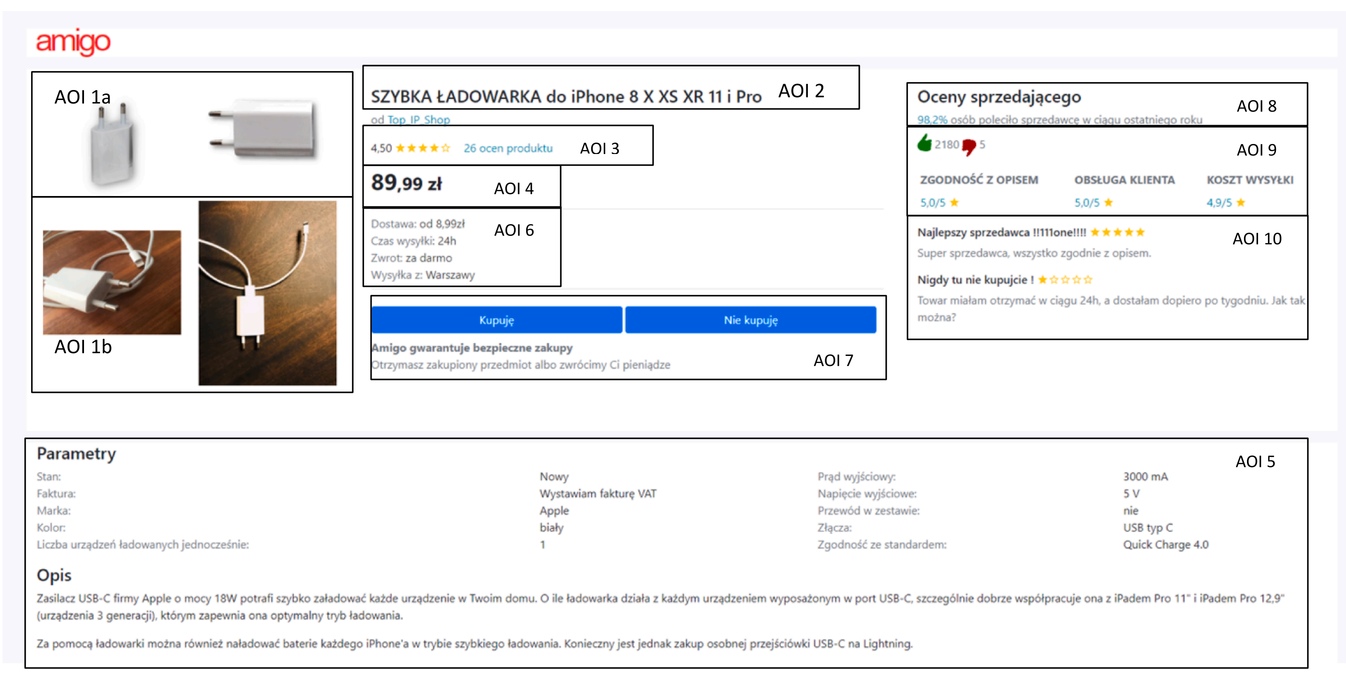

Fig. 3. Areas of Interest (AOI) for a product page of a low involvement purchase: an iPhone charger. AOI product signals: 1a - photograph/catalogue, 1b - photograph/user, 2 – title, 3 - product rating, 4 – price, 5 - product description; AOI logistics signals: 6 - logistics (price with a delivery cost/ delivery cost, time of delivery, return cost, location of a seller), 7 – "buy" and "not buy" buttons; AOI seller signals: 8 - feedback score, 9 - seller rating, 10 – reviews.

4.2. Salience of market signals for listing pages

To test the hypothesis relating to what market signals are salient when consumers evaluate online marketplace listings for the same product, we analyzed the average number of fixations (i.e., the total number of maintained gazes at one point on a sampling rate of 60 Hz on average) in two ways. First, the AOI were gathered into groups of three pictures, three titles, three product ratings, etc., as would be seen on a listings page. Second, the AOI for the first product were distinguished, because according to the heat maps of fixations, subjects looked mainly at the first product in the listings.

As detailed in Table 4, the highest number of fixations occurred for the three pictures of iPhones (i.e., 4.23) and was three times higher than for the three pictures of chargers (i.e., 1.23). The difference between

Table 4
Comparison of number of fixations (in count) on a listings page for high and low involvement goods, with the aggregated AOIs (e.g., three pictures of all iPhones, three titles of all chargers).

AOI name	All products in the list			1. product in the list		
	List of 3 chargers	List of 3 iPhones	Student *t*-test (standard error)	List of 3 chargers	List of 3 iPhones	Student *t*-test (standard error)
Picture	1.2273	4.2273	−1.6664***(0.6708)	0.3636	1.5909	−4.2095***(0.2915)
Title	2.0455	2.9773	−1.5420* (0.6042)	0.9318	1.3863	−1.3801*(0.3293)
Product rating	2.1818	1.9091	0.4908(0.5556)	0.8181	0.9318	−0.3733(0.3044)
Price	2.0227	2.6136	−1.2462*(0.4742)	0.7954	1.3409	−2.2120(0.2466)
Buy button	1.3409	1.6591	−0.7692(0.4137)	0.7272	0.9545	−0.8927(0.2546)
Cost of delivery	1.6818	1.1136	1.3099*(0.4338)	0.6818	0.6364	0.1871(0.2430)
Who bought	0.4091	0.6364	−1.0863*(0.2092)	0.1818	0.2727	−0.7866(0.1156)

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

these two values was statistically significant at $p < 0.001$. The second longest viewed AOI was the title, which was seen on average 2.98 times for the three iPhones and 2.05 for the three chargers. The difference between these values was also statistically significant at $p < 0.1$. Price received the third-highest number of fixations (i.e., 2.61 and 2.02 for the three iPhones and three chargers respectively). The difference was statistically significant at $p < 0.1$. These three areas of interest, (i.e., picture, title, and price) belong to the AOI category of product signals, and as the above results show, subjects devoted a higher number of fixations to a high-involvement good than for a low-involvement good. This result is consistent with H2.

For the AOI "product rating" subjects looked almost equally long for both types of goods (i.e., 1.91 and 2.18 for three iPhones and three chargers, respectively). In addition, regarding logistics signals, subjects looked more frequently at the buy button for the three iPhones (1.66), but they looked more frequently at the cost of delivery in the case of the three chargers (1.68). The difference for the "buy button" was not statistically significant, but it was statistically significant for the AOI "cost of delivery" at $p < 0.1$. It is worth highlighting that, on average, subjects looked longer at the AOI cost of delivery of three chargers (1.68) than at the AOI cost of delivery of three iPhones (1.11). It seems that when buying a high-involvement good (which was more expensive), the costs of delivery are less important to users than when buying a cheaper, low-involvement good.

The lowest number of fixations was found for the AOI "who bought" (0.64 for three iPhones and 0.41 for three chargers, on average). The difference was statistically significant at $p < 0.1$. Two reasons may explain why this AOI receives the number of fixations. First, this AOI was located on the right-hand side of the screen, relatively far from other AOIs. Second, users may not consider this piece of information as particularly valuable in their decision-making.

Table 5 reports the average number of fixations for just the first product in the listings. It indicates that when looking at the first product in the list, the number of fixations was the highest for the first picture of an iPhone (1.59) and was around four times higher than for the first charger (0.36). This difference was statistically significant at $p < 0.001$. Another statistically significant difference at $p < 0.1$ concerned the AOI title, in which case the number of fixations for the first iPhone was equal to 1.39 and for the first charger – 0.93. Overall, subjects looked longer at the AOIs of the high-involvement good than at the AOIs of the low-involvement good, again consistent with H2. The remaining differences between the AOIs were not statistically significant, meaning that subjects looked about the same number of times at these market signals for the first iPhone and the first charger in the listing.

In terms of the average time spent on the AOIs, subjects devoted most time to the pictures of the three iPhones (i.e., 978.68 ms) but only 217 ms looking at the three pictures of chargers ($p < 0.001$). It seems that pictures on a listing page are more important for high than for the low involvement goods. Secondly, subjects spent around 516.12 ms looking at the price of the three iPhones but only 359.14 ms – at the three chargers. The difference between these AOIs was statistically significant at $p < 0.1$, meaning that the comparison of prices is particularly important for a high involvement good. At the same time, the AOI cost of delivery received longer attention in the case of the low-involvement good (367.30) than than high involvement good (162.86). This may reflect that delivery costs are a higher proportion of total costs in the case of the low involvement good, and thus take on higher *relative* importance.

Another AOI group, which was characterized by a significant statistical difference at $p < 0,1$was the AOI group called "who bought". Namely, subjects spent 143.38 ms on this AOI group for the three iPhones and 86.64 ms for the three chargers, on average ($p < 0.1$). The differences between the remaining AOI groups were not statistically significant (i.e., title, product rating, buy button).

4.3. Salience of market signals for high and low involvement purchases for product pages

As detailed in Table 6, the highest average number of fixations was found for the AOI "product description" of an iPhone at 34.6, which was three times higher than the average number of fixations for the AOI "product description" of a charger (11.3). The difference between these two values was statistically significant at $p < 0.001$, thereby suggesting that subjects looked a significantly greater number of times at this AOI for a high-involvement good than for a low-involvement good. One reason for the higher number of fixations lies in the fact that this AOI was the biggest one in terms of prominence on the online marketplace (over 30 % of the screen) and contained most of the text. Regarding

Table 5
Comparison of time of fixations (in ms) for high- versus low-involvement goods on a listings page.

AOI name	All products in the list			1. product in the list		
	3 chargers	3 iPhones	Student *t*-test (standard error)	3 chargers	3 iPhones	Student *t*-test (standard error)
Picture	217.0000	978.6818	−4.3160***(176.4782)	45.1818	479.7955	−3.6509***(119.0413)
Title	369.3864	416.8864	−0.4682(101.4447)	178.5000	188.2727	−0.1639(59.6298)
Product rating	502.4545	431.3182	0.3211(221.5255)	164.6591	222.5682	−0.6569(88.1583)
Price	359.1364	516.1591	−1.2398*(126.6517)	178.8636	218.5000	−0.6122(64.7483)
Buy button	254.6364	360.4773	−0.9360(113.0811)	156.8636	225.2273	−0.8590(79.5821)
Cost of delivery	367.2955	162.8636	2.1230**(96.2940)	194.8409	88.8864	1.5880**(66.7208)
Who bought	86.6364	143.3864	−1.0128*(56.0343)	58.9772	33.5909	0.7340(34.5850)

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 6
Comparison of number of fixations (in count) for high- versus low-involvement good on a product page.

no	name of AOI	Charger	iPhone	t-statistics
AOI product signals				
1	Price	1.6591(0.2738)	1.8181(0.2967)	−0.3940
2a	Photo (catalogue)	1.1136(0.2186)	2.0227(0.3386)	−2.2553**
2b	Photo (user)	3.4772 (0.7067)	3.1818(0.6205)	0.3141
3	Title	0.8863(0.1816)	1.2954(0.2380)	−1.3664*
4	Product rating	0.6591 (0.1298)	0.9545(0.1281)	−1.1550
5	Product description	11.3181(2.2989)	34.6363(3.9516)	−5.1005***
AOI logistics signals				
6	Logistics	1.7500(0.4216)	3.6364(0.7131)	−2.2771**
7	Buy buttons	0.6364(0.1723)	1.9090(0.5458)	−2.2236**
AOI seller signals				
8	Feedback score	1.7954(0.3419)	3.1818(0.6641)	−1.8560**
9	Seller rating	3.9773(0.6515)	3.6818(0.6319)	0.3255
10	Reviews	4.5455(0.9403)	6.0455(0.9287)	−1.1350*

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

specific AOI product signals, the differences between the number of fixations for the high and low involvement goods were statistically significant for “photo catalogue” at $p < 0.05$ and “title” at $p < 0.1$. Subjects devoted over one fixation to the “title” of an iPhone. While not every subject looked at the title on a product page for a charger, subjects looked at least once at the title on a similar page for an iPhone. Differences between the high and low involvement goods on the three remaining AOIs (i.e., price, user photo, and product rating) were not statistically significant.

Furthermore, Table 6 shows that in the group of AOI seller signals, subjects overall devoted a higher number of fixations for a high-involvement good than for a low-involvement good, consistent with H3. For example, the AOI “reviews” was characterized by a higher number of fixations for a high-involvement good (6.05) than for a low-involvement good (4.55) (at $p < 0.1$). Also, subjects devoted 3.18 fixations for a high-involvement good and 1.80 fixations for a low-involvement good for the AOI “feedback score” ($p < 0.05$). However, they gave approximately a similar number of fixations for the AOI “seller rating” (around 3.8 fixations), so the difference was not statistically significant. Finally, both AOIs (i.e., logistics and buttons), which were classified to the group “AOI logistics signals”, were statistically significant at $p < 0.05$. In both cases, subjects gave a higher number of fixations for a high-involvement good (i.e., an iPhone) than for a low-involvement good (i.e., a charger).

Table 7 analyses differences in total time fixations for the low and high involvement goods. It indicates that users devoted the most time to the “product description” AOI (7755.21 ms) for the high involvement good. This was about three times longer than in the case of the charger page (2667.46 ms). The difference was statistically significant at $p < 0.01$. The analysis reveals that the AOI “product description” matters. It belongs to the category AOI product signals and along with the AOI photo catalogue is characterized by a statistically significant difference. When it comes to the AOI photo catalogue, subjects looked longer at the catalogue picture of an iPhone (362.41 ms) than for the charger (216.59 ms) ($p < 0.05$).

However, the difference between the user generated picture of an iPhone (676.27 ms) and of a charger (571.34 ms) was not statistically significant. Similar results were found for the AOI price, at which subjects looked 457.70 ms at the price of an iPhone and 387.55 ms at the price of a charger. The difference was not statistically significant. The differences between the two remaining AOIs (i.e., title and product rating) were also not statistically significant but in both cases, subjects looked longer at the AOIs of an iPhone (338.30 ms and 173.93 ms, respectively) than of a charger (173.93 ms and 123.61 ms, respectively).

Table 7
Comparison of the time of fixations (in ms) for high- versus low-involvement good on a product page.

no	name of AOI	Charger	iPhone	t-statistics
AOI product signals				
1	Price	387.5455 (83.0746)	457.7045 (101.5773)	−0.5347
2a	Photo (catalogue)	216.5909 (52.3922)	362.4091 (64.5151)	−1.7545**
2b	Photo (user)	571.3409 (128.7231)	676.2727 (163.6675)	−0.5039
3	Title	245.9773 (75.0444)	338.2955 (88.9347)	−0.7933
4	product rating	123.6136 (32.5425)	173.9318 (40.8344)	−0.9637
5	product description	2667.4550 (528.3800)	7755.2050 (1012.1060)	−4.4562***
AOI logistics signals				
6	Logistics	472.7727 (118.3492)	891.1364 (198.4252)	−1.8108**
7	Buttons	130.0227 (54.6287)	574.5682 (233.6202)	−1.8529**
AOI seller signals				
8	feedback score	503.4545 (114.6833)	895.3636 (202.0526)	−1.6869**
9	seller rating	955.6364 (179.5147)	950.6364 (201.2565)	0.0185
10	Reviews	1072.6590 (251.128)	1350.6820 (206.9487)	−0.8544

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

5. Discussion

5.1. Theoretical implications

Signaling theory seeks to explain how actors use cues (i.e., market signals) to make judgements regarding quality when faced with limited information (Connelly et al., 2011; Gneezy, 2023). Early work in this domain focused on how sellers of high-quality goods could distinguish themselves from those offering lower quality in the presence of information asymmetry (Spence, 1973), followed by research on the signals deemed relevant by buyers in both offline and online environments (Frota Neto et al., 2016; Van Nguyen et al., 2020). This literature pays little attention to how the nature of the good influences consumers' processing of market signals, prompting recent studies regarding the differences in consumer behavior for search and experience goods (Maslowska et al., 2020; Jin et al., 2023). This paper augments signaling theory by considering how consumers process market signals for high and low involvement goods, using the examples of an iPhone and an iPhone charger respectively. The paper makes three main contributions to the literature.

Firstly, we theorize how consumers' processing of market signals varies according whether purchases relate to high and low involvement goods, finding empirical support for all hypotheses. Specifically, for high, as opposed to low, involvement goods, both interview and eye-tracking based evidence indicates that: (i) users of online marketplaces pay greater attention to costly market signals, which are beyond sellers' direct control, (ii) pay greater attention to market signals for high involvement goods, and (iii) pay relatively greater attention to costly market signals in the case of high involvement goods. For low involvement goods, with minimal risks involved in a purchase, consumers rely most on a small set of market signals such as price and photographs to make decisions, consistent with heuristic processing (Jin et al., 2023), with less time spent considering market signals overall. In contrast, high involvement goods elicit deeper processing. Specifically, the eye-tracking study found that for product pages, consumers devoted a higher number of fixations, in the case of the high involvement good, for the following market signals: price, photo catalogue, photo user, title, product rating, logistics, buttons, feedback score, and reviews.

Most of these are costly signals and this finding is consistent with the notion that users of online marketplaces pay relatively greater attention to costly market signals, which are beyond sellers' direct control, for high involvement goods. The extension of signaling theory to consider differences between high and low involvement goods helps explain the relative importance of market signals and how this differs based on the nature of the purchase (Maslowska et al., 2020).

Secondly, the paper contributes regarding the methods employed to generate and test theories of consumers' processing of market signals. While methods relying on self-reporting can yield insights, they may not prove reliable, since attention to market signals can be non-conscious and not recalled (Wedel and Pieters, 2008; Yang, 2015). Eye-tracking based studies thus offer an important extension to the extant literature on digital marketing (Mikalef et al., 2021), offering a more precise understanding of users' attention to market signals. Yet while improving precision, eye-tracking based studies alone fail to provide insights into users' conceptualizations of market signals. Consequently, the combination of interview and eye tracking studies is appropriate to address the weaknesses of employing each method independently. When combining interview and eye-tracking based research, this paper highlights the importance of holistic assessments of consumers' processing of market signals, rather than studying one or two cues in isolation. This is because users make transitions between different market signals (Maslowska et al., 2020), with attention varying depending on the nature of the good. For instance, while attention to market signals is significantly greater generally for high involvement goods, the eye-tracking results indicate that attention to the costs of delivery is less relevant when users scrutinize listings for high-involvement goods. This may reflect that the costs of delivery are lower as a percentage of total costs for high involvement goods.

Finally, responding to calls for future research considering consumers' processing of multiple signals (Li et al., 2015; Maslowska et al., 2020), the paper contributes to the digital marketing literature by identifying the salient market signals for users when making purchases from online marketplaces. Based on a literature review and an analysis of the eBay platform, we identified 13 market signals present in online marketplaces (i.e., price, photograph, title, number sold, postage cost, delivery time, eBay premium service badge, seller rating / feedback score, reviews, and location of seller, payment method, and seller start date). Study 1 indicates that users perceive all but two of these market signals (payment method and seller start date) relevant for judging product quality for both types of goods. Furthermore, photographs (notably user-generated ones) are a crucial market signal, as is country of origin. While much prior research identifies country of origin as a salient attribute affecting consumer behavior (Donthu et al., 2021; Wang et al., 2022), its study in the context of online marketplaces is limited.

5.2. Managerial implications

The analysis generates three sets of insights for online marketplace sellers and platform managers. Firstly, for sellers, Studies 1 and 2 identify what signals buyers consider when evaluating listings and how they scrutinize them. This information provides a checklist as to what sellers should include in their listings – for instance domestic sellers should emphasize their country of origin. Generally, sellers should pay most attention to high-cost signals, especially for goods with greater product involvement. This includes investing in high quality, user generated images of products. Similarly, product descriptions attract considerable scrutiny, especially for high involvement goods, and online marketplaces could post tips on how best to describe products and how user generated photographs and videos can improve product appeal by reducing uncertainty. Perusal of online marketplaces like eBay reveals many incomplete listings and poor-quality photographs. Removing common faults in listings can add value to online transactions for both buyers and sellers. Specifically, paying attention to costly signals can help sellers with high-quality products distinguish themselves from lower quality rivals, increasing their sales volumes and prices achieved.

Secondly, the results generate actionable insights for online platform managers regarding communications priorities. The studies reveal that while some market signals are both scrutinized and well understood by users, much confusion remains. For instance, Study 1 identifies that while users regard the eBay premium service badge as an indicator of seller credibility, few understand it. Consequently, there is a danger that buyers make decisions which are not in their best interests, as they interpret this signal inaccurately. For eBay specifically, educating users as to what the premium badge signifies, should be a communications priority. This could be done through a simple pop-up notification.

Finally, the analysis provides insights for online marketplaces regarding how they display listings. Users typically see a small number of market signals in search results and then must click on specific listings to view more detailed information regarding, in the case of eBay, seller ratings and number sold. The limited range of signals visible initially is appropriate for low involvement purchases where users are happy to form a consideration set based on prices and photographs. However, this is inadequate for high involvement purchases. A specific insight of the analysis is that online marketplaces should ensure that sellers' costly signals are displayed in the initial search results (e.g., seller's feedback scores) so that users can evaluate seller credibility when screening the vast number of listings of the same product. This would aid consumer decision making and improve the user experience. Evidence from studies of nutritional labelling indicates that with the use of colors and a clear layout, it is feasible to present multiple cues in a manner comprehensible to consumers without information overload (Muller and Prevost, 2016). Similarly, Study 1 reveals that, especially for low involvement products, buyers often do not scrutinize text-based reviews. Yet these reviews can convey useful information to buyers. Word clouds help summarize and convey key messages of voluminous, unstructured text data, being generated automatically through a range of software packages (Stanca et al., 2023). Online marketplaces could experiment with the inclusion of word clouds of text-based reviews from previous buyers and evaluate the degree to which users process the information provided.

6. Conclusions

Drawing on two studies, this paper assesses the relative importance of market signals to users of online marketplaces, and how this differs between high and low involvement goods. Study 1 investigates the importance of specific market signals displayed in search results, for users' decisions, with interviews highlighting the importance of country of origin, particularly for high involvement goods, which has received limited attention in the online marketplace literature. Study 2 addresses potential inaccuracies in self-reported information, by employing an eye-tracking methodology. Consistent with our hypotheses, users of online marketplaces overall pay relatively greater attention to costly market signals, which are beyond sellers' direct control, in the case of high involvement goods.

While providing theoretical and practical insights, the studies possess limitations that can guide future research. In this paper, we utilized an iPhone and iPhone charger as exemplary high and low involvement goods, which allowed for control of the brand name. Future research, could repeat the studies with a wider range of stimuli, testing for consistency across product categories and cultures, as well as the size and location of market signals on an online marketplace (Maslowska et al., 2020). Secondly, future studies could consider psychological traits (Costa and McCrae, 1998; De Raad and Kokkonen, 2000) as potential determinants of users' processing of market signals. For example, it may be that those users with above average levels of conscientiousness spend longer evaluating market signals, or that those characterized by higher levels of neuroticism pay greater attention to negative reviews. Finally, future work could investigate why consumers ignore some market signals. For instance, the eye-tracking study identified that the market signal "who bought" received the lowest number of fixations. Further investigation could ascertain whether it lacks value for users *per se*, and if so why, or whether users ignore it due to its location on the webpage.

CRediT authorship contribution statement

Matthew Gorton: Writing – original draft, Writing – review & editing. **Ewelina Marek-Andrzejewska:** Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **Gu Pang:** Writing – original draft, Writing – review & editing. **Witold Andrzejewski:** Data curation, Investigation. **Yong Lin:** Writing – review & editing.

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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