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Research article

Pricing when customers have loss aversion and limited attention

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Abstract: We investigate the optimal pricing problem for a seller who provides a single product to customers characterized by loss aversion and limited attention. We fully examine the interactive impacts of these two characteristics on pricing strategies. Our findings indicate that the seller's pricing strategy critically depend on the customers' reference point and limited attention. The analysis reveals several counterintuitive findings: for instance, the high-quality seller's revenue exhibits a non-monotonic relationship with information cost, while the negative impact of loss aversion only appears when the reference point is high. These findings provide clear strategic guidance: The high-quality seller must commit to information transparency to demonstrate its quality, while also establishing a favorable reference point and reducing the negative impact of loss aversion through reliable guarantees. Conversely, the low-quality seller should leverage information obfuscation and anchor a lower reference point to maximize revenue. This study offers systematic analytical tools for understanding sellers' strategies in complex environments and lays a solid foundation for future theoretical development.

Keywords: uncertain quality; pricing; loss aversion; limited attention; information cost
Mathematics Subject Classification: 91A20, 91A05

1. Introduction

1.1. Background and motivation

In some studies, each customer is generally assumed to be completely rational and to make decisions based on maximizing her/his own expected utility. However, as proposed by Kahneman and Tversky [1], people are loss-averse under uncertainty. The decision made by the loss-averse customer depends not only on her/his inherent preference for the outcome itself but also on the comparison between the decision outcome and the reference point. The reference point denotes the customer's psychological expectation of the outcome; see [2, 3]. If the outcome of the decision is better than the reference point, the customer will perceive a sense of gain; otherwise, she/he will perceive a sense of loss. Loss aversion refers to the fact that customers experience a more intense sense of loss compared with the equivalent gains. Loss aversion is widely present in individual behavior and exerts a substantial influence on the customer's consumption behavior in the market (see [4, 5]).

These customers' attention is limited, which drives them to obtain the important information. The limited cognitive abilities also limit our ability to process information. Moreover, there are incurring costs associated with obtaining and processing information. Therefore, customers need to allocate their attention appropriately and choose how much information to obtain, and then make purchasing decisions based on this information. In order to characterize the limited attention of customers, Sims [6] introduced the framework of rational inattention theory, in which entropy is used to measure the quantity of information obtained by customers. Rational inattention theory allows customers to optimally acquire and process the information they need. In fact, the probabilistic choices following the generalized multinomial logit (GMNL) model are used to capture the rationally inattentive customers' optimal information processing strategy; see [7–9].

For instance, consider a customer looking to purchase a mobile phone. While she/he can easily observe information such as the brand and price, the phone's performance quality (e.g., the processor's stability, battery life) remains uncertain, constituting a typical case of quality uncertainty. She/He forms a reference point based on her/his prior belief about quality. Due to limited attention, acquiring information about quality comes at a cost (proportional to the amount of information acquired). As a result, she/he cannot fully grasp all information. More importantly, influenced by loss aversion, if the phone she/he purchases performs below her/his reference point in actual use, she/he will perceive this as a loss. The negative impact of such a loss far outweighs the satisfaction derived from an equivalent performance exceeding expectations, thereby significantly influencing her/his purchasing decision. Thus, she/he faces a complex trade-off: Determining how much of her/his limited attention to allocate to acquiring information to avoid potential significant perceived loss, while also weighing the inherent costs of acquiring the information.

Quality-based differential pricing is a widely adopted pricing strategy used by the seller [10, 11]. However, before making the purchase decisions, customers do not know about the quality of the product. In the scenario with uncertainty, both loss aversion and limited attention jointly exert a substantial influence on customers' purchasing decisions. Additionally, facing customers with loss aversion and limited attention, the seller's pricing decision will be more complex. On the basis of the findings above, we investigate the following questions:

- What are the impacts of loss aversion on customers' purchase probability, the seller's revenue-optimal price, and optimal revenue?
- What are the impacts of limited attention on customers' purchase probability, the seller's revenue-optimal price, and optimal revenue?

We examine a model in which a seller provides a single product to customers who have loss aversion and limited attention. Customers are unaware of the real quality of the product, but have a prior belief about the quality. They can observe the product's price. In our model, customers first generate the reference point of product quality such that their utility is made up of two portions: Intrinsic utility and gain–loss utility. Then the customers choose the optimal information strategy to obtain and process information, and the customers' purchase decisions are captured by the probabilistic choices following the GMNL model. The seller knows the actual product quality before setting the price. Moreover, the seller learns that customers have loss aversion and limited attention. The seller's strategy is to set the revenue-optimal price of the product to maximize the revenue. We use backward induction to solve the seller's optimal price problem for revenue maximization. (i) Given any price, we derive the customers' optimal purchase decisions, which are characterized by the conditional purchase probability. (ii) Anticipating the purchase decisions made by customers, the seller sets the revenue-optimal price of the product to maximize her/his revenue.

1.2. Contributions of this paper

This paper represents the first study to integrate loss aversion and rational inattention within the context of product pricing. Unlike the studies by Boyacı and Akçay [8] and Matějka [12], our work incorporates the customers' loss aversion regarding the product's quality. Compared with Zhang and Li [3], our work endogenizes customers' information processing by introducing the rational inattention framework. This enables us to analyze the interaction between two key levers—the information cost and the reference point—on the seller's strategy. We find that the impact of the information cost on high-quality sellers' revenue is nonmonotonic and is further modulated by loss aversion and the reference level. Moreover, the impact of the degree of loss aversion depends on the reference level. This interaction directly leads to distinct optimal strategies for high-quality and low-quality sellers. High-quality sellers must coordinately manage the information cost and reference point to demonstrate their quality, while low-quality sellers can leverage the high information cost to conceal their disadvantages. The specific contributions and managerial insights are described below.

Exploring the impacts of loss aversion on the customers' purchase probability, the seller's revenue-optimal price, and optimal revenue. First, all these metrics decrease as the reference level increases. Second, the impact of the degree of loss aversion depends on the reference level. When the reference level is high, the customers' expectations are correspondingly elevated. In this scenario, an increase in the degree of loss aversion significantly suppresses the customers' purchase intention and the sellers' revenue, leading to a decline in the aforementioned metrics. Conversely, when the reference level is low, customer expectations are modest, and purchasing behavior is perceived more as a gain rather than a potential loss. As a result, the customers' purchasing behavior remains unaffected by the degree of loss aversion, and thus the aforementioned metrics are also insensitive to changes in the degree of loss aversion.

Exploring the impacts of limited attention on the customers' purchase probability, the seller's revenue-optimal price, and optimal revenue. When the prior expected quality is low (high), the unconditional purchase probability of customers decreases (increases) with the information cost. Second, limited attention exerts asymmetric effects on high-quality and low-quality sellers. For low-quality sellers, their optimal revenue always increases with the information cost. In contrast, the relationship between optimal revenue and information cost for high-quality sellers is non-monotonic. Only when the information cost exceeds a critical threshold does their optimal revenue begin to rise accordingly. This occurs because, beyond this point, customers rely entirely on prior beliefs, causing the revenue-maximizing prices of both high-quality and low-quality firms to converge.

The findings of this paper provide a theoretical framework for optimal pricing strategies and profound managerial insights for sellers facing customers with both loss aversion and limited attention. Specifically, sellers must synergistically manage two key behavioral levers: The information cost and reference point. High-quality sellers should proactively reduce the information cost (e.g., by providing detailed product transparency reports, introducing third-party certifications, and offering free trials) to validate their price premiums. They should also use marketing communications to establish favorable reference points while mitigating the negative effects of loss aversion through strong assurance guarantees. Conversely, low-quality sellers may adopt market obfuscation strategies (e.g., using ambiguous product descriptions or restricting the visibility of user-generated content) to maintain higher information costs. They should also aim to anchor the customers' reference points at lower levels, thereby leveraging customers' limited attention to secure higher revenues. For platforms and regulatory agencies, this study underscores the necessity of strategically designing the information environment. Platforms can modulate information costs by optimizing reputation systems (e.g., through authenticity verification and structured reviews), thereby directing resources toward high-quality sellers. Regulatory agencies, by using this model, can implement standardized information disclosure in industries with severe information asymmetry (such as financial services and healthcare) to protect customers' rights and ensure market fairness.

1.3. ***Structure of the paper***

The organization of the remainder of this paper is outlined below. The literature review will be provided in Section 2. We present the basic model and the loss aversion utility of customers and their purchasing decisions under loss aversion and limited attention in Section 3. In Section 4, we obtain the customers' unconditional purchase probability, the revenue-optimal price, and optimal revenue of the seller, and study how loss aversion and rational inattention influence them. We draw the conclusion of this paper in Section 5. The appendix contains all the proofs of the propositions, corollaries, and remarks.

2. Literature review

This paper involves three streams of the literature: Loss aversion, rational inattention, and product pricing.

One of the key focuses of this article lies in the application of loss aversion to product pricing. The prospect theory and reference-dependent model were first proposed by Kahneman and Tversky [1], and they also showed loss aversion behavior. Subsequently, it is becoming widely recognized that reference dependence and loss aversion could have significant economic consequences. Tereyağoğlu [13] proposed that the pricing strategy is an effective way to address customers' loss aversion behavior. One branch of loss aversion focuses on a stochastic, endogenous reference point and uses a state-independent model to evaluate a decision outcome. The reference-dependent preferences framework proposed by Kőszegi and Rabin [2, 14] has received widespread attention. In this framework, they assume that the reference point for loss-averse customers is endogenous and stochastic, and provide definitions for the customers' gain–loss utility function and personal equilibrium. Much empirical studies also confirm the framework's utility (e.g., [15–18]). According to this theoretical framework, in the field of supply chains, many studies have considered how loss aversion influences the pricing problems. For example, Heidhues and Kőszegi ([19–21]) examined how loss aversion influences the pricing within different real situations. Lindsey [22] considered the state-dependent pricing problem in transportation systems with loss-averse customers and examined how loss aversion influences welfare-optimal prices. Baron et al. [23] considered how loss aversion influences the sales strategy under a stochastic reference point in a news vendor problem. They found that the company prefers the feature of variable demand over determined demand. Courty and Nasiry [24] analyzed how loss aversion influences a firm's optimal pricing for media and entertainment products, and found that adopting a unified pricing approach for multiple quality categories is optimal when the quality threshold is reached. Uppari and Hasija [25] adopted a more comprehensive approach to establishing multiple news vendor models based on prospect theory and evaluated their abilities to simulate news vendor behavior. The differences between the models were mainly reflected in the assumptions of the reference point. Fogel [26] was the first to introduce the quality reference effect into customer choice and competition models. Subsequently, research on customers' loss aversion toward quality has garnered attention from some scholars. Chang et al. [27] studied the relationship between service quality and the behavioral intentions of loss-averse customers in the restaurant industry. In their study, customers exhibited loss aversion only toward quality. Carbajal and Ely [28] investigated a price discrimination model under loss aversion and state-dependent reference points. They assumed that the reference point for loss-averse customers was solely the product's quality, and customers evaluated consumption outcomes based on the actual purchased quality and the reference quality level. Zhang and Li [3] studied the relationship between loss aversion and quality disclosure in both monopolistic and competitive markets. Their model also assumed that customers are loss-averse only with regard to product quality. They found that loss aversion is detrimental to the company in a monopolistic market, but beneficial to companies in a competitive market. Another branch of the loss aversion literature uses is a state-dependent model to evaluate a decision outcome. Giorg and Post [29] used endogenous expectation caused by the planned behavior in a state-dependent model to determine the stochastic reference point. Focusing on price discrimination, Carbajal and Ely [28] analyzed the strategies of a revenue-maximizing monopolist, taking the state-dependent reference point and loss aversion into account. In our model, we assume that customers are only loss-averse to the quality of the product. In other words, customers only perceive the losses and gains in terms of the product's quality, but not the product's price.

Our research also has a strong link to the literature on rational inattention and information acquisition. People have long recognized that decisions are influenced by customers' limited attention and the available information they have [30, 31]. Simon [30] introduced "bounded rationality", claiming that the decision-making process after the customers obtain the available information can be regarded as completely rational. This is of great significance to the study of behavioral economics, and has also been applied in the field of operational management. Özer and Zheng [32] studied behavioral problems in pricing management and provided insights into the impacts of different behavioral patterns on a company's marketing and pricing decisions. To further explain the limited attention of customers, Sims [6, 33] introduced the rational inattention framework to model the cost of obtaining and processing information. When obtaining and processing information is expensive, customers with limited attention can freely allocate their attention and obtain the information they deem to be useful. This rationalizes the customers' choice behavior. The theory of rational inattention is also more widely applied in the field of macroeconomics. In terms of price setting, most literature focuses on monetary policy and considers sellers with limited attention. Maćkowiak and Wiederholt [34] studied the optimal pricing problem under rational inattention and found that the optimal distribution of attention shifts in response to changes in monetary policy, and firms with rational inattention pay more attention to special conditions than overall conditions. Woodford [35] considered the binary choice problem and studied the state-dependent pricing problem of the rationally inattentive firm. Matějka [36] studied the sales and discrete pricing problem of the rationally inattentive seller, and showed that given the seller's limited information content, unsymmetrical and discrete pricing emerges as the optimal strategy. Afterward, Matějka [12] considered the situation where the rationally inattentive customers acquire and process the information on the price. Matějka and McKay [37] studied the market equilibrium problem in the context of customers exhibiting rational inattention. Specifically, they considered multiple sellers facing stochastic costs and producing products with stochastic quality. The customers need to obtain and process the information on the price, and the sellers set the product prices according to the cost and the given quality. Since direct analysis of the problem is complex, they discussed the role of prior belief and heterogeneity. In terms of pricing problems with rational inattention, Matějka [12] and Boyacı and Akçay [8] are closely related to our research. Matějka [12] demonstrated that when the choices are discrete, the rationally inattentive customer's optimal strategy leads to choice probabilities following the GMNL form. Boyacı and Akçay [8] studied the pricing problem when customers have limited attention. They analyzed the optimal product pricing and sellers' revenues in the absence of signals, and then explored the perfect Bayesian equilibria when the price can transmit the quality signal. In the model presented in this article, we also assume that customers with rational inattention need to obtain information on the product's quality and adopt the GMNL form of choice probabilities. But the difference is that we assume that the product's price cannot convey signals about its quality. This is a common approach in the rational inattention literature (e.g., Matějka and McKay [7]). This assumption applies to the following scenarios: (i) The market information's asymmetry is extremely severe, and the price signal mechanism is almost malfunctioning [38]; (ii) the customers' attention is very scarce, and their information processing capability is fully utilized to evaluate direct quality information, making them unable to decode the price signal [6]; and (iii) the seller lacks brand reputation and cannot provide guarantees for pricing [39]. Under this assumption, we can more conveniently analyze the interactive effects of two core behavioral factors—limited attention and loss aversion—on the customers' decisions and the seller's pricing.

Pricing, as a regulatory mechanism, has important applications in the field of economics. Product pricing is a key link in marketing strategy, which directly affects customers' behavior, market share, and the seller's revenue. With the increasing research on marketing and economics, the methods for analyzing differential pricing are more abundant (e.g., [22, 40–42]). In contrast to the previous literature, customers are not only loss-aversion but also have limited attention.

3. Basic model

In this section, we proceed to develop a formal model that integrates loss aversion with rational inattention.

Before developing the model, we present the sequence of events in Figure 1. First, nature determines the product's quality based on the prior belief τ. Then, the seller sets the product price p according to the actual product quality. Subsequently, the customer forms the reference point r, followed by choosing an information strategy F and obtaining product information. Finally, the customer makes her/his purchase decision.

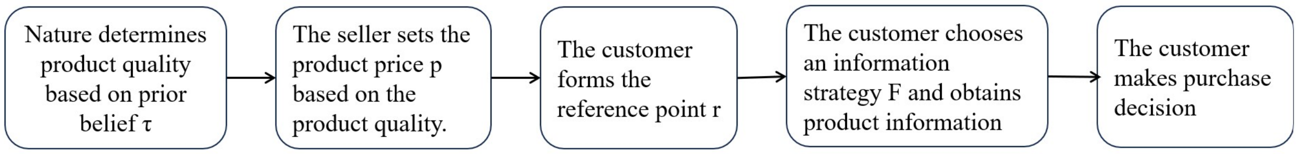

Figure 1. Sequence of events.

Consider a scenario in which a seller provides a single product with a price $p > 0$ to rationally inattentive customers with loss aversion. Loss aversion and rational inattention will be discussed in more detail in the following two subsections. The quality of the product is unknown. The distribution G represents the prior distribution of product quality, where the product has high quality q_H with a probability of $\tau \in (0, 1)$, and low quality q_L with a probability of $1 - \tau$. Let $\Omega := \{H, L\}$. We suppose that the prior distribution is common to the seller and customers. The seller possesses comprehensive information regarding the product and knows its actual quality. For ease of reference, we provide a clear summary of the key notation in Table 1.

Table 1. Summary of key notation.

Symbol	Meaning
i	Level of quality and $i \in \{H, L\}$
q_H, q_L	High quality and low quality of the product
τ	Prior probability that the product is of high quality
p	Product price
u_i	The customer's intrinsic utility given $i \in \{H, L\}$
r	Reference point
β	Reference level
$\mu(\cdot)$	Gain–loss utility function
α	Degree of loss aversion
U_i	The customer's loss-aversion utility given $i \in \{H, L\}$
$F(s, i)$	Information strategy
$\hat{c}$	Total information cost
λ	Unit information cost (referred to as information cost in the text)
g_i	Prior belief at quality level $i \in \{H, L\}$ and $g_H = \tau$
k	$k = 1$ if $r \in [q_L, q_H]$ and $k = 2$ if $r \in [0, q_L)$
π_0	Unconditional purchase probability
π_i	Conditional purchase probability given $i \in \{H, L\}$
π_0^k	Unconditional purchase probability given $k \in \{1, 2\}$
π_i^k	Conditional purchase probability given $i \in \{H, L\}$ and $k \in \{1, 2\}$
R_i^k	The seller's expected revenue given $i \in \{H, L\}$ and $k \in \{1, 2\}$
p_i^{k*}	Revenue-optimal price given $i \in \{H, L\}$ and $k \in \{1, 2\}$
R_i^{k*}	Optimal revenue given $i \in \{H, L\}$ and $k \in \{1, 2\}$

We now provide further elaboration on the two key characteristics of customers: Loss aversion and limited attention. First, we present the customer's loss-averse utility function, followed by an analysis of their purchase decisions under limited attention.

Customer's loss aversion utility. A customer's expectation about product quality has a significant influence on her/his utility. In general, when the expectation is high, utility tends to be low, and vice versa. This expectation is called the benchmark or reference point. The utility of a loss-averse customer is made up of two parts: Intrinsic utility and gain–loss function.

The *intrinsic utility* comes from the decision outcome of the customer, and it depends on whether she/he purchases the product. We use u_i to denote the customer's intrinsic utility, with $u_i = q_i - p$ for $i \in \Omega$ when the customer purchases the product and $u_i = 0$ when the customer abandons the product.

The loss-averse customer does not know the actual quality of product, and she/he forms a psychological expectation of the product's quality, i.e., a reference point. Here, customers are only loss-averse to uncertain levels of product quality. Although this assumption is relatively strong, previous studies (such as [3, 26–28]) provide ample justification and support for it. This assumption helps isolate the specific interaction mechanism between quality uncertainty and limited attention by excluding the confounding factor of price-related loss aversion, while still maintaining the model's tractability and generating significant theoretical insights. By noting that they know the prior distribution of product quality, we define the *reference point* using a linear combination of q_H and q_L, that is

$$r = \beta q_H + (1 - \beta) q_L. \tag{3.1}$$

The parameter $\beta \in [-q_L/(q_H - q_L), 1]$ measures the reference level of the customers, which follows $r \in [0, q_H]$. In the marketing and operations management literature, the case of a convex combination (i.e., $0 \leq \beta \leq 1$) has been commonly used to form reference points and make decisions; see, e.g., [43,44]. While the condition $\beta < 0$ precisely captures a strategic tendency towards defensive pessimism in customers' decision-making under uncertainty. According to the reference point theory of Kőszegi and Rabin [2], reference points can be shaped not only by internal expectations but also by external circumstances or the status quo (i.e., $r = 0$). Within this framework, $\beta < 0$ can be interpreted as an active mechanism for downward expectation adjustment: When facing quality uncertainty, loss-averse customers [45] systematically lower their expectations to an extremely low level to pre-emptively avoid disappointment [46]. This strategy is prevalent in real-world markets. The empirical study on online reviews by Luca [47] demonstrates that negative word-of-mouth exerts a powerful influence on shaping customers' beliefs and behaviors. This indirectly confirms that customers, under the sway of negative information, are prone to forming systematically pessimistic expectations, thereby adopting very low reference points. Thus, $\beta < 0$ serves as a refined characterization of customers' adaptive strategies in complex information environments, significantly enhancing the model's behavioral realism and explanatory power. Consequently, we combine these two cases and extend the reference point to the interval $[0, q_H]$.

The *gain–loss utility* measures a type of difference coming from the comparison between the reference point and the actual product quality. Given the reference point r and the product quality q_i for $i \in \Omega$, we define the gain–loss utility function $n(q_i|r) = \mu(q_i - r)$, where

$$\mu(x) = \begin{cases} x, & x \geq 0, \\ \alpha x, & x < 0. \end{cases} \tag{3.2}$$

In (3.2), the parameter $\alpha > 1$ is the customers' degree of loss aversion, and it means that customers value the losses more than the equivalent gains. Here, $x \geq 0$ (and $x < 0$) means that the actual product quality is higher (and lower) than the reference point, resulting in a gain (and loss) in utility for the customer.

Recall that the utility of a loss-averse customer is made up of intrinsic utility and the gain–loss function. Given the product quality q_i, $i \in \Omega$, when the customer decides to purchase, her/his utility is

$$U_i = q_i - p + \mu(q_i - r). \tag{3.3}$$

where r is given by (3.1) and the function $\mu(\cdot)$ is given by (3.2). Furthermore, when the loss-averse customer does not purchase, her/his utility is $U_0 = 0$.

Purchase decisions under limited attention. A rationally inattentive customer observes the product price p but she/he does not know the actual product quality. She/He only has a prior belief regarding the distribution of product quality, which is common to all customers. The customer has the option to inquire about the quality of product and receives a signal s to update her/his belief accordingly. She/He can choose an action to maximize her/his expected payoff. We use $i \in \Omega$ to represent the level of quality. Hereafter, the level of quality is referred to as the level. The rational inattention theory allows that the customer can select an information-processing strategy before receiving any signal. The information strategy is adequately represented by the notation $F(s, i)$, which is a joint distribution of the signals and the levels. Under this information strategy, the prior belief must be equal to the marginal distribution of the levels, which ensures that the prior distribution of the customer is consistent with her/his posterior belief. Under this constraint, the customer's objective is to choose the information strategy $F(s|i)$ to maximize her/his objective function, taking her/his information cost $\hat{c}(F)$ and expected payoff into account. The total information cost is incurred by the varying levels of precision in the induced signals. In the literature on rational inattention, the amount of information is measured by the entropy, which is quantified by the reduction in uncertainty. Specifically, let $H(Q)$ represent the entropy associated with the uncertain belief Q; it measures the uncertainty of the belief Q. If Q is a discrete distribution, and the probability of the level $i \in \Omega$ is P_i, then its entropy is given by

$$H(Q) = -\sum_{i \in \Omega} P_i \log(P_i),$$

Therefore, when the information strategy is F, the total information cost is

$$\hat{c}(F) = \lambda \left(H(G) - E_s[H(F(\cdot|s))] \right), \tag{3.4}$$

where $\lambda \geq 0$ is interpreted as the cost per unit of information obtained and processed by the customer. The conditional distribution $F(\cdot|s)$ is thought of as the updated belief over different levels following the receipt of the signal s. The expression in (3.4) shows that the quantity of information obtained and processed by the customer is the entropy of the prior belief minus the entropy of $F(\cdot|s)$ following the receipt of the signal s. In the field of information theory, the term *mutual information* is specifically used to refer to this difference.

A customer has two alternative actions: To purchase or not to purchase. The level space is $\Omega = \{H, L\}$; that is, the level of the product quality has the prior belief G given before. The customer's decision making is divided into two steps. First, she/he chooses an information strategy F to enhance her/his understanding of the level. Second, she/he makes a decision based on the uncertain beliefs formed during the first step. Specifically, in the second step, the customer has a belief Q and then she/he chooses the action that generates the maximum expected payoff for her/him. Let $W(Q)$ represent the expected payoff when the customer chooses the optimal action under her/his belief Q. Therefore, the customer's objective function can be expressed as

$$\max_F \sum_{i\in\Omega} \int_s W(F(\cdot|s))F(ds,i) - \hat{c}(F), \tag{3.5}$$

$$s.t. \quad \int_s F(ds,i) = g_i, \quad \forall i \in \Omega, \tag{3.6}$$

where the first component in (3.5) represents the expected payoff resulting from choosing the optimal action stems from the posterior belief, whereas the second component indicates the total information cost resulting from the information strategy F. Equation (3.6) represents the marginal consistency condition, which requires that the marginal distribution of the information strategy $F(s,i)$ selected by the customer over quality levels $i \in \{H, L\}$ to align with the prior belief g_i. This ensures that any information strategy under consideration adheres to Bayesian rationality. In this setting, the customer with rational inattention needs to make the following decisions: (i) What information does she/he need to obtain and how much information does she/he need to obtain; (ii) which action should she/he choose after processing this information.

An essential property of rational inattention theory is that under the optimal strategy, each posterior belief becomes uniquely associated with a single, distinct action. This property was formally established in Lemma 1 of [7]. This leads to two direct results. First, each action corresponds to a particular signal. Second, the joint distribution between states and signals matches that between actions and states. Consequently, the total information cost can be expressed as a function of actions and states, and is no longer related to signals. Due to the symmetry inherent in mutual information, the total information cost is expressed as

$$\begin{aligned}\hat{c}(F) = c(\Pi, G) = \lambda[&-\pi_0 \log \pi_0 - (1-\pi_0)\log(1-\pi_0) \\ &+ g_H(\pi_H \log \pi_H + (1-\pi_H)\log(1-\pi_H)) \\ &+ g_L(\pi_L \log \pi_L + (1-\pi_L)\log(1-\pi_L))].\end{aligned} \tag{3.7}$$

Thus, the rationally inattentive customer's objective function is simplified into a simpler maximization problem, where the customer's decision variable is the level-dependent choice without considering the signals and posterior beliefs. Specifically, let S_P denote the set comprising signals that result in a purchase. When the product quality is q_i, the customer's conditional purchase probability π_i is determined by

$$\pi_i = \int_{s\in S_P} F(ds|i), \quad i \in \Omega. \tag{3.8}$$

Equation (3.8) quantifies the probability of a customer choosing to purchase, given that the actual product quality is q_i. This probability equals the sum of the conditional probabilities $F(s|i)$ for all signals $s \in S_P$ that would lead her/him to purchase. Equation (3.8) transforms the customer's complex internal information strategy $F(s,i)$ into an analyzable probability π_i. Consequently, π_i stands as one of the most critical endogenous indicators in the entire model. Let $\Pi = \{\pi_H, \pi_L\}$ represent the set of the customer's conditional purchase probabilities, which is also her/his purchasing strategy. Thus, the customer's unconditional purchase probability (i.e., the average of conditional purchase probabilities over all levels) is

$$\pi_0 = g_H \pi_H + g_L \pi_L. \tag{3.9}$$

In this way, the rationally inattentive customer's decision-making problem is simplified into

$$\max_{\Pi=\{\pi_H,\pi_L\}} \sum_{i\in\Omega} g_i(\pi_i U_i + (1-\pi_i)U_0) - c(\Pi, G), \tag{3.10}$$
$$s.t. \quad 0 \le \pi_i \le 1, \quad \forall i \in \Omega.$$

In (3.10), the first component represents the customer's expected payoff when employing the purchasing strategy Π (see the appendix for proof), and the second component represents the total information cost as defined in (3.7). The generalized multinomial logit (GMNL) formula is adhered to by the conditional choice probabilities resulting from the customer's optimal strategy, according to rational inattention theory, when $\lambda \ge 0$; see [12]. In our model, given the product quality $q_i, i \in \Omega$ and the corresponding probability, it follows by the GMNL formula that the conditional probability π_i for the customer to purchase the product at price p

$$\pi_i = \frac{\pi_0 e^{U_i/\lambda}}{\pi_0 e^{U_i/\lambda} + (1-\pi_0)e^{U_0/\lambda}}, \quad i \in \Omega. \tag{3.11}$$

when $\lambda = 0$, the customer can know the product's actual quality without incurring any cost and purchases the product if $U_i > U_0$ and does not purchase it otherwise.

We notice that the unconditional purchase probability π_0 is independent of the quality of the product according to (3.9) and (3.11). The unconditional purchase probability π_0 represents the probability that the rationally inattentive customer purchases the product before processing any information, and it depends on the unit information cost λ and the prior belief G. The conditional purchase probability π_i in (3.11) demonstrates the relationship among three factors, namely utility, beliefs, and cost of information, which affect the customer's decision-making. First, if the unconditional purchase probability $\pi_0 > 0$, then the higher the customer's utility U_i is, the more likely she/he will purchase the product. The influence of prior belief G is reflected through the unconditional purchase probability π_0. When π_0 is large, even if the utility is low, the probability of the customer purchasing the product is relatively high. The dependence of π_0 on the information cost λ stems from the forward-looking nature of the customer's decision-making in rational inattention theory. Specifically, π_0 is not an exogenously given or isolated "initial impulse", but rather an equilibrium outcome derived from the customers' optimization of their information strategy after anticipating the costs and benefits of subsequent information acquisition. This implies that π_0 fundamentally reflects the expected level of the customers' optimal information strategy. Furthermore, when the information cost $\lambda \downarrow 0$, the customer knows the product's actual quality, and she/he can make the optimal choice with certainty at each level at this point. With the increase in the information cost λ, the customer's decision relies more on her/his prior belief, since she/he has less knowledge about the product's quality. When the information cost $\lambda \uparrow \infty$, the customer can only make decision based on the prior belief. Thus, the dependence of π_0 on λ precisely captures its core characteristic as an ex ante planning variable resulting from the customers' global optimization of the entire information acquisition and decision-making process.

It is worth mentioning that (3.11) is not the analytical solution for the conditional purchase probability, as it depends on π_0, which is also determined by the customer. Equations (3.9) and (3.11) need to be solved together to obtain a complete explicit solution. When the unconditional purchase probability π_0 is obtained, the conditional purchase probabilities can be obtained according to (3.11).

This completes the construction of the formal base model for this study. In the following section, we will proceed to analyze the model and present our key findings and conclusions.

4. Model analysis

Based on the theoretical foundation established in the previous section, this section proceeds with an analysis of the model. We first present the main results of the model and verify the robustness of the conclusions through graphical analysis. Building on these findings, we further derive management insights with practical implications.

Recall that the customers' reference point satisfies the expression (3.1). In view of the form of the reference point, we will deal with the seller's optimal pricing in two cases: $r \in [q_L, q_H]$ and $r \in [0, q_L)$.

We first analyze the case in which $r \in [q_L, q_H]$ with $\beta \in [0, 1]$. When the quality of the product is q_H, the customers' loss aversion utility of purchasing can be expressed as

$$U_H = (2-\beta)q_H - (1-\beta)q_L - p. \tag{4.1}$$

When the quality of the product is q_L, the customers' loss aversion utility of purchasing can be expressed as

$$U_L = (1+\alpha\beta)q_L - \alpha\beta q_H - p. \tag{4.2}$$

Additionally, the utility of not purchasing is $U_0 = 0$.

For simplicity of notation, we let

$$\begin{aligned} q_H^1 &= (2-\beta)q_H - (1-\beta)q_L, \\ q_L^1 &= (1+\alpha\beta)q_L - \alpha\beta q_H. \end{aligned}$$

By combining (3.9) and (3.11) from §3 (see the appendix for proof), the customers' unconditional purchase probability with $r \in [q_L, q_H]$ can be expressed as

$$\pi_0^1(p) = \frac{e^{p/\lambda}(e^{p/\lambda} - \tau e^{q_H^1/\lambda} - (1-\tau)e^{q_L^1/\lambda})}{(e^{q_H^1/\lambda} - e^{p/\lambda})(e^{q_L^1/\lambda} - e^{p/\lambda})}. \tag{4.3}$$

If $U_L > U_0$ or $U_H < U_0$ holds, the customers do not need to process any information when making their purchasing decisions. In other words, without processing any information about the product, customers can make the following decisions: to purchase the product if $p < q_L^1$ and not to purchase if $p > q_H^1$.

By solving $\pi_0^1(p) = 0$, we obtain $p = \overline{p}^1 = \lambda \ln[\tau e^{q_H^1/\lambda} + (1-\tau)e^{q_L^1/\lambda}]$; by solving $\pi_0^1(p) = 1$, we obtain $p = \underline{p}^1 = q_H^1 + q_L^1 - \lambda \ln[\tau e^{q_L^1/\lambda} + (1-\tau)e^{q_H^1/\lambda}]$. Thus, the customers only process information to make their decisions when $\underline{p}^1 < p < \overline{p}^1$. If $p < \underline{p}^1$ or $p > \overline{p}^1$, the customers can make purchasing decisions without obtaining any information, i.e. $\pi_0^1(p) = 1$ if $p < \underline{p}^1$ and $\pi_0^1(p) = 0$ if $p > \overline{p}^1$. As a result, we entirely represent the customers' unconditional purchase probability as follow:

$$\pi_0^1(p) = \begin{cases} 1, & p < \underline{p}^1, \\ \frac{e^{p/\lambda}(e^{p/\lambda} - \tau e^{q_H^1/\lambda} - (1-\tau)e^{q_L^1/\lambda})}{(e^{q_H^1/\lambda} - e^{p/\lambda})(e^{q_L^1/\lambda} - e^{p/\lambda})}, & \underline{p}^1 \le p \le \overline{p}^1, \\ 0, & p > \overline{p}^1. \end{cases} \tag{4.4}$$

Remark 1 (The monotonicity properties of the price range). *(i) $\overline{p}^1$ decreases in λ, while $\underline{p}^1$ increases in λ. Moreover, when λ is sufficiently large, $\overline{p}^1$ and $\underline{p}^1$ will converge to the same value. This price ensures that the expected utility of purchasing is not lower than the utility of not purchasing, i.e., $\tau U_H + (1-\tau)U_L \ge 0$. At this point, the customers only make purchasing decisions based on their prior belief. (ii) $\overline{p}^1$ and $\underline{p}^1$ both decrease in β and α, and increase in τ. As β increases, the customers' reference point rises, which diminishes their utility from purchasing the product. This reduction in utility lowers the unconditional purchase probability, leading the seller to decrease the price. Conversely, an increase in α reduces the utility of purchasing a low-quality product, thereby lowering the conditional purchase probability for the low-quality product. Although the utility of purchasing a high-quality product remains unaffected, its conditional purchase probability is indirectly reduced due to the decline in the unconditional purchase probability. This also results in the seller lowering the price. On the other hand, an increase in the prior belief τ naturally raises the customers' overall purchase probability, allowing the seller to increase the price—an intuitive outcome.*

Next, we analyze the case in which the reference point $r \in [0, q_L)$ with $\beta \in [-q_L/(q_H - q_L), 0)$. When the product quality is q_i, the customers' loss aversion utility of purchasing is

$$U_i = 2q_i - r - p, \quad i \in \Omega. \tag{4.5}$$

The utility of not purchasing is $U_0 = 0$.

By using (3.9) and (3.11) (where the proof follows the same logic as Equation (4.3)), the customers' unconditional purchase probability with $r \in [0, q_L]$ is expressed as

$$\pi_0^2(p) = \frac{e^{p/\lambda}(e^{p/\lambda} - \tau e^{(2q_H - r)/\lambda} - (1-\tau)e^{(2q_L - r)/\lambda})}{(e^{(2q_H - r)/\lambda} - e^{p/\lambda})(e^{(2q_L - r)/\lambda} - e^{p/\lambda})}. \tag{4.6}$$

By solving $\pi_0^2(p) = 0$, we have $p = \overline{p}^2 = \lambda \ln[\tau e^{(2q_H - r)/\lambda} + (1-\tau)e^{(2q_L - r)/\lambda}]$, and by solving $\pi_0^2(p) = 1$, we have $p = \underline{p}^2 = 2q_H + 2q_L - 2r - \lambda \ln[\tau e^{(2q_L - r)/\lambda} + (1-\tau)e^{(2q_H - r)/\lambda}]$. Thus, the customers only process information to make their decisions when $\underline{p}^2 < p < \overline{p}^2$. If $p < \underline{p}^2$ or $p > \overline{p}^2$, the customers can make purchasing decisions without obtaining any information, i.e. $\pi_0^2(p) = 1$ if $p < \underline{p}^2$ and $\pi_0^2(p) = 0$ if $p > \overline{p}^2$. Information cost, reference level, and prior belief have the same impact on $\underline{p}^2$ and $\overline{p}^2$ as on $\underline{p}^1$ and $\overline{p}^1$. However, $\underline{p}^2$ and $\overline{p}^2$ are not affected by the degree of loss aversion because customers will not perceive the loss when $r \in [0, q_L]$.

We represent the customers' unconditional purchase probability with $r \in [0, q_L)$ as

$$\pi_0^2(p) = \begin{cases} 1, & p < \underline{p}^2, \\ \frac{e^{p/\lambda}(e^{p/\lambda} - \tau e^{(2q_H - r)/\lambda} - (1-\tau)e^{(2q_L - r)/\lambda})}{(e^{(2q_H - r)/\lambda} - e^{p/\lambda})(e^{(2q_L - r)/\lambda} - e^{p/\lambda})}, & \underline{p}^2 \le p \le \overline{p}^2, \\ 0, & p > \overline{p}^2. \end{cases} \tag{4.7}$$

According to (3.11), given the price p and the product quality q_i for $i \in \Omega$, the seller's expected revenue is represented by

$$R_i^k(p) = p \cdot \pi_i^k(p) \text{ for } k \in \{1, 2\}, \tag{4.8}$$

where the form of $\pi_i^k(p)$ depends on whether π_0 is (4.4) or (4.7). Here, note that the different forms of the reference point are characterized by the superscript $k \in \{1, 2\}$.

When the quality of the product is q_i, denote p_i^{k*} as the revenue-optimal price, and the corresponding optimal revenue is R_i^{k*} for $k \in \{1, 2\}$. First, we present the following proposition in which the seller's revenue-optimal prices are presented and discussed.

Proposition 2 (**The range of revenue-optimal price**). $p_i^{k*} \in [\underline{p}^k, \overline{p}^k]$ *for* $i \in \Omega$ *and* $k \in \{1, 2\}$.

Proposition 2 suggests that the revenue-optimal price consistently falls within the designated price range where the customers need to process information. This means that the high-quality seller cannot fully extract the customers' surplus, while the low-quality seller can charge a price higher than her/his product's quality. For high-quality sellers, since the customers cannot costlessly verify the product's quality, setting prices that reflect the actual quality may arouse suspicion and lead to purchase rejection. Consequently, high-quality sellers are compelled to lower their prices. This price discount essentially constitutes an information rent they must pay to establish trust. By offering this concession, they aim to overcome information barriers and attract customers. In contrast, low-quality sellers can strategically exploit market ambiguity to profit. They set prices above their actual quality level but close to the market's average expected quality, successfully blending in among the other sellers. Due to the customers' limited information processing capacity, they cannot accurately distinguish each seller's quality, allowing low-quality sellers to effectively charge customers a certain amount of information ambiguity tax and extract premiums that do not correspond to their actual quality.

In order to derive the revenue-optimal price, we first substitute $\pi_0^k(p)$ back into $\pi_i^k(p)$ for $i \in \Omega$, $k \in \{1, 2\}$, and then optimize $R_i^k(p)$. Note that the seller's revenue function exhibits concavity in terms of the conditional purchase probability; see [48] for a similar case. In the end, we transform the price into a function of the purchase probability as follows:

$$p(\pi_i^k) = q_i + \mu(q_i - r) + \lambda \ln\left[\frac{\pi_0^k}{1 - \pi_0^k} \cdot \frac{1 - \pi_i^k}{\pi_i^k}\right], \quad i \in \Omega, \quad k \in \{1, 2\}. \tag{4.9}$$

Hence, we can reformulate (4.8) using π_i^k

$$R_i^k(\pi_i) = p(\pi_i^k) \cdot \pi_i^k. \tag{4.10}$$

Use π_i^{k*} to denote the optimal conditional purchase probability that maximizes the expected revenue. For $\pi_i^k \in (0, 1)$, $p(\pi_i^k)$ is well defined and makes sense. For $\pi_i^k = 1$, we have $p < \underline{p}^k$ such that the seller chooses $p(1) = \underline{p}^k$ to maximize $R_i^k(\pi_i^k)$. For $\pi_i^k = 0$, we have $p > \overline{p}^k$, the expected revenue $R_i^k(0) = 0$, regardless of the price. Thereby, we define $p(0) = \overline{p}^k$. Hence, p_i^{k*} can be determined uniquely via π_i^{k*}.

By noting that π_0^k is associated with π_i^k, through the transformation of Equation (4.9), we can determine the convexity and concavity, as well as the monotonicity of $R_i^k(p)$ with respect to p and π_i^k.

The following proposition summarizes these properties.

Proposition 3 (**The properties of** $R_i^k(\pi_i^k)$ **and** $R_i^k(p)$). *(i)* $R_i^k(\pi_i^k)$ *is concave in* π_i^k *for* $i \in \Omega$, $k \in \{1,2\}$. *(ii) For* $k \in \{1,2\}$, $R_H^k(p)$ *is concave in* p, *and* $R_L^k(p)$ *is both convex and decreasing in* p *for* $p \in [\underline{p}^k, \overline{p}^k]$.

From Proposition 3(i), the concavity of $R_i^k(\pi_i^k)$ ensures the existence and uniqueness of the optimal conditional purchase probability. From Proposition 3(ii), the high-quality seller's expected revenue $R_H^k(p)$ has a unique revenue-optimal price. Furthermore, when the quality of product is q_L, the seller can maximize her/his expected revenue by charging the price $\underline{p}^k$; at this point, all customers purchase the product with probability 1.

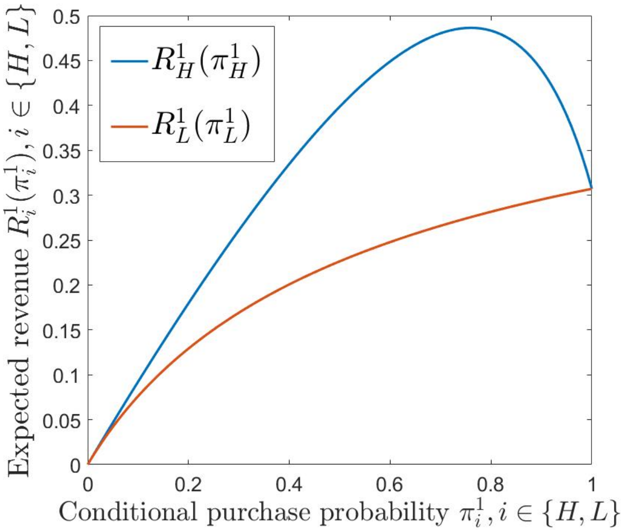

Figure 2. The impact of the conditional purchase probability π_i^1 on the expected revenue $R_i^1(\pi_i^1), i \in \{H, L\}$, where $q_H = 1, q_L = 0.5, \tau = 0.5, \alpha = 2, \lambda = 0.5$, and $\beta = 0.5$.

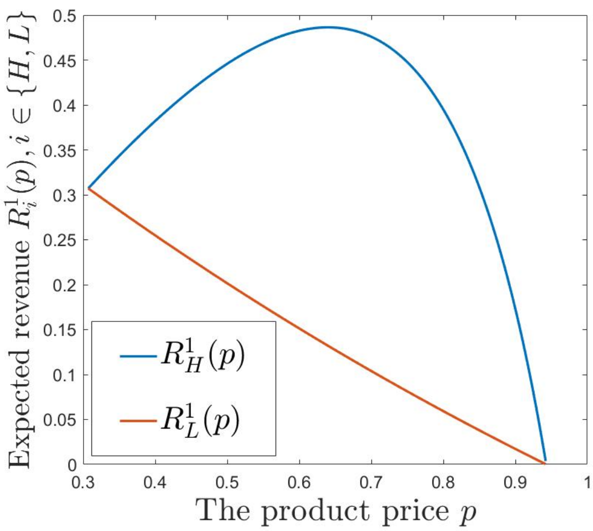

Figure 3. The impact of the price p on expected revenue $R_i^1(p), i \in \{H, L\}$, where $q_H = 1, q_L = 0.5, \lambda = 0.5, \tau = 0.5, \alpha = 2$, and $\beta = 0.5$.

Figure 2 shows the trend of the expected revenue as the conditional purchase probability varies, and Figure 3 shows the trend of the expected revenue as the product price varies. The differences in the curves' shapes between these two figures stem from the shift in the decision variables and carry significant managerial implications. In Figure 2, the concavity of the $R_i^1(\pi_i^1), i \in \{H, L\}$ curves (as described in Proposition 3(i)) originates from the endogeneity of demand within the rational inattention framework. The conditional purchase probability $\pi_i^1, i \in \{H, L\}$ is the result of the seller influencing the customers' decisions through pricing and information strategy. Increasing π_i^1 means that the seller must attract more customers by lowering the price or improving the information transparency, and the marginal cost of such attraction is increasing. In the initial stage, the seller only needs to slightly reduce the price to attract customers, leading to rapid revenue growth. However, as π_i^1 approaches 1, the seller must significantly lower the price, which slows down revenue growth or even reduces revenue, resulting in a concave function. This clearly reveals the inherent difficulty of expanding market share in markets with limited attention.

When the decision variable shifts to price p, the revenue curve diverges (as described in Proposition 3(ii)). For the high-quality product, the revenue curve is concave. This indicates that the high-quality seller faces the traditional price trade-off, where at the optimal price point, the marginal revenue from a price increase equals the marginal loss in demand. However, for the low-quality product, the revenue curve exhibits a decreasing and convex characteristic. Its optimal price is always at the lower bound of the price interval, i.e., $\underline{p}^1$ (Corollary 1). This is because, any price above $\underline{p}^1$ leads to a sharp decline in purchase probability due to the customers' loss aversion. The low-quality seller lacks room for price trade-offs, and her/his optimal strategy is to set the price at $p_L^{1*} = \underline{p}^1$ to ensure that all customers purchase ($\pi_L^{1*} = 1$). The convexity of the curve indicates that near $\underline{p}^1$, even a slight price increase causes an accelerated decline in revenue, posing extremely high risks.

These two distinct patterns offer managers the following insights: High-quality sellers should precisely set prices to find the optimal price point rather than blindly pursuing market share. Additionally, they should actively reduce customers' information costs λ through methods such as advertising and information disclosure, helping customers recognize their high quality to support higher prices. In contrast, low-quality sellers should focus on maximizing customer demand (purchase probability) and rely on economies of scale for revenue. At the same time, they have an incentive to increase customers' information costs λ (e.g., by obfuscating product information) to exploit the customers' limited attention.

Corollary 1 (The revenue-optimal price and revenue for a low-quality product). *When the quality of the product is q_L, the revenue-optimal price p_L^{k*} and optimal revenue R_L^{k*} are given by*

$$R_L^{k*} = p_L^{k*} = \underline{p}^k \text{ for } k \in \{1, 2\}. \tag{4.11}$$

In the following, we show the properties of the customers' unconditional purchase probability, the seller's revenue-optimal prices p_L^{k*}, and the optimal revenues R_L^{k*} under two forms of the reference point. We first analyze the impacts of the information cost λ on the unconditional purchase probability $\pi_0^k(p)$ and the optimal revenues R_H^{k*} and R_L^{k*}. The following proposition presents these impacts.

Proposition 4 (The impact of information cost). *(i) A unique threshold τ_c^k for $k \in \{1, 2\}$ exists such that when $\tau < \tau_c^k$, $\pi_0^k(p)$ decreases in λ, and when $\tau \geq \tau_c^k$, $\pi_0^k(p)$ increases in λ.*

(ii) R_L^{k*} increases in λ for $k \in \{1, 2\}$.

(iii) A unique threshold λ_c^k exists such that R_H^{k*} increases in λ if $\lambda \geq \lambda_c^k$ and R_H^{k*} decreases in λ if $\lambda < \lambda_c^k$ for $k \in \{1, 2\}$.

Proposition 4(i) indicates that when the prior belief in the high-quality product is low (i.e., $\tau < \tau_c^k$), the unconditional purchase probabilities decrease with the information cost, while when the prior expected quality is high (i.e., $\tau \geq \tau_c^k$), the unconditional purchase probabilities increase with the information cost. As shown in Figure 4, because the increase in the information cost λ reduces the information about the product's quality obtained by customers, and the customers become more dependent on the prior belief. When τ is low, the prior belief in the high-quality product is low, which makes the customers unwilling to purchase, thereby reducing the probability of purchase. When τ is high, the prior belief of the high-quality product is also high, which makes customers more willing to purchase it and thus increases the probability of purchase. Proposition 4(i) reveals that the impact of the information cost on purchase decisions is not fixed but is moderated by the prior belief. The implication is that a seller's strategy should be tailored to her/his brand reputation (i.e., the level of the prior belief τ). For new brands or those with a poor reputation (low τ), the core strategy should be to reduce the information cost (e.g., by providing free samples and ensuring transparent product information). In contrast, for established brands (high τ), sellers can appropriately leverage the customers' limited attention, as a higher information cost may instead strengthen the customers' tendency to rely on their existing positive impressions when making purchase decisions.

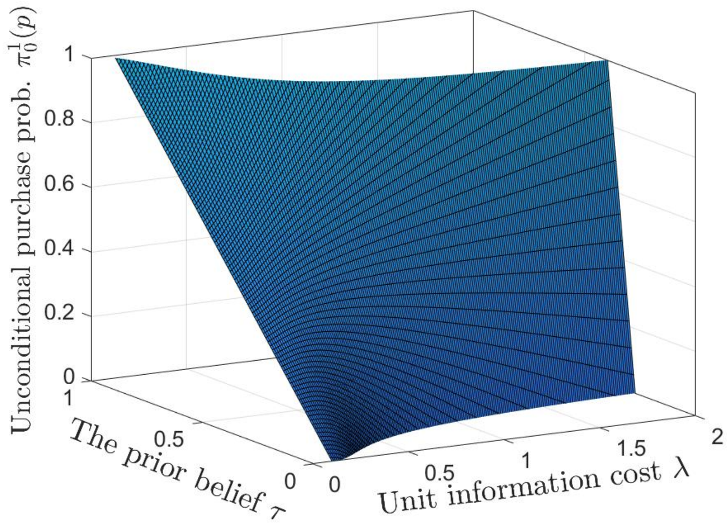

Figure 4. The impacts of the information cost λ and the prior belief τ on the unconditional purchase probability $\pi_0^1(p)$, where $q_H = 1, q_L = 0.5, p = 0.5, \alpha = 1.5$, and $\beta = 0.5$.

Proposition 4(ii) indicates that the increase in the information cost improves the low-quality seller's optimal revenue. When the information costs is low, customers can clearly identify the product's quality, which prevents low-quality sellers from setting prices that exceed their actual product value. However, as the information cost increases, customers receive less insight into the product's quality, enabling the low-quality seller to charge a premium over the product's quality. Therefore, the low-quality seller tends to hide information about the product's quality, which allows it to exploit the customers' rational inattention to earn higher revenue. However, Proposition 4(iii) indicates that the optimal revenue of the high-quality seller does not exhibit a monotonic relationship with changes in the information cost. In environments with a low information cost ($\lambda < \lambda_c^k$), where customers can easily access information, any increase in the information costs will harm the revenue of high-quality sellers. When the information cost exceeds a critical threshold ($\lambda > \lambda_c^k$), customers become unable to distinguish between high-quality and low-quality sellers and must rely on the prior belief to make decisions. At this point, both sellers' pricing strategies are the same, resulting in the high-quality seller's optimal revenue increasing with λ.

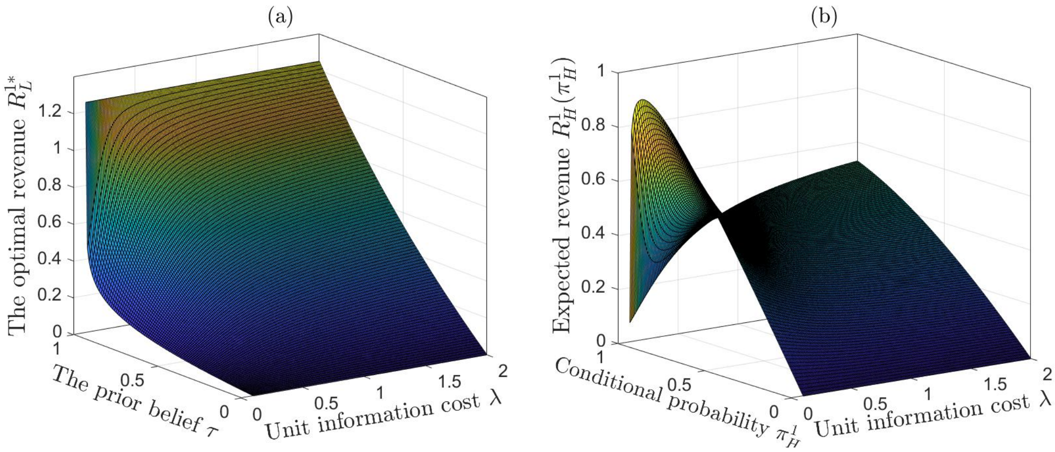

Figure 5. (a) The impacts of the information cost λ and the prior belief τ on the low-quality seller's optimal revenue R_L^{1*}, where $q_H = 1, q_L = 0.5, \alpha = 2$, and $\beta = 0.5$.
(b) The impacts of the information cost λ and conditional purchase probability π_H^1 on the high-quality seller's expected revenue $R_H^1(\pi_H^1)$, where $q_H = 1, q_L = 0.5, \tau = 0.5, \alpha = 2$, and $\beta = 0.5$.

Figure 5(a) presents a three-dimensional trend diagram of the optimal revenue for the low-quality seller as it varies with the information cost and the prior belief. Regardless of the prior belief, the optimal revenue for the low-quality seller always increases with the information cost λ, which is consistent with Proposition 4(ii). Furthermore, we also observe that the optimal revenue R_L^{1*} increases with the prior belief τ (as shown later in Proposition 7(ii)). Figure 5(b) illustrates a three-dimensional trend diagram of the expected revenue for the high-quality seller as it varies with the information cost and conditional purchase probability. The optimal revenue for the high-quality seller decreases when λ is low and only increases when λ is high. This aligns with Proposition 4(iii). We observe that high-quality sellers achieve higher revenue under a low information cost, indicating that they should make efforts to reduce the information cost to obtain greater revenue. Regarding Figure 5, it is particularly important to clarify that the reason why the low-quality seller's optimal revenue can exceed that of the high-quality seller lies in the former's more favorable prior belief. When the prior belief is held constant (as in Figure 5(b), where $\tau = 0.5$), the low-quality seller's optimal revenue remains lower than that of the high-quality seller.

We notice that when the information cost is sufficiently high, the high-quality product's optimal conditional purchase probability is $\pi_H^{1*} = 1$, which means that the high-quality seller's revenue-optimal price will be the same as the low-quality seller's revenue-optimal price. In other words, when the information cost is sufficiently high, the high-quality seller's revenue-optimal price will converge to the low-quality seller's revenue-optimal price.

Proposition 4(ii) and (iii) reveal the impact of the information cost on sellers' pricing strategies. The implication is that low-quality sellers should strive to increase the difficulty for customers to obtain information, such as by obfuscating product details and restricting sales personnel, to achieve higher revenue. In contrast, high-quality sellers should adopt measures like offering free trials and providing authoritative third-party evaluation reports to lower the information barriers. For example, when purchasing electronic products on e-commerce platforms, the abundance of online product reviews constitutes the information cost for customers. Low-quality sellers (e.g., counterfeit products or inferior small brands) can further increase this information cost by fabricating positive reviews and creating fake transaction records. This allows them to set prices higher than their product's quality, deceiving time-constrained or inattentive customers. On the other hand, negative reviews of high-quality sellers (e.g., reputable brands or genuinely superior products) are more likely to be discovered and trusted by customers. Therefore, they need to invest in managing reviews and providing detailed official information, which effectively reduces customers' information cost and helps defend their price premiums.

Next, we analyze the impacts of the reference level. The following proposition gives the impacts of the reference level on the customers' unconditional purchase probability, revenue-optimal prices, and the optimal revenues.

Proposition 5 (**The impact of the reference level**). *(i) The unconditional purchase probability* $\pi_0^k(p)$ *decreases with the reference level* β *for* $p \in [\underline{p}^k, \overline{p}^k]$, $k \in \{1, 2\}$.

(ii) The revenue-optimal prices p_L^{k*} *and* p_H^{k*}*, the optimal revenues* R_L^{k*} *and* R_H^{k*} *decrease with* β *for* $k \in \{1, 2\}$.

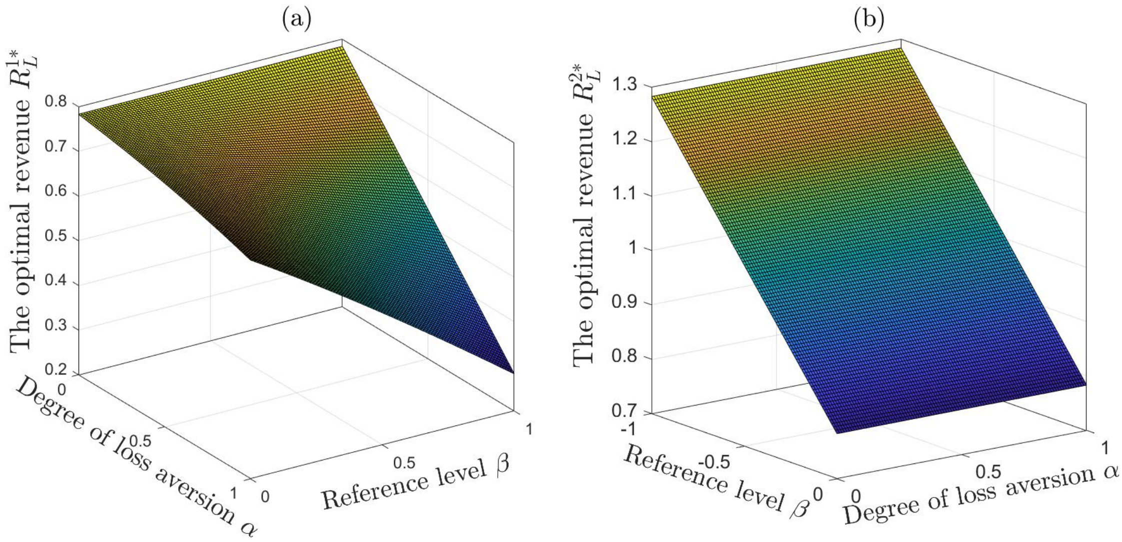

Figure 6. The impacts of the reference level β and the degree of loss aversion α on the low-quality seller's optimal revenue $R_L^{k*}, k \in \{1, 2\}$, where $q_H = 1, q_L = 0.5$, and $\lambda = 0.5, \tau = 0.5$.

From Proposition 5(i), intuitively, as the parameter β increases, the customers' unconditional purchase probability decreases. The increase in β improves the customers' reference point, which reduces the utility of the customers' purchase and hence lowers their purchase probability.

Proposition 5(ii) demonstrates that both the seller's revenue-optimal prices and optimal revenues decrease with the reference level. An increase in β elevates the customers' reference point, reducing their purchase utility and, consequently, their purchase probability. This effect compels the seller to lower her/his revenue-optimal prices, ultimately diminishing the optimal revenues.

Figure 6 presents a three-dimensional trend diagram illustrating how the optimal revenue of the low-quality seller varies with the reference level and the degree of loss aversion. Regardless of the degree of loss aversion, the optimal revenue always decreases as the reference level increases, as indicated in Proposition 5(ii). The difference lies in how the optimal revenue responds to the degree of loss aversion: Under high reference levels ($\beta \in (0, 1)$), the optimal revenue decreases with an increasing degree of loss aversion, as shown in Figure 6(a). In contrast, under low reference levels ($\beta \in [-\frac{q_L}{q_H - q_L}, 0)$), the optimal revenue remains unaffected by the degree of loss aversion, as depicted in Figure 6(b). This occurs because when $\beta \in [-\frac{q_L}{q_H - q_L}, 0)$, customers do not perceive a loss and are therefore not influenced by the degree of loss aversion α, which is a result encompassed in Proposition 6.

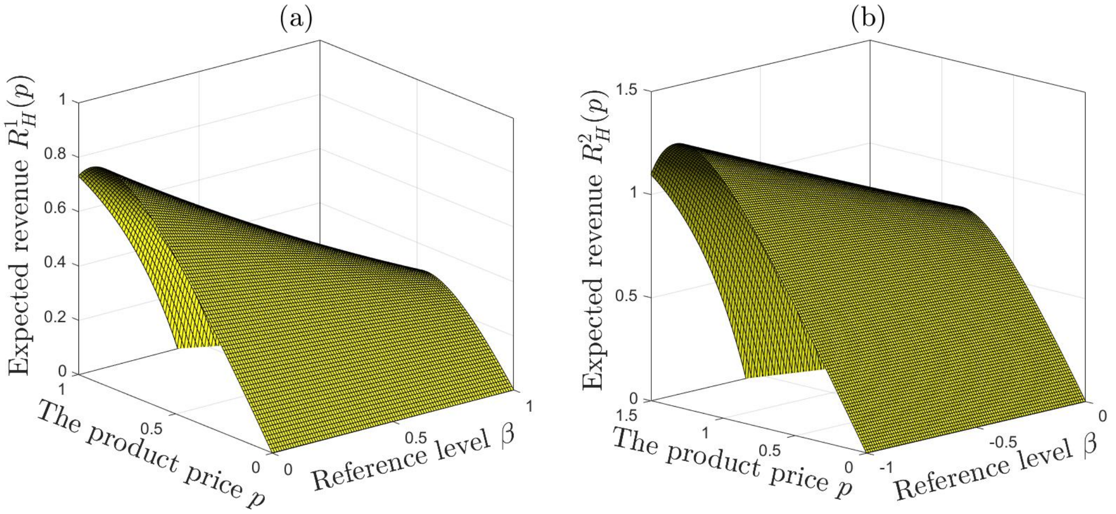

Figure 7. The impacts of the reference level β and the product price p on the high-quality seller's expected revenue $R_H^k(p), k \in \{1, 2\}$, where $q_H = 1, q_L = 0.5, \lambda = 0.5, \tau = 0.5$, and $\alpha = 1.5$.

Figure 7 presents a three-dimensional diagram showing how the high-quality seller's expected revenue varies with the reference level and product price. It can be clearly observed that both the optimal revenue and the revenue-optimal price decrease as the reference level increases, which aligns with Proposition 5(ii). However, under low reference levels (Figure 7(b)), both the optimal revenue and the revenue-optimal price are higher than those under high reference levels (Figure 7(a)). This occurs because the customers perceive higher utility when purchasing products under low reference levels, enabling the sellers to charge higher prices and consequently achieve greater revenue. The same rationale applies to Figures 8 and 9.

Proposition 5 implies that managing and appropriately lowering the customers' reference points is key to achieving a pricing premium. Sellers should proactively set benchmarks for customer comparisons, anchoring customers' reference points in a position that is favorable to themselves. For example, high-end brands can elevate reference points by emphasizing unique experiences to justify premium pricing, while mass-market brands may highlight extreme cost-effectiveness to prevent customers from comparing their products with high-end products. Secondly, when launching new products, sellers should avoid over promising. Instead, they should adopt conservative expectation management. For instance, when introducing a new car, downplaying the performance parameters in the promotional materials allows the users to discover its unexpectedly superior performance during actual testing, thereby creating a sense of surprise and generating a positive gain in utility. Furthermore, sellers can also employ decoy effects to construct an internal reference system that guides the customers' decision-making.

Next, we analyze how the degree of loss aversion influences the customers' unconditional purchase probability, revenue-optimal prices, and the optimal revenues. The following proposition summarizes these findings.

Proposition 6 (**The impact of the degree of loss aversion**). *(i)* $\pi_0^1(p)$ *decreases in* α*, while* $\pi_0^2(p)$ *is independent of* α *for* $p \in [\underline{p}^1, \overline{p}^1]$.

(ii) p_L^{1*}, p_H^{1*}, R_L^{1*}, *and* R_H^{1*} *all decrease with* α. *However,* p_L^{2*}, p_H^{2*}, R_L^{2*}, *and* R_H^{2*} *are all independent of* α.

From Proposition 6(i), intuitively, when $\beta \in [0, 1]$, the unconditional purchase probability decreases in α. An increase in α intensifies the customers' loss aversion, reducing their utility from purchasing the low-quality product. This lowers both the conditional purchase probability for the low-quality product and the unconditional purchase probability. However, when $\beta \in [-\frac{q_L}{q_H-q_L}, 0)$, the unconditional purchase probability remains unaffected by loss aversion. In this range, the customers' reference point is sufficiently low that even purchasing the low-quality product does not generate a perception of loss.

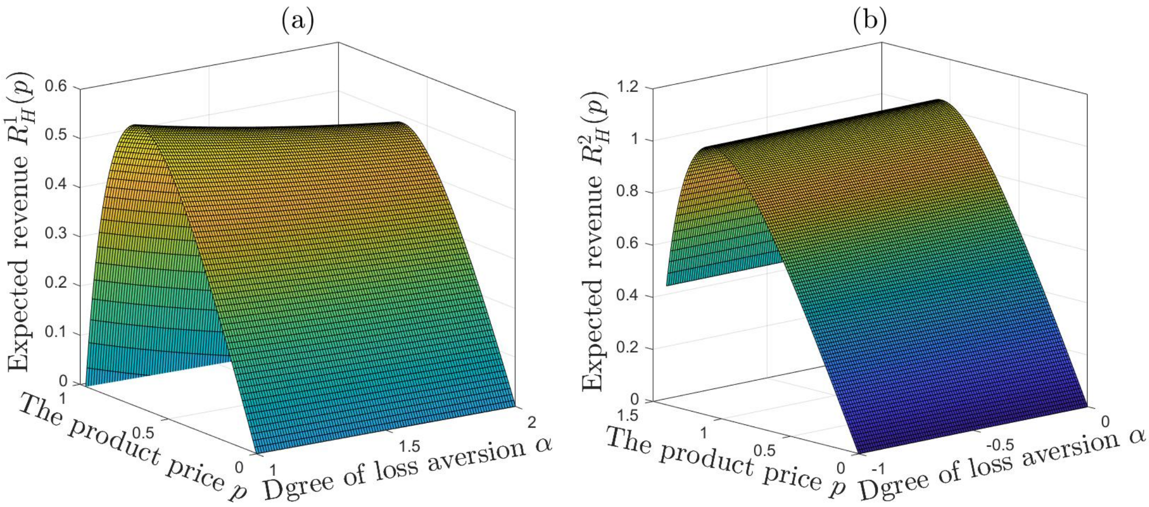

Figure 8. (a) The impacts of the degree of loss aversion α and the product price p on the high-quality seller's expected revenue $R_H^1(p)$, where $q_H = 1, q_L = 0.5, \lambda = 0.5, \beta = 0.5$, and $\tau = 0.5$.
(b) The impacts of the degree of loss aversion α and the product price p on the high-quality seller's expected revenue $R_H^2(p)$, where $q_H = 1, q_L = 0.5, \lambda = 0.5, \beta = -0.5$, and $\tau = 0.5$.

Proposition 6(ii) establishes that for $\beta \in [0, 1]$, both the revenue-optimal prices and optimal revenues decrease with α. The increase in the degree of loss aversion (increased α) reduces customers' utility of purchasing the low-quality product, lowering their conditional purchase probability. Although α does not directly affect utility of purchasing the high-quality product, under limited attention, the reduced conditional purchase probability for the low-quality product indirectly affects the high-quality product through the unconditional purchase probability. This interdependence ultimately leads to decreased purchase probability for both product types, forcing the seller to lower revenue-optimal prices and consequently reducing the optimal revenues. When $\beta \in [-\frac{q_L}{q_H-q_L}, 0)$, the revenue-optimal prices and optimal revenues of the seller are all independent of α. This is because, at this point, the customers' reference point is low, and even if they purchase the low-quality product, they will not perceive a loss. This means that the seller's revenue-optimal prices and optimal revenues will not be affected by α.

Figure 8 illustrates the three-dimensional trend of the high-quality seller's expected revenue in relation to the degree of loss aversion and product price. As stated in Proposition 6(ii), under high reference levels (Figure 8(a)), both the optimal revenue and the revenue-maximizing price decrease with an increase in the degree of loss aversion, whereas under low reference levels (Figure 8(b)), they remain unaffected by the degree of loss aversion.

Proposition 6 indicates that sellers should adopt differentiated strategies to address the customers' loss aversion according to their market positioning. When targeting the high-end market (where the customers have high reference points), the sellers must make every effort to avoid the customers' perception of loss. For instance, offering long-term warranties and authoritative certifications can help alleviate concerns about uncertain product quality, thereby reducing perceived losses. For products with low reference points, customers do not perceive losses. In this case, sellers should focus on highlighting the benefits or improvements brought by the purchase. For example, providing free trials allows the customers to experience the core value first, encouraging them to pay for advanced features, where the payment is perceived as a gain rather than a loss to their current state. Additionally, sellers can emphasize how the product delivers positive emotional experiences (such as convenience or pleasure) to the customers.

The following proposition provides the impacts of the prior belief τ on the unconditional purchase probability, the revenue-optimal prices, and the optimal revenues.

Proposition 7 (**The impact of the prior belief**). *(i) The unconditional purchase probability* $\pi_0^k(p)$ *increases with* τ *for* $p \in [\underline{p}^k, \overline{p}^k]$ *for* $k \in \{1, 2\}$.

(ii) The revenue-optimal prices p_L^{k*} *and* p_H^{k*}*, and the optimal revenues* R_L^{k*} *and* R_H^{k*} *all increase with* τ *for* $k \in \{1, 2\}$.

Proposition 7(i) indicates that the unconditional purchase probability increases with respect to the prior belief. Because the increase in τ improves the prior probability of the high-quality product, which naturally makes the customers more willing to purchase, thereby increasing the unconditional purchase probability. Proposition 7(ii) indicates that the seller's revenue-optimal prices and optimal revenues also increase with respect to the prior belief, which is also intuitive. The increase in prior belief increases the purchase probability of customers, allowing the sellers to charge higher prices and thus obtain higher revenues. Figure 9 displays the three-dimensional trend of the high-quality seller's expected revenue as it varies with prior belief and the product price. As described in Proposition 7(ii), regardless of the reference level, both the optimal revenue and the revenue-optimal price increase with prior belief.

In light of the managerial interpretations of the key findings developed in this section, we will provide a comprehensive summary of the research findings and managerial implications in the subsequent section.

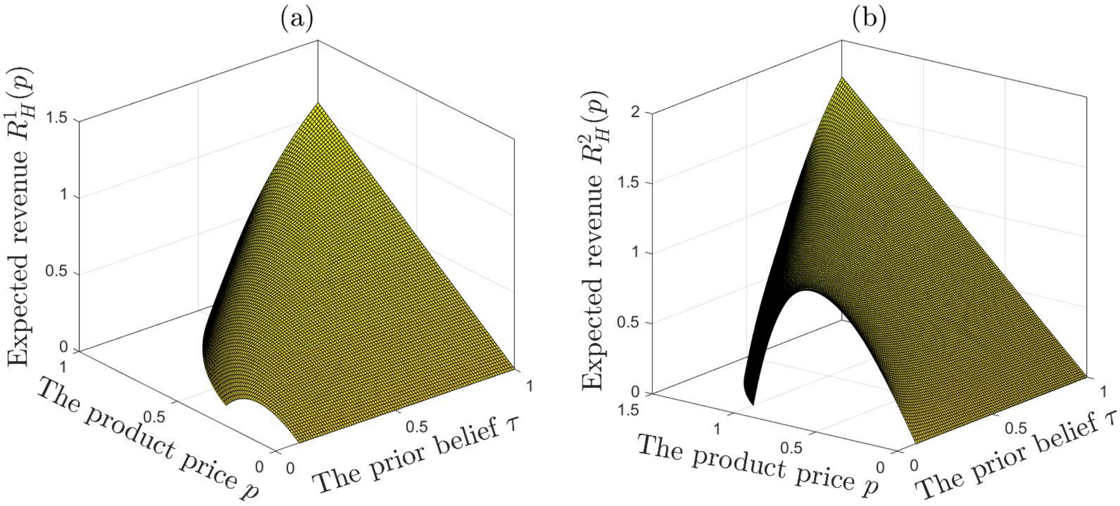

Figure 9. (a) The impacts of the prior belief τ and the product price p on the high-quality seller's expected revenue $R_H^1(p)$, where $q_H = 1, q_L = 0.5, \lambda = 0.5, \beta = 0.5$, and $\alpha = 2$.
(b) The impacts of the prior belief τ and the product price p on the high-quality seller's expected revenue $R_H^2(p)$, where $q_H = 1, q_L = 0.5, \lambda = 0.5, \beta = -0.5$, and $\alpha = 2$.

5. Conclusions

In this paper, we investigate the optimal pricing strategy for a monopoly seller facing loss-averse and rationally inattentive customers. The findings of this study reveal that customer decision-making is jointly regulated by the information cost, reference point, degree of loss aversion, and prior belief. Their impacts exhibit significant asymmetry. An increase in the information cost consistently improves the revenue of low-quality sellers, while it is nonmonotonic for high-quality sellers. The increase in the reference level systematically reduces purchase probability and the sellers' revenue, as it directly raises the customers' reference point and intensifies perceived losses. The negative impact of loss aversion only appears when the reference point is high, highlighting the highly context-dependent nature of its effect. The prior belief has a monotonic amplification effect on all positive indicators, underscoring the core value of intangible assets such as brand reputation in guiding customers' decision-making. These findings collectively characterize customers' purchasing behavior in complex information environments and provide a theoretical foundation for the sellers' strategy formulation.

On the basis of the findings above, this study provides managerial and policy implications for different market participants. For sellers, high-quality brands (such as luxury goods and high-end electronic products) must proactively reduce the information cost (e.g., by introducing third-party certification and offering long-term warranties) to break down information barriers. They should also leverage marketing communication to establish a favorable reference point and mitigate the negative impact of loss aversion through reliable assurance commitments. Furthermore, they should continuously cultivate their brand's reputation to enhance the prior belief, thereby supporting price premiums. In contrast, low-quality sellers or new market entrants should maintain high information cost by obfuscating information and simultaneously anchor a lower reference point to avoid loss aversion. For regulatory agencies, in industries with severe information asymmetry (such as financial products and healthcare), standardized key information disclosure rules can be implemented to mandatorily reduce the information costs related to quality dimensions, thereby protecting customers' rights and ensuring the market's fairness and efficiency.

Finally, to construct a more comprehensive theoretical framework, this study can be extended in several directions. First, competitive market structures can be introduced to examine how multiple sellers engage in price and quality competition when facing customers with behavioral biases. Second, the model can be extended to the scenario of multiple product combinations to investigate how sellers can jointly price product lines with quality correlations. Third, heterogeneity in the information cost can be considered; that is, different customer groups have differences in information processing capabilities and costs. How should sellers design targeted marketing strategies for precise market segmentation? Fourth, constructing a dynamic multi-period model will be a core challenge and opportunity, aimed at characterizing how customers update their beliefs and reference points on the basis of past purchasing experiences, and how sellers adjust their long-term pricing and information disclosure strategies accordingly. Furthermore, while this study does not include specific industry case studies due to data accessibility constraints, the analytical framework established here provides a clear pathway for future empirical testing. For instance, subsequent research could leverage publicly available data from O2O(Online to Offline) food delivery platforms or online electronics markets to conduct rigorous econometric tests of this paper's theoretical predictions. These extensions would collectively promote the theoretical framework to approach the complexity of the real market, thereby generating more universal management insights and policy recommendations.

Author contributions

Ying Li: Conceptualization, methodology, validation, formal analysis, investigation, writing–original draft, writing–review and editing, visualization.

Jian Cao: Validation, writing–review and editing, supervision, project administration.

Yongjiang Guo: Resources, writing–review and editing, supervision, project administration, funding acquisition.

All authors reviewed and edited the manuscript.

Use of Generative AI tools declaration

The authors declare they have not used artificial intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare no conflict of interest.

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