



Consumer Privacy and Differential Pricing on Digital Platforms: A Comparative Institutional Analysis

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Abstract

This paper develops a theoretical model consisting of a single platform and two heterogeneous consumer types to examine the interaction among consumer authorization, platform privacy protection, and discriminatory pricing. After obtaining consumers' authorization to use their data, the platform identifies consumer types and simultaneously determines the level of privacy protection and the discriminatory surcharge, while consumers choose between authorized and non-authorized purchasing options according to their utilities. These choices generate two internal demand structures, which are connected by an authorized-demand composition adjustment state. The results show that the two sets of structure-specific optimal decisions cannot simultaneously satisfy their corresponding demand conditions under the same parameter configuration. After incorporating demand-structure consistency, the platform's optimal privacy protection level and discriminatory surcharge initially remain unchanged and subsequently decline as low-type consumers' product valuation increases. The implementable-profit comparison shows that the first demand region is more profitable when low-type consumers' valuation is relatively low, whereas the second demand region becomes more profitable when their valuation is sufficiently high. Within the intermediate range, the profit bounds of the two demand regions coincide at the adjustment point. Numerical analysis further shows that changes in the base price and privacy-management cost alter the valuation thresholds and operating ranges but do not change the main transition mechanism.

Keywords: consumer authorization; privacy protection; discriminatory pricing; platform pricing decisions; demand structure



1. Introduction

1.1. Research Background

With the rapid development of the platform economy and digital technologies, consumer data has become an important resource for platforms to identify users, match demand, and generate revenue. By collecting and processing consumers' browsing records, transaction histories, interest preferences, and past behaviors, platforms can improve matching efficiency, enhance service experiences, and further strengthen monetization capabilities[1][4]. At the same time, however, consumers have become increasingly concerned about the continuous tracking, excessive collection, and improper use of their personal information, making privacy a key issue that platforms can no longer avoid in their operations[2][3].

From the consumer perspective, data use has a clear dual nature. On the one hand, platform use of data can improve recommendation accuracy, reduce search costs, and enhance personalized service experiences. On the other hand, once information is identified, stored, and further utilized by the platform, consumers may face privacy intrusion, persistent profiling, and even differential treatment[1][3]. Therefore, consumers do not unconditionally accept platform data collection and personalization services; rather, they weigh service benefits against privacy costs, and this trade-off further affects their willingness to authorize, purchasing behavior, and acceptance of platform services[2][4].

From the platform perspective, the importance of data lies not only in service optimization but also in the enhancement of identification and operational capabilities. The more complete the information a platform holds about consumers, the stronger its ability to identify user types, characterize consumption preferences, and implement differentiated operations. In particular, in transaction-oriented platforms, data are not used solely for recommendation and advertising; they may also be further employed for pricing design and revenue extraction, thereby creating a more direct link between privacy issues and platform pricing decisions[4][5]. This implies that privacy is no longer merely a matter of consumer perception, but has become embedded in the platform's operational decisions and pricing mechanisms.

These mechanisms can be observed in actual digital-platform operations. A staff report issued by the Federal Trade Commission documents that major social media and video-streaming services collected and retained extensive information from both users and non-users. The report also identifies concerns regarding limited transparency, inadequate privacy controls, and the extensive commercial use of personal data. These findings provide practical motivation for treating consumer authorization and privacy choices as important determinants of the information available to platforms. Such information may subsequently support consumer identification and other data-driven operations [Error! Reference source not found.].

Meanwhile, reported differential-pricing practices have appeared in online retailing, subscription renewal, ride-hailing, airline ticketing, and hotel-booking services. Consumers with different membership status, transaction histories, device characteristics, or degrees of platform familiarity

may receive different prices, discounts, coupons, or renewal offers for comparable products or services [33]. Although not every observed price difference necessarily constitutes unlawful discrimination, these practices demonstrate that consumer data and user identification may become important inputs into platform pricing. Taken together, the two types of practices reveal a continuous operational mechanism: consumers first decide whether to authorize data use; the platform then obtains information that improves consumer identification; and the enhanced identification capability may subsequently support differential pricing. At the same time, the platform may invest in privacy protection to mitigate consumers' disutility from data disclosure and maintain their willingness to authorize.

Furthermore, in more specific online transaction and channel operation settings, privacy concerns interact with payment convenience, channel relationships, and coordination mechanisms, thereby affecting firms' promotion, pricing, and revenue allocation [6]. At the same time, research on digital product and platform service operations also shows that platform pricing is often shaped by a broader set of operational factors. Li, Wu, and Xu [7] show that opinion leader influence in social e-commerce significantly affects platforms' service investment decisions. Li and Lev [8] demonstrate that consumer AI learning affects the dynamic pricing path of experience goods. Li, Lyu, Lyu, et al. [9] further show that, under bilateral platform intervention, optimal pricing is jointly determined with quality improvement strategies. Li, He, and Xu [10] point out that, in augmented reality service settings, product returns, cooperation mechanisms, pricing, and customer satisfaction are also closely interconnected. These studies suggest that privacy issues do not remain at the level of information disclosure alone, but further penetrate the actual operational behavior of platforms and firms.

Overall, the more a platform relies on consumer data, the stronger its capability for identification and differentiated operations; meanwhile, the more sensitive consumers are to privacy loss, the more likely their authorization intentions and purchasing decisions are to change. Consequently, privacy protection, data authorization, and platform pricing are closely interrelated, and this constitutes the practical background of this study.

1.2. Research Questions

Existing studies have examined privacy issues from the perspectives of personalization services, marketing avoidance, online advertising, and platform pricing. However, some key mechanisms in platform transaction settings still lack further analysis. In particular, when a platform can identify consumer types after obtaining their authorization and then implement discriminatory pricing, how consumer authorization, platform privacy protection, and discriminatory pricing jointly affect market demand structure and the platform's optimal decisions remains insufficiently understood.

Against this backdrop, this paper focuses on the following questions. First, how does consumers' choice between authorization and non-authorization affect the formation and segmentation of platform demand? More specifically, how do the authorized purchase threshold for high-type consumers, the authorized purchase threshold for low-type consumers, and the indifference

threshold between the two types jointly determine changes in market demand structure? Second, under heterogeneity in consumer valuation and privacy sensitivity, how are the platform's optimal level of privacy protection and optimal discriminatory surcharge determined? Finally, when low-type consumers shift from being outside the authorized purchasing region to entering it, how do the platform's demand structure, incentives for privacy protection, and pricing logic change accordingly? And how do these changes reveal the underlying trade-off between data utilization and privacy protection?

1.3. Research Approach and Contributions

To address the above questions, this paper develops a theoretical model consisting of a single platform and two heterogeneous consumer types. The platform earns revenue by providing products or services, identifies consumer types after obtaining data authorization, and imposes an additional surcharge on high-type consumers. At the same time, the platform can mitigate the disutility caused by information disclosure by increasing its level of privacy protection. Consumers, in turn, make purchasing decisions based on their own valuations, privacy sensitivities, and utility levels under authorization and non-authorization.

Compared with the existing literature, this paper does not focus on consumers' acceptance of personalization in the general sense, nor on advertising fees or two-sided pricing structures under platform competition. Instead, it is more closely aligned with actual platform transaction practices and specifically investigates how the type-identification capability formed after consumer authorization further changes the platform's discriminatory pricing behavior. Within this framework, this paper incorporates consumer authorization, platform privacy protection, and discriminatory pricing into a unified analytical system, and characterizes changes in the platform's optimal decisions through demand thresholds and shifts in demand structure.

This study makes three main contributions. First, it develops a unified analytical framework that links consumer authorization, platform identification, privacy protection, and differential pricing. Unlike studies that examine privacy mainly through personalization services, advertising revenues, or regulatory constraints, this paper focuses on a transaction-oriented setting in which authorization enables the platform to identify consumer value and implement differential pricing.

Second, the study explains how the platform's privacy-protection and pricing decisions jointly reshape the composition of authorized demand. Rather than treating different market configurations as externally given scenarios, the model shows how they emerge from the interaction between platform decisions and consumers' choices among alternative transaction states.

Third, the analysis identifies how the value composition of authorized demand and privacy-management cost jointly affect the platform's operating decisions and profitability. It further shows that an expansion of authorized demand does not necessarily generate a corresponding increase in platform profit, because the commercial value of authorization depends on both the consumers attracted and the cost required to maintain their willingness to authorize.

2. Literature Review

2.1. Consumer Privacy Concerns and Personalization Services

Goldfarb and Tucker [11] examine the impact of privacy regulation on the effectiveness of online advertising and show that privacy protection rules can significantly alter the effectiveness of data-driven marketing. Their study indicates that privacy is not merely a matter of whether consumers are willing to share information; rather, it directly affects the platform's ability to use data to improve matching and conversion. Tucker [12] further finds, in the context of personalized advertising on social networks, that when platforms provide consumers with more explicit privacy controls, consumers' responses to personalized advertising change accordingly. This suggests that consumers' perceptions of control over their privacy can themselves shape the effectiveness of personalization strategies. Taylor [13] argues that consumer information is valuable because firms can use it to improve marketing and pricing decisions. Acquisti and Varian [14] further show that the accumulation of purchase-history information enhances firms' ability to identify consumers and makes conditioned pricing possible. In this sense, personalization services and privacy issues naturally extend into the domain of price formation. Casadesus-Masanell and Hervas-Drane [15], from the perspective of platform competition, analyze the strategic role of privacy and show that platforms can differentiate themselves through different levels of information disclosure and privacy protection. Their study suggests that privacy has become not only a matter of consumer welfare but also an endogenous strategic variable in platform competition.

2.2. Information Disclosure, Data Externalities, and Platform Pricing

Ichihashi [16] studies online consumer information disclosure and examines how consumers trade off more accurate recommendations against the risk of being identified and subjected to discriminatory pricing. The study shows that consumers' disclosure decisions, in turn, affect firms' data utilization and pricing decisions. From the perspective of information externalities, Choi, Jeon and Kim [17] discuss personal data collection and show that even when consumers understand the consequences of data collection and consent to disclosure, excessive data collection may still arise because of data externalities. This implies that relying solely on individual consent does not necessarily lead to a socially optimal allocation of data. Campbell, Goldfarb and Tucker [18] further connect privacy regulation with market structure and show that privacy regulation based on consumer consent can reshape competition in data-intensive industries. Their study indicates that privacy protection rules affect not only the boundary of data use but also firms' entry, expansion, and competitive behavior. Acemoglu et al. [19] argue that the sharing of personal data generates externalities, which depress data prices and lead to excessive data sharing. This extends privacy issues beyond the one-platform–one-consumer relationship to the broader question of allocative efficiency in data markets. Chen, Simchi-Levi, and Wang [20] further investigate the feasibility of dynamic personalized pricing under privacy protection constraints, showing that privacy protection and data-driven pricing are not simply opposed to each other; rather, they involve a new trade-off between revenue generation and learning. Montes, Sand-Zantman, and

Valletti [21] examine the value of personal information in online markets and show that when firms can use consumers' private information for price discrimination, privacy costs affect prices, profits, and consumer surplus. The study is particularly relevant to this paper because it demonstrates that privacy issues can directly enter the mechanism of discriminatory pricing. Ichihashi [22], in later work, further shows from the perspective of dynamic privacy choices that the interaction between consumers and platforms over privacy protection is not one-shot, but evolves over continued platform use and data accumulation. This extends privacy analysis to a dynamic setting.

2.3. Channels, Supply Chains, and the Consequences of Data Utilization

Goldfarb and Tucker [23] discuss privacy from the perspective of the digital marketplace as a whole and point out that privacy protection has become deeply embedded in modern market operations, influencing firm behavior through information flows, marketing practices, and revenue mechanisms. Their study suggests that privacy is not an external add-on to platform operations, but a foundational institutional factor in digital markets. Xu, Wang, and Zhang [**Error! Reference source not found.**] investigate consumer privacy policy in the context of online retail supply chains and show that even when privacy policies are intended to protect consumers, their implementation does not necessarily improve the welfare of all parties; in some cases, it may even harm consumers, retailers, and suppliers simultaneously. This indicates that the consequences of privacy policy must be evaluated within specific market structures. Goldfarb and Que [25] provide a systematic review of the economics of digital privacy and argue that research on digital privacy has expanded from a narrow focus on information protection to broader issues such as data-driven innovation, platform competition, consumer welfare, and policy design. Their review offers a clear framework for understanding the broader research landscape on privacy. Lefouili, Madio, and Toh [26] link privacy regulation to quality-enhancing innovation and show that restrictions on information disclosure may alter firms' incentives for quality improvement and innovation. Their study suggests that privacy policy affects not only static pricing and data use, but also firms' long-term innovation decisions. Gopal et al. [**Error! Reference source not found.**] further examine how government data protection policies affect information sharing between websites and third parties, showing that government intervention changes the equilibrium among websites, users, and third parties. This extends privacy analysis to the level of regulation and platform ecosystems.

2.4. Privacy Regulation, Data Markets, and Firm Decisions

Acquisti, Taylor and Wagman [28] systematically review the central issues in the economics of privacy and point out that the economic value of personal information disclosure, the welfare implications of privacy loss, and consumers' understanding of these trade-offs are all highly complex. Their review helps clarify the theoretical foundations of digital privacy research at a higher level. Goldberg, Johnson and Shriver [29] evaluate the economic effects of the GDPR and show that privacy regulation can affect website traffic and revenues, implying that privacy policy may alter firms' data acquisition capabilities and platform performance. Fainmesser, Galeotti, and Momot [30] further study firms' incentives to collect and protect user data in digital markets and

show that the intensity of privacy protection is systematically related to firms' underlying business models. This suggests that platforms' privacy protection choices are also shaped by their revenue sources and modes of operation.

2.5. Literature Review Summary

Overall, the existing literature has examined consumer privacy from several complementary perspectives. Studies on personalization and privacy concerns mainly investigate how privacy protection and consumer perceptions affect the effectiveness of data-driven services. Research on information disclosure and personalized pricing emphasizes that consumer information improves firms' identification capabilities and may support conditioned or discriminatory pricing. Other studies focus on privacy regulation, platform competition, data externalities, and privacy-preserving pricing mechanisms.

Although these studies provide important foundations, the mechanisms of consumer authorization, platform identification, privacy protection, and discriminatory pricing are generally examined separately. In particular, relatively limited attention has been paid to transaction-oriented platforms in which consumers first decide whether to authorize data use, the platform subsequently identifies consumer types, and the resulting pricing and privacy-protection decisions endogenously change the composition of authorized demand. Table 1 compares representative studies along these dimensions.

Table 1. Comparison of Representative Literature and This Study

Representative study	Explicit consumer authorization or disclosure choice	Consumer identification based on data	Endogenous privacy-protection decision	Discriminatory-pricing decision	Endogenous authorized-demand composition
Lee et al. (2011)	No	No	Yes	No	No
Acquisti and Varian (2005)	No	Yes	No	Yes	No
Ichihashi (2020)	Yes	Yes	No	Yes	No
Montes et al. (2019)	Yes	Yes	No	Yes	No
Chen, Simchi-Levi, and Wang (2025)	No	Yes	No	Yes	No
This study	Yes	Yes	Yes	Yes	Yes

Note: "Yes" indicates that the corresponding mechanism is explicitly incorporated as a core element of the analytical model; "No" indicates that it is not treated as a central endogenous mechanism.

As shown in Table 1, prior studies have provided important insights into privacy protection, information disclosure, consumer identification, and personalized pricing. However, few studies integrate all these mechanisms into a unified transaction-oriented framework. More importantly, many existing studies treat market segments or pricing environments as given, rather than examining how platform decisions and consumer authorization choices jointly determine the realized composition of authorized demand.

To address this gap, this paper integrates consumer authorization, platform identification, endogenous privacy protection, discriminatory pricing, and authorized-demand composition into a unified analytical framework. The resulting demand structures are not imposed as exogenous scenarios but emerge endogenously from consumer utility comparisons and platform decisions. This framework makes it possible to examine how changes in the composition of authorized demand affect the platform’s operating decisions and profit outcomes.

3. Model Development and Solution

3.1. Model Description

Consider a market consisting of a single platform and two representative consumer types. The platform earns sales revenue by providing products or services and, after obtaining consumers' authorization to use their data, identifies consumer types and then implements discriminatory pricing. The platform simultaneously determines the privacy protection level x and the discriminatory surcharge Δp . Here, x denotes the degree of protection adopted by the platform to mitigate consumers' privacy concerns, while Δp denotes the additional price surcharge imposed on high-type consumers once they are identified by the platform.

Figure 1 illustrates the basic decision structure of the model. Given the exogenous base price, the platform simultaneously determines the privacy protection level and the discriminatory surcharge, while consumers are divided into high-type and low-type groups and may choose whether to authorize the platform to use their data.

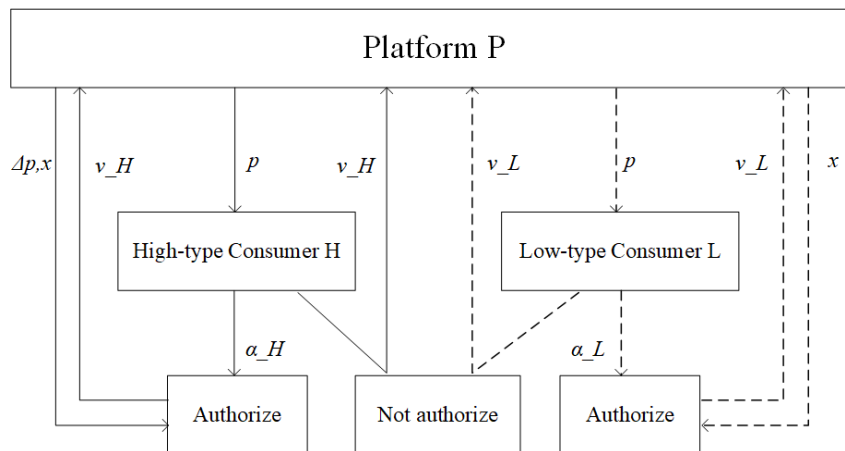


Figure 1. Platform - Consumer Decision Structure

Let the consumer set be $i \in \{H, L\}$. Consumers are heterogeneous in both their valuation of the platform product or service and their sensitivity to information disclosure. Prior analytical studies commonly distinguish consumers according to differences in the benefits or demand they derive from a product. For example, Hann et al. [2] distinguish between high- and low-benefit consumers. Accordingly, we assume that high-type consumers have a higher product valuation than low-type consumers, such that $v_H > v_L$.

Consumers may also differ in the privacy disutility they experience from information disclosure. Gal-Or et al. [Error! Unknown switch argument.] account for heterogeneity in users' privacy concerns in digital-platform markets. We therefore assume that high-type consumers are more sensitive to information disclosure than low-type consumers, such that $\alpha_H > \alpha_L$.

For analytical parsimony, the model combines these two dimensions into a two-type consumer classification. High-type consumers have relatively higher product valuations and privacy sensitivity, whereas low-type consumers have relatively lower product valuations and privacy sensitivity. This joint classification is a modelling assumption and does not imply that a higher product valuation necessarily causes greater privacy sensitivity.

As shown in Figure 1, once consumers authorize the platform to use their data, the platform can identify consumer types and impose an additional surcharge only on high-type consumers; if consumers do not authorize, the platform cannot identify them through authorized data, and they purchase only at the uniform base price.

The platform charges a uniform base price p . Once consumers authorize the platform to use their data, high-type consumers are identified and charged an additional surcharge Δp , whereas low-type consumers, even if they authorize, are not subject to any extra charge. At the same time, the platform can partially offset the disutility caused by information disclosure by increasing its privacy protection level x , but this gives rise to privacy management costs. Let the information disclosure level perceived by consumers be $t \in [0, 1]$, and let the platform choose a uniform privacy protection level satisfying $x \geq 0$. A larger x indicates a stronger mitigating effect on the disutility from information disclosure. The platform incurs privacy management costs, which are assumed to take the quadratic form kx^2 , where $k > 0$ is the privacy management cost coefficient. For simplicity, the total mass of potential consumers is normalized to 1, so that the demand in what follows can be interpreted directly as the length or share of the corresponding consumer interval.

To facilitate the subsequent derivations and focus on the relative differences between the two consumer types, we normalize the high-type consumer valuation and privacy sensitivity to one, such that $v_H = \alpha_H = 1$. This treatment follows the common normalization practice in analytical modelling, under which a benchmark type or state is set to one to simplify the analysis [Error! Unknown switch argument.].

After this normalization, we further set $\alpha_L = \frac{1}{2}$ as a parsimonious benchmark parameterization satisfying $\alpha_H > \alpha_L > 0$. This value preserves the assumed difference in privacy sensitivity and simplifies the analytical expressions. It is adopted for analytical tractability rather than interpreted as an empirically estimated privacy-sensitivity coefficient.

Under these settings, the analysis focuses on how the base price p , the valuation of low-type consumers v_L and the privacy management cost coefficient k jointly affect the platform's optimal privacy protection and discriminatory pricing decisions under different demand structures.

3.2. Notation

The main notation used in this paper is defined in Table 2.

Table 2. Notation

Symbol	Definition
N	Total number of potential consumers
v_H	High-type consumers' valuation of the platform product/service
v_L	Low-type consumers' valuation of the platform product/service
α_H	High-type consumers' privacy sensitivity, reflecting their aversion to information disclosure
α_L	Low-type consumers' privacy sensitivity
p	Base price of the product/service
Δp	Additional surcharge imposed on identified high-type consumers
t	Information disclosure level perceived by consumers in the platform environment
x	Platform privacy protection level
k	Privacy-management cost coefficient

3.3. Consumer Utility Functions and Thresholds

Under authorized purchase, the utilities of high-type and low-type consumers are respectively given by

$$U_H^A = v_H - p - \Delta p - \alpha_H(t - x),$$

$$U_L^A = v_L - p - \alpha_L(t - x).$$

Under non-authorized purchase while still buying from the platform, the utilities of the two consumer types are respectively

$$U_H^N = v_H - p, \quad U_L^N = v_L - p.$$

It follows that authorized purchase has a twofold effect: on the one hand, it makes high-type consumers face an additional surcharge; on the other hand, the platform's privacy protection partly mitigates the disutility caused by information disclosure.

Based on the above utility comparisons, three key thresholds can be derived: the authorized purchase threshold for high-type consumers t_H , the authorized purchase threshold for low-type consumers t_L , and the indifference threshold between authorized purchases of high-type and low-type consumers t_{HL} . Under the normalized setting, these three thresholds are

$$t_H = x - p - \Delta p + 1,$$

$$t_L = 2v_L - 2p + x,$$

$$t_{HL} = x - 2v_L - 2\Delta p + 2.$$

Economically, the three thresholds describe different marginal consumer choices. The threshold t_H identifies the marginal consumer who is indifferent between an authorized purchase under the high-type transaction state and a non-authorized purchase. Similarly, t_L represents the corresponding authorized-purchase threshold for low-type consumers. The threshold t_{HL} is the point at which the utilities associated with the high-type and low-type authorized transaction states are equal. It therefore determines the internal boundary between the two types of authorized demand.

The economic role of these thresholds depends not only on their individual values but also on their relative ordering. In particular, the relative positions of t_L , t_H , and t_{HL} determine whether low-type consumers have a positive authorized-demand interval. Thus, the two demand structures are generated endogenously by consumer utility comparisons and the platform’s decisions, rather than being imposed as exogenous market scenarios.

We define

$$\overline{\Delta p} = 1 + p - 2v_L.$$

as the discriminatory-surcharge level at which the ordering of the three thresholds changes. This value is not an externally imposed upper bound on the platform’s pricing decision. The platform remains free to determine Δp . Rather, $\overline{\Delta p}$ identifies the point at which the selected surcharge changes the composition of authorized demand. These thresholds jointly determine the segmented form of platform demand. Moreover, a higher v_L reduces $\overline{\Delta p}$, implying that low-type consumers enter the authorized purchasing region under a lower discriminatory surcharge when their product valuation is higher.

3.4. Demand Structures and Platform Profit

Depending on the relative ordering of t_H , t_L and t_{HL} , the model gives rise to two internal demand structures. The relative ordering of these thresholds determines whether the authorized-demand interval of low-type consumers is empty or positive. Therefore, the two demand structures differ not merely in their mathematical threshold conditions, but in the resulting composition of authorized demand.

The first demand structure is $t_L < t_H < t_{HL}$, which is equivalent to $\Delta p < \overline{\Delta p}$. Under this case, low-type consumers have not yet entered the authorized purchasing region, so authorized demand from low-type consumers is zero. The market is composed only of authorized demand from high-type consumers and non-authorized demand, that is,

$$D_L = 0, \quad D_H = t_H, \quad D_3 = 1 - t_H.$$

When $\Delta p = \overline{\Delta p}$, the three thresholds coincide: $t_L = t_H = t_{HL}$. At this point, authorized demand from low-type consumers contracts to zero. Therefore, the equality case has the same demand composition as the first demand structure and can be regarded as the upper boundary of the first demand structure rather than as a separate demand structure. Accordingly, the applicable range of the first demand structure can be written as $\Delta p \leq \overline{\Delta p}$.

The second demand structure is $t_{HL} < t_H < t_L$, which is equivalent to $\Delta p > \overline{\Delta p}$. Under this case, low-type consumers begin to enter the authorized purchasing region, so authorized demand from

low-type consumers becomes positive. The market is therefore divided into three parts: authorized demand from high-type consumers, authorized demand from low-type consumers, and non-authorized demand, i.e.,

$$D_L = t_L - t_{HL}, \quad D_H = t_{HL}, \quad D_3 = 1 - t_L.$$

Hence, compared with the first demand structure, the key feature of the second demand structure is that low-type consumers move from being outside the authorized purchasing region to entering it, so that authorized demand from low-type consumers changes from zero to a positive level. This means that the composition of market demand changes. Accordingly, the valuation of low-type consumers v_L enters the platform's optimal decision expressions directly under the second demand structure.

To illustrate more intuitively how market demand is divided under the two internal demand structures, Figure 2 presents a schematic diagram of the two demand structures.

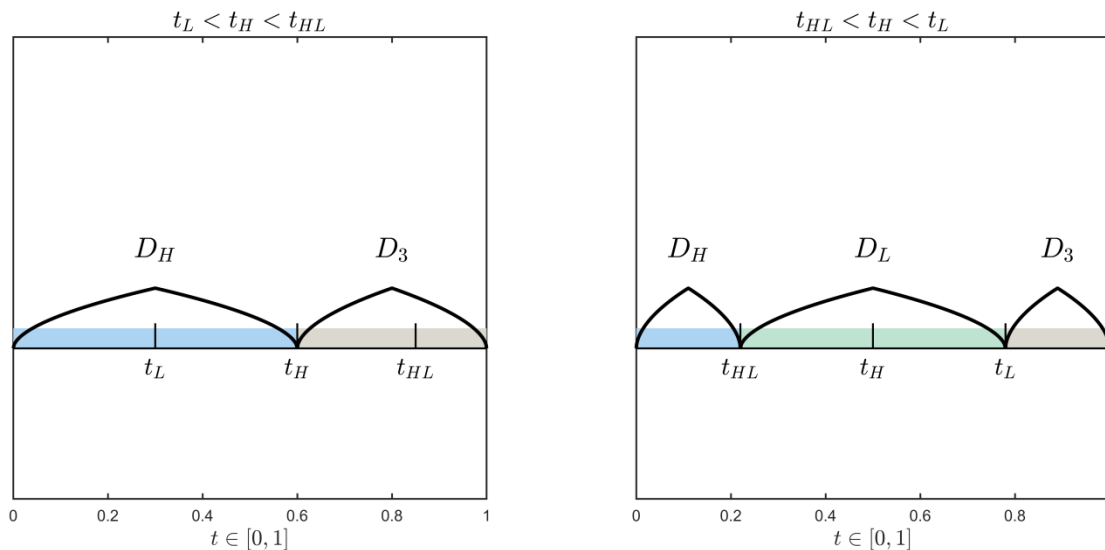


Figure 2. Two Internal Demand Structures

As shown in Figure 2, under the first demand structure, low-type consumers have not yet entered the authorized purchasing region, so the market consists only of authorized demand from high-type consumers and non-authorized demand. Under the second demand structure, low-type consumers begin to enter the authorized purchasing region, and the market is further divided into authorized demand from high-type consumers, authorized demand from low-type consumers, and non-authorized demand.

This indicates that the fundamental difference between the two demand structures lies in whether low-type consumers enter the authorized purchasing region, and this change forms the basis for the subsequent differences in the platform's optimal decisions and profit outcomes. It should be emphasized that the platform does not directly select a demand structure. Instead, it determines the privacy-protection level and discriminatory surcharge. These decisions affect consumers' utility comparisons and threshold ordering, which in turn determine the demand structure that is ultimately realized.

Platform profit consists of sales revenue and privacy management cost:

$$\Pi_P = p(D_H + D_L + D_3) + \Delta p D_H - kx^2.$$

Since total demand has been normalized to 1, the platform profit functions under the two internal demand structures can be simplified as follows:

When $\Delta p \leq \overline{\Delta p}$, the first demand structure $t_L < t_H < t_{HL}$ applies, and the platform profit is

$$\Pi_{P1} = p + \Delta p t_H - kx^2;$$

When $\Delta p > \overline{\Delta p}$ the second demand structure $t_{HL} < t_H < t_L$ applies, and the platform profit is

$$\Pi_{P2} = p + \Delta p t_{HL} - kx^2.$$

At the boundary $\Delta p = \overline{\Delta p} = 1 + p - 2v_L$, the demand composition remains the same as that under the first demand structure. Moreover, for any given and identical privacy protection level x , the two profit expressions satisfy

$$\Pi_{P1}(x, \overline{\Delta p}) = \Pi_{P2}(x, \overline{\Delta p}).$$

Therefore, the two platform profit functions are continuously connected at the boundary. This boundary does not constitute a third demand structure or require the construction of a new profit function. It remains the upper boundary of the first demand structure, while the platform’s optimal privacy protection level at this boundary will be determined in the subsequent model solution.

Thus, under the two internal demand structures, the platform faces a single operating decision problem consisting of two connected demand regions, rather than two unrelated optimization problems. The platform jointly determines x and Δp , while the selected discriminatory surcharge further determines the realized composition of authorized demand.

3.5. Model Solution

We first consider the first demand structure $t_L < t_H < t_{HL}$. Under this demand structure, the platform determines the privacy protection level x and the discriminatory surcharge Δp to maximize its profit:

$$\max \Pi_{P1} = p + \Delta p t_H - kx^2,$$

subject to $\Delta p \leq \overline{\Delta p}$, where $\overline{\Delta p} = 1 + p - 2v_L$.

Temporarily disregarding the restriction imposed by the demand structure, maximizing platform profit yields

$$\begin{aligned} x_1^* &= \frac{1 - p}{4k - 1}, \\ \Delta p_1^* &= \frac{2k(1 - p)}{4k - 1}, \\ \pi_{P1}^* &= \frac{k - p + 2kp + kp^2}{4k - 1}. \end{aligned}$$

For these decisions to sustain the first demand structure, the following condition must hold: $\Delta p_1^* \leq \overline{\Delta p}$. Let $\Delta p_1^* = \overline{\Delta p}$, that is, $\frac{2k(1-p)}{4k-1} = 1 + p - 2v_L$. Solving this equation gives the first valuation threshold:

$$v_L^{(1)} = \frac{6kp + 2k - p - 1}{8k - 2}.$$

Therefore, when $v_L \leq v_L^{(1)}$, the optimal decisions derived under the first demand structure can sustain the corresponding authorized-demand composition.

We next consider the second demand structure $t_{HL} < t_H < t_L$. Under this demand structure, the platform solves

$$\max \Pi_{p2} = p + \Delta p t_{HL} - kx^2.$$

subject to $\Delta p > \overline{\Delta p}$. Temporarily disregarding the restriction imposed by the demand structure, maximizing platform profit yields

$$\begin{aligned} x_2^* &= \frac{2(1 - v_L)}{8k - 1}, \\ \Delta p_2^* &= \frac{4k(1 - v_L)}{8k - 1}, \\ \pi_{p2}^* &= \frac{4k - p + 8kp - 8kv_L + 4kv_L^2}{8k - 1}. \end{aligned}$$

For these decisions to sustain the second demand structure, the following condition must hold: $\Delta p_2^* > \overline{\Delta p}$. Let $\Delta p_2^* = \overline{\Delta p}$, that is, $\frac{4k(1-v_L)}{8k-1} = 1 + p - 2v_L$. Solving this equation gives the second valuation threshold:

$$v_L^{(2)} = \frac{8kp + 4k - p - 1}{12k - 2}.$$

Therefore, when $v_L > v_L^{(2)}$, the optimal decisions derived under the second demand structure can sustain the corresponding authorized-demand composition.

Comparing the two valuation thresholds gives

$$v_L^{(2)} - v_L^{(1)} = \frac{2k^2(1 - p)}{(4k - 1)(6k - 1)} > 0.$$

Hence, $v_L^{(1)} < v_L^{(2)}$. When $v_L^{(1)} < v_L \leq v_L^{(2)}$, the optimal surcharge derived under the first demand structure exceeds its applicable range, whereas the optimal surcharge derived under the second demand structure is insufficient to generate positive authorized demand from low-type consumers. In this case, the platform maintains the discriminatory surcharge at the level at which the composition of authorized demand begins to change. We refer to this situation as the authorized-demand composition adjustment state.

Under the authorized-demand composition adjustment state, the platform sets

$$\Delta p_A^* = \overline{\Delta p} = 1 + p - 2v_L.$$

Substituting this surcharge into the platform profit function gives

$$\Pi_{pA}(x) = p + (1 + p - 2v_L)(x + 2v_L - 2p) - kx^2.$$

Maximizing the above profit with respect to x yields

$$x_A^* = \frac{1 + p - 2v_L}{2k}.$$

The corresponding platform profit is

$$\pi_{pA}^* = p + 2(v_L - p)(1 + p - 2v_L) + \frac{(1 + p - 2v_L)^2}{4k}.$$

The above results are summarized in Theorem 1.

Theorem 1. The platform’s optimal privacy protection level, discriminatory surcharge, and profit depend on low-type consumers’ valuation of the product, v_L .

When $v_L \leq v_L^{(1)}$, the market exhibits the first demand structure $t_L < t_H < t_{HL}$, and the platform implements the following optimal decisions:

$$(x_1^*, \Delta p_1^*, \pi_{p1}^*) = \left(\frac{1-p}{4k-1}, \frac{2k(1-p)}{4k-1}, \frac{k-p+2kp+kp^2}{4k-1} \right);$$

When $v_L^{(1)} < v_L \leq v_L^{(2)}$, the platform operates under the authorized-demand composition adjustment state, and its optimal decisions are

$$(x_A^*, \Delta p_A^*, \pi_{pA}^*) = \left(\frac{1+p-2v_L}{2k}, 1+p-2v_L, p+2(v_L-p)(1+p-2v_L) + \frac{(1+p-2v_L)^2}{4k} \right).$$

When $v_L > v_L^{(2)}$, the market exhibits the second demand structure $t_{HL} < t_H < t_L$, and the platform implements the following optimal decisions:

$$(x_2^*, \Delta p_2^*, \pi_{p2}^*) = \left(\frac{2(1-v_L)}{8k-1}, \frac{4k(1-v_L)}{8k-1}, \frac{4k-p+8kp-8kv_L+4kv_L^2}{8k-1} \right).$$

Theorem 1 shows that the platform does not predetermine which demand structure will arise. Instead, its privacy protection and discriminatory-pricing decisions influence consumers’ authorization and purchasing choices. When low-type consumers have a relatively low valuation of the product, the market contains only authorized demand from high-type consumers and non-authorized demand. When their valuation is in an intermediate range, the platform maintains its operating decisions at the point at which the composition of authorized demand begins to adjust. When their valuation is sufficiently high, low-type consumers generate positive authorized demand, and the market exhibits the second demand structure.

To ensure that the above optimal decisions are economically meaningful, the optimal privacy protection levels and discriminatory surcharges must be positive.

Under the first demand structure, $x_1^* > 0$ and $\Delta p_1^* > 0$ require $p < 1, k > \frac{1}{4}$. Under the second demand structure, $x_2^* > 0$ and $\Delta p_2^* > 0$ require $v_L < 1, k > \frac{1}{8}$. Under the authorized-demand composition adjustment state, $x_A^* > 0$ and $\Delta p_A^* > 0$ require $v_L < \frac{1+p}{2}$. Moreover, $\frac{1+p}{2} - v_L^{(2)} = \frac{k(1-p)}{6k-1} > 0$. Therefore, when $v_L \leq v_L^{(2)}$, both the privacy protection level and the discriminatory surcharge under the authorized-demand composition adjustment state are positive.

To provide a unified basis for the subsequent analysis, we consider the common parameter range

$$p \leq v_L < 1, \quad k > \frac{1}{4},$$

and further require all relevant demand shares to be nonnegative. The explicit demand-feasible upper bound and the resulting effective numerical range are presented in Section 3.6.

This common parameter range only ensures that the platform’s decision variables are positive. It does not imply that the two sets of optimal decisions derived under the first and second demand structures can be implemented simultaneously under the same parameter configuration. The

demand structure that actually emerges continues to depend on the relationship between $v_L, v_L^{(1)}$, and $v_L^{(2)}$.

It is necessary to further clarify that $p \leq v_L < 1$ is the common parameter range that ensures the platform's decision variables are positive. For the horizontal comparison of platform profits in the two demand regions, it is also necessary to ensure that the first demand structure has an implementable space under the positive discriminatory surcharge. Since $\overline{\Delta p} = 1 + p - 2v_L$, this comparison further requires $p \leq v_L < \frac{1+p}{2}$. When $v_L \geq \frac{1+p}{2}$, the first demand structure no longer has an implementable space, and the market can only form the second demand structure. Therefore, the profit comparison between the two demand regions is no longer conducted.

Proposition 1. Sensitivity Analysis of the Platform's Optimal Decisions

(1) Under the first demand structure $t_L < t_H < t_{HL}$, $\frac{\partial x_1^*}{\partial p} < 0, \frac{\partial \Delta p_1^*}{\partial p} < 0, \frac{\partial x_1^*}{\partial v_L} = 0, \frac{\partial \Delta p_1^*}{\partial v_L} = 0$. Let $\frac{\partial \pi_{p1}^*}{\partial v_L} = 0$, when $\frac{1}{4} < k < \frac{1}{2}$, define $p_1^\pi = \frac{1-2k}{2k}$. If $p < p_1^\pi$, then $\frac{\partial \pi_{p1}^*}{\partial p} < 0$. If $p > p_1^\pi$, then $\frac{\partial \pi_{p1}^*}{\partial p} > 0$. When $k \geq \frac{1}{2}$, we have $\frac{\partial \pi_{p1}^*}{\partial p} > 0$.

(2) Under the authorized-demand composition adjustment state, $\frac{\partial x_A^*}{\partial p} > 0, \frac{\partial \Delta p_A^*}{\partial p} > 0, \frac{\partial x_A^*}{\partial v_L} < 0, \frac{\partial \Delta p_A^*}{\partial v_L} < 0$, and $\frac{\partial \pi_{pA}^*}{\partial v_L} < 0$. Define $v_L^p = \frac{8kp+2k-p-1}{12k-2}$. If $v_L < v_L^p$, then $\frac{\partial \pi_{pA}^*}{\partial p} < 0$. If $v_L > v_L^p$, then $\frac{\partial \pi_{pA}^*}{\partial p} > 0$. When $k \geq \frac{1}{2(1+p)}$, we have $v_L^p \leq v_L^{(1)}$, and hence $\frac{\partial \pi_{pA}^*}{\partial p} > 0$ throughout the authorized-demand composition adjustment range. When $\frac{1}{4} < k < \frac{1}{2(1+p)}$, we have $v_L^{(1)} < v_L^p < v_L^{(2)}$. In this case, an increase in the base price reduces platform profit when low-type consumers' product valuation is below v_L^p , but increases platform profit when their valuation is above v_L^p .

(3) Under the second demand structure $t_{HL} < t_H < t_L$, $\frac{\partial x_2^*}{\partial p} = 0, \frac{\partial \Delta p_2^*}{\partial p} = 0, \frac{\partial x_2^*}{\partial v_L} < 0, \frac{\partial \Delta p_2^*}{\partial v_L} < 0, \frac{\partial \pi_{p2}^*}{\partial p} > 0, \frac{\partial \pi_{p2}^*}{\partial v_L} < 0$.

(4) From the perspective of the platform's overall optimal decisions, When $v_L \leq v_L^{(1)}$, $\frac{\partial x^*}{\partial v_L} = \frac{\partial \Delta p^*}{\partial v_L} = \frac{\partial \pi_p^*}{\partial v_L} = 0$. When $v_L^{(1)} < v_L \leq v_L^{(2)}$, $\frac{\partial x^*}{\partial v_L} < 0, \frac{\partial \Delta p^*}{\partial v_L} < 0$, and $\frac{\partial \pi_p^*}{\partial v_L} < 0$. When $v_L > v_L^{(2)}$, $\frac{\partial x^*}{\partial v_L} < 0, \frac{\partial \Delta p^*}{\partial v_L} < 0$, and $\frac{\partial \pi_p^*}{\partial v_L} < 0$.

Proposition 1 shows that, under the first demand structure, the platform primarily adjusts privacy protection and the discriminatory surcharge in response to the base price. Under the authorized-demand composition adjustment state, both the base price and low-type consumers' product valuation affect the platform's decisions. Under the second demand structure, low-type consumers' product valuation becomes an important determinant of the platform's privacy protection and discriminatory-pricing decisions.

From an overall perspective, as low-type consumers' product valuation increases, the platform's optimal privacy protection level and discriminatory surcharge initially remain unchanged and

subsequently decline. The emergence of authorized demand from low-type consumers expands the identifiable consumer base, but does not necessarily increase platform profit.

Proof.

Under the first demand structure, $x_1^* = \frac{1-p}{4k-1}$, $\Delta p_1^* = \frac{2k(1-p)}{4k-1}$. Therefore, $\frac{\partial x_1^*}{\partial p} = -\frac{1}{4k-1} < 0$, $\frac{\partial \Delta p_1^*}{\partial p} = -\frac{2k}{4k-1} < 0$. Because neither expression contains v_L , $\frac{\partial x_1^*}{\partial v_L} = \frac{\partial \Delta p_1^*}{\partial v_L} = 0$. Platform profit satisfies $\frac{\partial \pi_{p1}^*}{\partial p} = \frac{2k+2kp-1}{4k-1}$. Setting this derivative equal to zero gives $p_1^\pi = \frac{1-2k}{2k}$.

Under the authorized-demand composition adjustment state, $x_A^* = \frac{1+p-2v_L}{2k}$, $\Delta p_A^* = 1 + p - 2v_L$. Therefore, $\frac{\partial x_A^*}{\partial p} = \frac{1}{2k} > 0$, $\frac{\partial \Delta p_A^*}{\partial p} = 1 > 0$, $\frac{\partial x_A^*}{\partial v_L} = -\frac{1}{k} < 0$, and $\frac{\partial \Delta p_A^*}{\partial v_L} = -2 < 0$. The effect of v_L on platform profit under the authorized-demand composition adjustment state is $\frac{\partial \pi_{pA}^*}{\partial v_L} = -\frac{2(4k-1)}{k} (v_L - v_L^{(1)})$. Because the authorized-demand composition adjustment state satisfies $v_L > v_L^{(1)}$, we have $\frac{\partial \pi_{pA}^*}{\partial v_L} < 0$. The effect of the base price on platform profit is $\frac{\partial \pi_{pA}^*}{\partial p} = \frac{(12k-2)v_L - (8k-1)p - 2k + 1}{2k}$. Setting this derivative equal to zero gives $v_L^p = \frac{8kp + 2k - p - 1}{12k - 2}$. Furthermore, $v_L^{(2)} - v_L^p = \frac{k}{6k-1} > 0$, and $v_L^p - v_L^{(1)} = -\frac{k[2k(1+p)-1]}{(4k-1)(6k-1)}$. These relationships determine the position of v_L^p within the authorized-demand composition adjustment range.

Under the second demand structure, $x_2^* = \frac{2(1-v_L)}{8k-1}$, $\Delta p_2^* = \frac{4k(1-v_L)}{8k-1}$. Therefore, $\frac{\partial x_2^*}{\partial p} = \frac{\partial \Delta p_2^*}{\partial p} = 0$, $\frac{\partial x_2^*}{\partial v_L} = -\frac{2}{8k-1} < 0$, and $\frac{\partial \Delta p_2^*}{\partial v_L} = -\frac{4k}{8k-1} < 0$. Platform profit satisfies $\frac{\partial \pi_{p2}^*}{\partial p} = 1 > 0$, and $\frac{\partial \pi_{p2}^*}{\partial v_L} = \frac{8k(v_L-1)}{8k-1} < 0$.

Proposition 2. Horizontal Comparison of the Platform’s Decision Variables

Within the common parameter range, if the respective applicability conditions of the two demand structures are temporarily disregarded, then $x_1^* > x_2^*$, and $\Delta p_1^* > \Delta p_2^*$. However, there is no single parameter configuration under which both sets of optimal decisions simultaneously satisfy their corresponding demand-structure conditions.

Specifically, when $v_L \leq v_L^{(1)}$, the market exhibits the first demand structure $t_L < t_H < t_{HL}$, and the platform implements the corresponding optimal decisions. When $v_L^{(1)} < v_L \leq v_L^{(2)}$, the platform implements the optimal decisions associated with the authorized-demand composition adjustment state. When $v_L > v_L^{(2)}$, the market exhibits the second demand structure $t_{HL} < t_H < t_L$, and the platform implements the corresponding optimal decisions. The platform’s decisions are continuous at the two valuation thresholds. When $v_L = v_L^{(1)}$, $x_1^* = x_A^*$, $\Delta p_1^* = \Delta p_A^*$. When $v_L = v_L^{(2)}$, $x_A^* = x_2^*$, $\Delta p_A^* = \Delta p_2^*$.

Proof.

Directly comparing the decisions associated with the first and second demand structures gives

$$x_1^* - x_2^* = \frac{(8k - 2)v_L - (8k - 1)p + 1}{(4k - 1)(8k - 1)},$$

and

$$\Delta p_1^* - \Delta p_2^* = \frac{2k[(8k - 2)v_L - (8k - 1)p + 1]}{(4k - 1)(8k - 1)}.$$

Setting these differences equal to zero gives the same formal threshold:

$$v_L^x = v_L^{\Delta p} = \frac{(8k - 1)p - 1}{8k - 2}.$$

Furthermore,

$$v_L^x - p = v_L^{\Delta p} - p = \frac{p - 1}{8k - 2} < 0.$$

Because the common parameter range requires $v_L \geq p$, we have $x_1^* > x_2^*$, and $\Delta p_1^* > \Delta p_2^*$ throughout this range. However, if both sets of optimal decisions were simultaneously consistent with their corresponding demand structures under the same parameter configuration, they would have to satisfy $\Delta p_1^* \leq \overline{\Delta p}$ and $\Delta p_2^* > \overline{\Delta p}$.

These two conditions would imply $\Delta p_1^* < \Delta p_2^*$, which contradicts $\Delta p_1^* > \Delta p_2^*$. Therefore, no parameter configuration allows both sets of optimal decisions to satisfy their respective demand-structure conditions simultaneously. Moreover, from the definitions of $v_L^{(1)}$ and $v_L^{(2)}$, when $v_L = v_L^{(1)}$, we have $\Delta p_1^* = \Delta p_A^*$, $x_1^* = x_A^*$. When $v_L = v_L^{(2)}$, we have $\Delta p_2^* = \Delta p_A^*$, $x_2^* = x_A^*$.

Proposition 2 indicates that the direct algebraic comparison between the two structure-specific decisions remains valid. However, this comparison reflects the platform’s preferred decisions implied by the two profit functions rather than two operating alternatives that can be implemented simultaneously under the same market conditions. Because the platform’s preferred surcharge may alter the composition of authorized demand, the platform must implement a combination of privacy protection and discriminatory pricing that is consistent with the demand structure generated by low-type consumers’ product valuation.

Before comparing platform profits, we define the highest profit attainable within each demand region.

Let $\hat{\pi}_{p1}$ denote the highest profit attainable subject to $\Delta p \leq \overline{\Delta p}$. When $v_L \leq v_L^{(1)}$, $\hat{\pi}_{p1} = \pi_{p1}^*$. When $v_L > v_L^{(1)}$, $\hat{\pi}_{p1} = \pi_{pA}^*$. Let $\hat{\pi}_{p2}$ denote the profit upper bound that the platform can attain or approach arbitrarily closely subject to the surcharge condition associated with the second demand structure. When $v_L \leq v_L^{(2)}$, $\hat{\pi}_{p2} = \pi_{pA}^*$. When $v_L > v_L^{(2)}$, $\hat{\pi}_{p2} = \pi_{p2}^*$. When $v_L \leq v_L^{(2)}$, π_{pA}^* is the profit upper bound that the platform can approach arbitrarily closely while strictly satisfying the second demand structure. The authorized-demand composition adjustment point itself remains the upper boundary of the first demand structure.

Proposition 3. Horizontal Comparison of Implementable Platform Profits

When $v_L < v_L^{(1)}$, $\hat{\pi}_{p1} > \hat{\pi}_{p2}$. When $v_L^{(1)} \leq v_L \leq v_L^{(2)}$, $\hat{\pi}_{p1} = \hat{\pi}_{p2} = \pi_{pA}^*$. When $v_L > v_L^{(2)}$, $\hat{\pi}_{p1} < \hat{\pi}_{p2}$.

Proposition 3 shows that when low-type consumers have a relatively low valuation of the product, maintaining a market composition containing only authorized demand from high-type consumers generates a higher profit for the platform. When low-type consumers’ product valuation lies within the intermediate range, the platform maintains its privacy protection and discriminatory surcharge at the point at which the composition of authorized demand begins to adjust, rather than immediately inducing positive authorized demand from low-type consumers. When low-type consumers have a sufficiently high valuation of the product, their entry into the authorized purchasing region creates greater incremental commercial value, and the operating decisions associated with the second demand structure generate a higher platform profit. These findings show that expanding authorized demand does not necessarily increase platform profit. The platform’s incentive to expand authorized demand from low-type consumers depends on whether their product valuation is sufficient to support the corresponding pricing adjustment and privacy protection expenditure.

Proof.

When $v_L < v_L^{(1)}$, $\hat{\pi}_{p1} = \pi_{p1}^*$, $\hat{\pi}_{p2} = \pi_{pA}^*$. Taking the difference gives

$$\hat{\pi}_{p1} - \hat{\pi}_{p2} = \pi_{p1}^* - \pi_{pA}^* = \frac{4k - 1}{k} (v_L - v_L^{(1)})^2 > 0.$$

Therefore,

$$\hat{\pi}_{p1} > \hat{\pi}_{p2}.$$

When $v_L^{(1)} \leq v_L \leq v_L^{(2)}$,

the highest profit within the decision region associated with the first demand structure is attained at the authorized-demand composition adjustment point. The profit attainable while strictly satisfying the second demand structure can also approach the profit at this point arbitrarily closely. Therefore,

$$\hat{\pi}_{p1} = \hat{\pi}_{p2} = \pi_{pA}^*.$$

When $v_L > v_L^{(2)}$, $\hat{\pi}_{p1} = \pi_{pA}^*$, $\hat{\pi}_{p2} = \pi_{p2}^*$. Taking the difference gives

$$\hat{\pi}_{p1} - \hat{\pi}_{p2} = \pi_{pA}^* - \pi_{p2}^* = -\frac{(6k - 1)^2}{k(8k - 1)} (v_L - v_L^{(2)})^2 < 0.$$

Therefore,

$$\hat{\pi}_{p1} < \hat{\pi}_{p2}.$$

3.6. Numerical Analysis and Sensitivity Tests

To further illustrate how changes in low-type consumers’ product valuation affect the platform’s privacy protection, discriminatory pricing, and demand structure, and to examine the sensitivity of the main results to changes in the base price and privacy-management cost, we conduct a numerical analysis. The benchmark parameters satisfy the common parameter range and the nonnegativity conditions established above and allow all three market states—the first demand structure, the authorized-demand composition adjustment state, and the second demand structure—to be displayed within the effective analysis range.

Because the high-type consumer valuation is normalized to one, all numerical values are dimensionless scenario parameters. For the benchmark analysis, we set $p = 0.35$ and $k = 0.60$. The base price represents a moderate price level relative to the normalized high-type consumer valuation, while the privacy-management cost coefficient satisfies the model conditions and allows the three operating states to be displayed within the effective analysis range. These values are used to illustrate the model mechanism rather than to calibrate a specific platform.

3.6.1. Optimal Privacy Protection and Discriminatory-Pricing Decisions

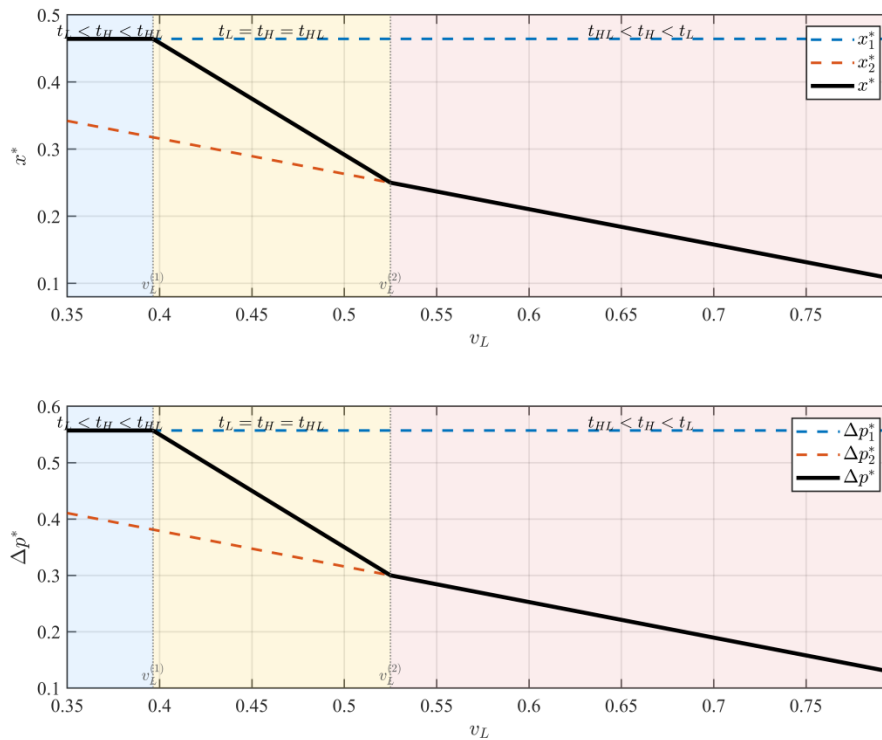


Figure 3. Effects of low-type consumers' product valuation on the platform's optimal decisions

When $v_L \leq v_L^{(1)}$, the consumer thresholds satisfy $t_L < t_H < t_{HL}$, and the market exhibits the first demand structure. The platform's optimal privacy protection level and discriminatory surcharge are x_1^* and Δp_1^* , respectively, and neither changes with v_L . This result indicates that when low-type consumers have not yet generated authorized purchasing demand, their product valuation does not directly affect the platform's current privacy-protection and discriminatory-pricing decisions. The platform mainly determines its operating decisions around the authorized demand of high-type consumers.

When $v_L^{(1)} < v_L \leq v_L^{(2)}$, the consumer thresholds satisfy $t_L = t_H = t_{HL}$, and the platform enters the authorized-demand composition adjustment state. Within this range, both the privacy protection level and the discriminatory surcharge decrease as v_L increases. As low-type consumers'

product valuation rises, they become more likely to enter the authorized purchasing region. The platform no longer needs to maintain a relatively high discriminatory surcharge. Instead, it simultaneously reduces the surcharge and privacy protection level, thereby allowing the authorized-demand composition to move gradually from a market containing only high-type authorized consumers toward one containing both consumer types.

When $v_L > v_L^{(2)}$, the consumer thresholds satisfy $t_{HL} < t_H < t_L$, and the market exhibits the second demand structure. Low-type consumers generate positive authorized purchasing demand, and the platform's optimal privacy protection level and discriminatory surcharge continue to decrease with v_L , although their rates of change differ from those in the adjustment state. The underlying reason is that as low-type consumers' product valuation increases, the valuation difference between high- and low-type consumers narrows. Consequently, the platform has less scope to extract additional revenue through type-based price differentiation, and its corresponding privacy-protection expenditure also declines.

Figure 3 also shows that, when the applicability conditions of the demand structures are temporarily disregarded, $x_1^* > x_2^*$ and $\Delta p_1^* > \Delta p_2^*$. However, the two sets of decisions cannot simultaneously satisfy their respective demand-structure conditions under the same parameter configuration. The platform's actual decision is therefore composed sequentially of x_1^* and Δp_1^* , the decisions under the adjustment state, and x_2^* and Δp_2^* .

The black solid lines connect continuously at the two valuation thresholds, indicating that changes in the demand structure do not cause abrupt jumps in the platform's operating decisions. Overall, as low-type consumers' product valuation increases, the platform's privacy protection level and discriminatory surcharge remain stable initially and then decline continuously.

3.6.2. Horizontal Comparison of Implementable Platform Profits

Figure 4 compares the highest profits attainable within the two demand regions. Here, $\hat{\pi}_{p1}$ denotes the highest profit attainable subject to the conditions associated with the first demand structure, whereas $\hat{\pi}_{p2}$ denotes the profit upper bound that the platform can attain or approach arbitrarily closely subject to the conditions associated with the second demand structure.

In Figure 4, R_1 denotes the implementable region associated with the first demand structure. When $v_L \geq \frac{1+p}{2}$, the upper bound of the discriminatory surcharge satisfies $\overline{\Delta p} = 1 + p - 2v_L \leq 0$. Because the platform is required to set a positive discriminatory surcharge, the first demand structure no longer has an implementable region. This case is denoted by $R_1 = \emptyset$.

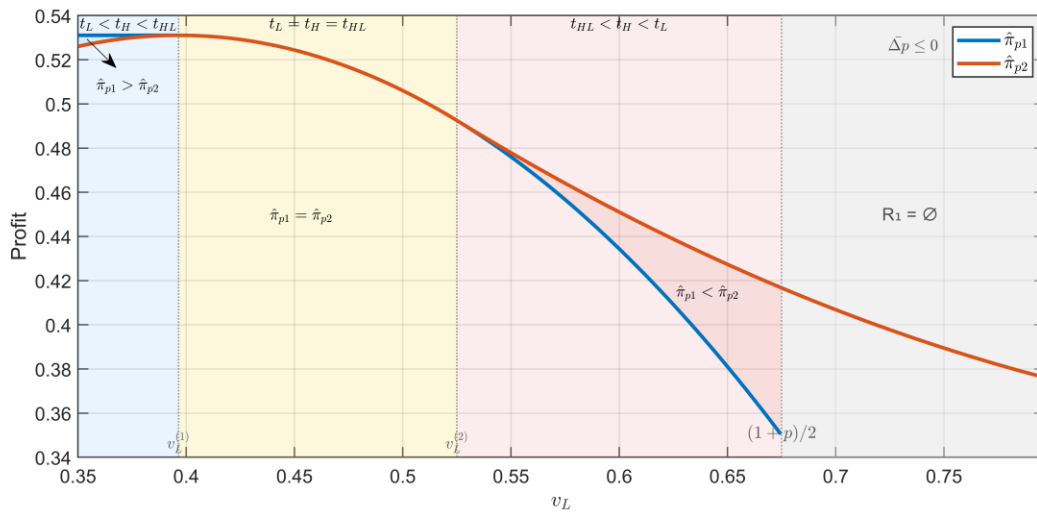


Figure 4. Comparison of implementable platform profits across the two demand regions

When $p \leq v_L < v_L^{(1)}$, we have $\hat{\pi}_{p1} > \hat{\pi}_{p2}$. In this range, low-type consumers have a relatively limited product valuation, and the additional revenue generated by inducing them to enter the authorized purchasing region is insufficient to support changes in the platform’s existing pricing and privacy-protection decisions. Maintaining a market composition dominated by the authorized demand of high-type consumers therefore generates a higher profit.

When $v_L^{(1)} \leq v_L \leq v_L^{(2)}$, we have $\hat{\pi}_{p1} = \hat{\pi}_{p2}$. This equality does not imply that the two demand structures can arise simultaneously or that the platform can freely choose between them. Rather, the highest profit in the decision region associated with the first demand structure is attained at the authorized-demand composition adjustment point, while the profit attainable under the strict conditions of the second demand structure can approach the same upper bound arbitrarily closely. Within this range, the platform does not immediately induce positive authorized purchasing demand from low-type consumers. Instead, it maintains its pricing and privacy-protection decisions at the point where the composition of authorized demand begins to adjust.

When $v_L^{(2)} < v_L < \frac{1+p}{2}$, we have $\hat{\pi}_{p1} < \hat{\pi}_{p2}$. At this stage, low-type consumers’ product valuation is sufficiently high for their entry into the authorized purchasing region to create greater incremental commercial value. Compared with continuing to maintain a market composition containing only high-type authorized demand, the operating decisions associated with the second demand structure generate a higher platform profit.

When $v_L \geq \frac{1+p}{2}$, we have $\overline{\Delta p} = 1 + p - 2v_L \leq 0$ and $R_1 = \emptyset$. Under the requirement of a positive discriminatory surcharge, the first demand structure no longer has an implementable region. Therefore, the two demand regions are no longer compared within this range, and the market can only exhibit the second demand structure.

Figure 4 shows that as low-type consumers’ product valuation increases, the platform’s profit advantage gradually shifts from the first demand structure to the second demand structure.

Expanding authorized demand from low-type consumers therefore does not necessarily increase platform profit. Such expansion becomes more profitable only when low-type consumers can create sufficient commercial value.

3.6.3. Sensitivity Analysis of the Base Price and Privacy-Management Cost

Figure 5 further illustrates how the market regions change with the base price p and privacy-management cost k . The gray solid line represents the boundary at which low-type consumers' product valuation equals the base price. The blue and orange dashed lines represent the two valuation thresholds, and the black solid line represents the upper bound determined by the nonnegativity condition for demand: $\bar{v}_L = \frac{16kp+8k-2p-3}{16k-4}$.

The blue, yellow, and red areas correspond to the first demand structure $t_L < t_H < t_{HL}$, the authorized-demand composition adjustment state, and the second demand structure $t_{HL} < t_H < t_L$, respectively. The gray area represents parameter combinations that do not satisfy the relevant feasibility conditions.

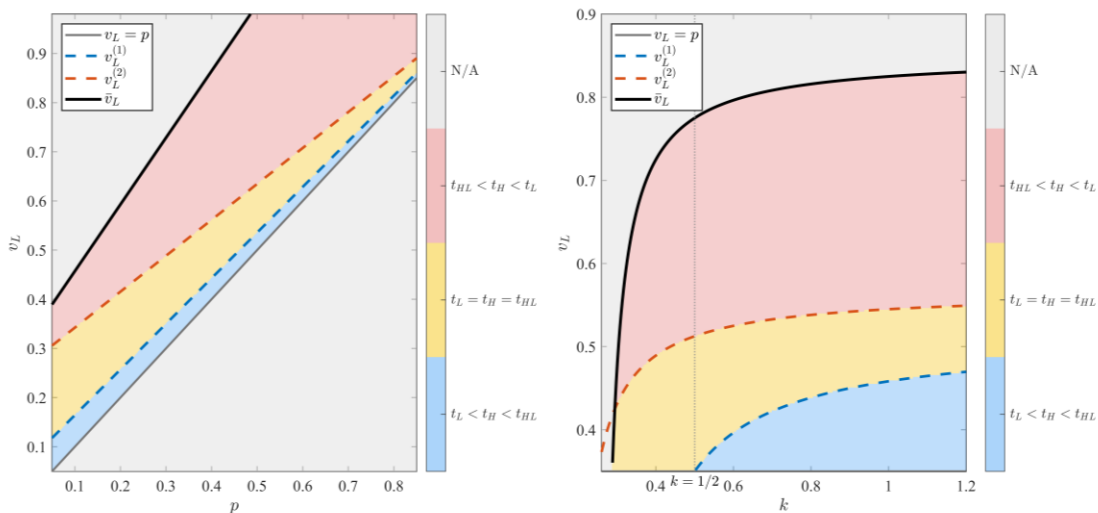


Figure 5. Platform operating regions under changes in the base price and privacy-management cost

(1) Effect of the Base Price

The left panel of Figure 5 fixes the privacy-management cost and examines how the demand state changes jointly with the base price and low-type consumers' product valuation. As the base price increases, $v_L^{(1)}$, $v_L^{(2)}$, and the demand-feasible upper bound all increase. This means that after the platform raises the base price, low-type consumers must have a higher product valuation before the market can move from the first demand structure into the authorized-demand composition adjustment state and subsequently into the second demand structure.

At the same time, the distance between the two valuation thresholds decreases as the base price rises, indicating that the range of the authorized-demand composition adjustment state becomes narrower. A higher base price increases the platform's revenue from basic sales and reduces the

need for a prolonged adjustment process before expanding authorized demand. Representative parameter results are reported in Table 3.

(2) Effect of the Privacy-Management Cost

The right panel of Figure 5 fixes the base price and examines how the demand state changes jointly with the privacy-management cost and low-type consumers’ product valuation.

When $\frac{1}{4} < k < \frac{1}{2}$, we have $v_L^{(1)} < p$. Because the effective market range requires $v_L \geq p$, the optimal decision associated with the first demand structure does not appear within the effective analysis range. The platform initially operates in the authorized-demand composition adjustment state and then enters the second demand structure as low-type consumers’ product valuation increases.

When $k \geq \frac{1}{2}$, we have $v_L^{(1)} \geq p$. The first demand structure then begins to appear within the effective market range. As the privacy-management cost increases, $v_L^{(1)}$ rises faster than $v_L^{(2)}$. Consequently, the range of the first demand structure expands, whereas the range of the authorized-demand composition adjustment state contracts.

This result indicates that the privacy-management cost not only affects the amount of privacy protection provided by the platform but also changes the market conditions under which different demand structures emerge. When privacy protection is relatively inexpensive, the platform can more readily expand authorized demand from low-type consumers. When the privacy-management cost rises, the platform is more likely to maintain a market dominated by high-type authorized consumers over a broader valuation range.

Table 3. Valuation thresholds under alternative parameter configurations

p	k	$v_L^{(1)}$	$v_L^{(2)}$	\bar{v}_L
0.25	0.60	0.3036	0.4519	0.6607
0.35	0.60	0.3964	0.5250	0.7964
0.45	0.60	0.4893	0.5981	0.9321
0.35	0.40	0.2417	0.4893	0.7250
0.35	0.60	0.3964	0.5250	0.7964
0.35	0.80	0.4386	0.5382	0.8159

Table 3 further shows that changes in the base price and privacy-management cost alter the two valuation thresholds and the effective demand range without changing the fundamental transition mechanism among the three market states.

An increase in the base price shifts both valuation thresholds upward and narrows the interval associated with the authorized-demand composition adjustment state. An increase in the privacy-management cost expands the applicable range of the first demand structure and compresses the range of the adjustment state.

4. Conclusion

This paper investigates how consumer authorization, platform identification, privacy protection, and differential pricing interact in a transaction-oriented digital platform. Given an exogenous base price, the platform jointly determines its privacy-protection level and discriminatory surcharge. Consumers then choose among non-authorized purchasing and alternative authorized transaction states according to their valuations and perceived privacy costs. This framework enables us to examine not only whether consumers authorize the use of their information, but also how authorization changes the composition of platform demand and the platform's subsequent operating decisions.

4.1. Main Findings

The analysis yields several main findings. First, the platform market may exhibit two internal demand structures, which differ in whether low-type consumers generate positive authorized demand. These configurations are not externally imposed market scenarios. Instead, they arise from the interaction between the platform's privacy-protection and pricing decisions and consumers' choices among the available transaction states. Therefore, consumer authorization affects not only the total amount of identifiable demand but also its internal value composition.

Second, the platform's discriminatory-pricing decision plays a dual role. A higher discriminatory surcharge enables the platform to extract more revenue from identified high-type consumers, but it may also change consumers' relative preferences across transaction states and thereby alter the composition of authorized demand. Consequently, a pricing decision derived for one demand configuration may not always sustain that configuration. When the platform's preferred pricing decision would induce a change in demand composition, its implementable decision may be located at the switching point between the two configurations. This finding shows that platform pricing and market segmentation should be analyzed jointly rather than sequentially.

Third, privacy protection is an integral part of the platform's revenue-generating mechanism. Stronger privacy protection reduces the disutility associated with data authorization and helps the platform maintain identifiable demand. However, privacy protection also creates management costs. The platform must therefore balance the commercial value generated from consumer identification against the cost of maintaining consumers' willingness to authorize. The resulting decision depends jointly on the value composition of authorized demand and the cost of privacy management.

Fourth, an expansion of authorized demand does not necessarily lead to a corresponding increase in platform profit. The entry of low-type consumers into the authorized purchasing region enlarges the platform's identifiable customer base, but these consumers may contribute less additional pricing revenue and may still require privacy-protection expenditure. Platform profitability therefore depends not only on the size of authorized demand, but also on which consumers are attracted and how costly it is to sustain their authorization.

The numerical analysis illustrates these mechanisms under different market and cost conditions. It shows how changes in consumer value and privacy-management cost affect the platform's privacy-protection decision, discriminatory-pricing decision, realized demand composition, and profitability. The results further demonstrate the importance of evaluating only those platform decisions that are consistent with the demand configuration they generate.

4.2. *Managerial Implications*

The findings provide several implications for platform managers. First, privacy protection and differential pricing should be managed as two interconnected operating decisions. Privacy protection is not merely a compliance activity, because it directly affects consumers' willingness to authorize and the amount of identifiable demand available to the platform. Differential pricing, in turn, determines how the platform converts the information obtained through authorization into commercial value. If privacy management and pricing are designed independently by different organizational functions, the resulting strategies may be inconsistent. Before adjusting differential prices, platform managers should assess whether the existing privacy-protection measures are sufficient to maintain consumer authorization and acceptance.

Second, platforms should not use the overall authorization rate as the sole indicator of successful data operations. A larger authorized customer base may appear beneficial, but its actual value depends on the composition of that demand. Managers should distinguish between authorized demand from high-type and low-type consumers and evaluate their respective conversion rates, additional revenues, and service requirements. Authorization creates commercial value only when the additional revenue generated through consumer identification is sufficient to cover the associated privacy-management cost.

Third, the intensity of privacy investment should be aligned with market conditions. When privacy protection can be provided at a manageable cost, stronger protection may support consumer trust, expand identifiable demand, and improve the effectiveness of data-driven operations. However, when privacy-management costs are high, continually increasing protection expenditure solely to attract more authorization may not be economically desirable. Platform managers should therefore evaluate consumer value, demand composition, pricing opportunities, and privacy costs together rather than pursuing the highest possible authorization rate or protection level in isolation.

Fourth, platform managers should recognize that pricing adjustments may reshape the market segment from which revenue is generated. A discriminatory surcharge is not simply an additional amount charged to identified consumers; it can also influence which authorized transaction state consumers select. Therefore, platforms should assess the possible changes in demand composition before implementing a new data-driven pricing policy. Pricing decisions should be evaluated not only according to the additional revenue obtained from each identified consumer, but also according to their broader effects on authorization and customer composition.

The findings also have implications for platform governance and public regulation. Consumer authorization, data utilization, consumer identification, and differential pricing constitute a

continuous operating process. A review focusing only on whether formal consent has been obtained may overlook how authorized information is subsequently used, whereas an assessment focusing only on observed price differences may fail to identify the role of consumer profiling. Platforms should provide consumers with a meaningful non-authorized purchasing option and communicate the purposes of data use and the consequences of authorization more clearly. Regulators should likewise examine the relationship between authorization practices and pricing decisions so that privacy protection and pricing fairness can be addressed within a coordinated governance framework.

4.3. *Limitations and Future Research*

This study has several limitations that provide opportunities for future research. First, the model considers a single platform and therefore does not capture competition for consumers or data among multiple platforms. Future studies could examine how platform competition affects privacy-protection investment, consumer authorization, and differential-pricing incentives. Competition may either encourage platforms to provide stronger privacy protection or intensify their incentives to monetize consumer information.

Second, the base price is treated as exogenous so that the analysis can focus on the interaction between privacy protection and the discriminatory surcharge. A natural extension would allow the platform to jointly determine the base price, discriminatory surcharge, and privacy-protection level. This extension could reveal whether adjustments in the base price substitute for or reinforce data-driven differential pricing.

Third, the current model focuses on product-selling revenue and does not include other important platform revenue sources. Future research could incorporate advertising revenue, data transactions with third parties, subscription fees, or commissions. These revenue mechanisms may change the commercial value of consumer authorization and consequently alter the platform's privacy-protection incentives.

Fourth, the analysis adopts a static setting. In practice, platforms accumulate consumer information over time, while consumers may update their authorization decisions after observing platform behavior. A dynamic model could examine how reputation, repeated authorization, data accumulation, and consumers' learning about privacy risks affect long-term pricing and privacy strategies.

Finally, future research could explicitly introduce regulatory instruments, such as limits on data collection, requirements for transparent consent, restrictions on differential pricing, privacy-related penalties, or minimum privacy-protection standards. The model could also be extended to evaluate consumer surplus and social welfare, thereby providing more direct guidance on how regulators can balance data utilization, platform innovation, pricing fairness, and consumer privacy.

Overall, this paper develops an analytical framework for understanding the continuous mechanism linking consumer authorization, platform identification, privacy protection, and differential pricing. By showing how platform decisions reshape the composition of authorized demand, the study moves beyond the simple view that more consumer data necessarily generate

greater platform profit. It highlights that the operational value of data depends on the consumers who authorize, the pricing opportunities created by identification, and the cost of maintaining privacy protection. These findings provide a foundation for further research on platform data governance and data-driven pricing in digital markets.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, the authors used artificial intelligence solely for grammar correction and language polishing. The authors reviewed and edited all AI-assisted output and take full responsibility for the content of the manuscript.

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References:

1. Lee, D., Ahn, J.-H., and Bang, Y. 2011. "Managing Consumer Privacy Concerns in Personalization: A Strategic Analysis of Privacy Protection." *MIS Quarterly*, 35(2), 423-444.
2. Hann, I.-H., Hui, K.-L., Lee, S.-Y. T., and Png, I. P. L. 2008. "Consumer Privacy and Marketing Avoidance: A Static Model." *Management Science*, 54(6), 1094-1103.
3. Wattal, S., Telang, R., Mukhopadhyay, T., and Boatwright, P. 2012. "What's in a 'Name'? Impact of Use of Customer Information in E-Mail Advertisements." *Information Systems Research*, 23(3, Part 1), 679-697.
4. Gal-Or, E., Gal-Or, R., and Penmetsa, N. 2018. "The Role of User Privacy Concerns in Shaping Competition Among Platforms." *Information Systems Research*, 29(3), 698-722.
5. Duan, Y., Liu, P., and Feng, Y. 2022. "Pricing Strategies of Two-Sided Platforms Considering Privacy Concerns." *Journal of Retailing and Consumer Services*, 64, 102781.
6. Choi, T.-M. 2020. "Mobile-App-Online-Website Dual Channel Strategies: Privacy Concerns, E-Payment Convenience, Channel Relationship, and Coordination." *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 50(12), 5468-5480.
7. Li, Z., Wu, L., and Xu, H. 2026. "Service Investment Strategies for Digital Products in Social E-commerce Environment: The Influence of Opinion Leader." *Asia Pacific Journal of Marketing and Logistics*, ahead-of-print.
8. Li, Z., and Lev, B. 2025. "Optimal Dynamic Pricing Strategy for Non-durable Experience Goods: The Role of Consumer AI Learning." *International Journal of Production Research*, 63(24), 10700-10724.
9. Li, Z., Lyu, R., Lyu, X., et al. 2026. "The Optimal Pricing and Quality Improvement Strategies for Digital Products under Bilateral Platform Intervention." *Electronic Commerce Research*, 26, 1529-1579.
10. Li, Z., He, P., and Xu, H. 2025. "Optimizing Cooperation Mechanisms for Augmented Reality (AR) Services: Balancing Product Returns, Pricing, and Customer Satisfaction." *Journal of Retailing and Consumer Services*, 85, 104263.
11. Goldfarb, A., and Tucker, C. 2011. "Privacy Regulation and Online Advertising." *Management Science*, 57(1), 57-71.
12. Tucker, C. E. 2014. "Social Networks, Personalized Advertising, and Privacy Controls." *Journal of Marketing Research*, 51(5), 546-562.
13. Taylor, C. R. 2004. "Consumer Privacy and the Market for Customer Information." *RAND Journal of Economics*, 35(4), 631-650.
14. Acquisti, A., and Varian, H. R. 2005. "Conditioning Prices on Purchase History." *Marketing Science*, 24(3), 367-381.
15. Casadesus-Masanell, R., and Hervas-Drane, A. 2015. "Competing with Privacy." *Management Science*, 61(1), 229-246.
16. Ichihashi, S. 2020. "Online Privacy and Information Disclosure by Consumers." *American Economic Review*, 110(2), 569-595.

17. Choi, J. P., Jeon, D.-S., and Kim, B.-C. 2019. "Privacy and Personal Data Collection with Information Externalities." *Journal of Public Economics*, 173, 113-124.
18. Campbell, J., Goldfarb, A., and Tucker, C. 2015. "Privacy Regulation and Market Structure." *Journal of Economics & Management Strategy*, 24(1), 47-73.
19. Acemoglu, D., Makhdoumi, A., Malekian, A., and Ozdaglar, A. 2022. "Too Much Data: Prices and Inefficiencies in Data Markets." *American Economic Journal: Microeconomics*, 14(4), 218-256.
20. Chen, X., Simchi-Levi, D., and Wang, Y. 2025. "Privacy-Preserving Dynamic Personalized Pricing with Demand Learning." *Management Science*, 71(2), 988-1011.
21. Montes, R., Sand-Zantman, W., and Valletti, T. 2019. "The Value of Personal Information in Online Markets with Endogenous Privacy." *Management Science*, 65(3), 1342-1362.
22. Ichihashi, S. 2023. "Dynamic Privacy Choices." *American Economic Journal: Microeconomics*, 15(2), 1-39.
23. Goldfarb, A., and Tucker, C. 2012. "Privacy and the Modern Market." *Journal of Economic Perspectives*, 26(3), 1-24.
24. Xu, F., Wang, X., and Zhang, F. 2025. "Consumer Privacy in Online Retail Supply Chains." *Management Science*, 71(10), 8371 - 8389.
25. Goldfarb, A., and Que, V. F. 2023. "The Economics of Digital Privacy." *Annual Review of Economics*, 15(1), 267-286.
26. Lefouili, Y., Madio, L., and Toh, Y. L. 2024. "Privacy Regulation and Quality-Enhancing Innovation." *Journal of Industrial Economics*, 72(2), 662-684.
27. Gopal, R. D., Hidaji, H., Kutlu, S. N., Patterson, R. A., and Yaraghi, N. 2023. "Law, Economics, and Privacy: Implications of Government Policies on Website and Third-Party Information Sharing." *Information Systems Research*, 34(4), 1375 - 1397.
28. Acquisti, A., Taylor, C., and Wagman, L. 2016. "The Economics of Privacy." *Journal of Economic Literature*, 54(2), 442-492.
29. Goldberg, S. G., Johnson, G. A., and Shriver, S. K. 2024. "Regulating Privacy Online: An Economic Evaluation of the GDPR." *American Economic Journal: Economic Policy*, 16(1), 325-358.
30. Fainmesser, I. P., Galeotti, A., and Momot, R. 2023. "Digital Privacy." *Management Science*, 69(6), 3157-3173.
31. Iyer, G., Narasimhan, C., and Niraj, R. 2007. "Information and Inventory in Distribution Channels." *Management Science*, 53(10), 1551-1561.
32. Federal Trade Commission. 2024. "A Look Behind the Screens: Examining the Data Practices of Social Media and Video Streaming Services." Staff Report, September 2024.
33. Yin, Y. 2024. "Research on Consumer Rights and Interests Protection in E-Commerce Platform Big Data 'Price Discrimination.'" *E-Commerce Letters*, 13(3), 4734-4741.