Production and Operations Management

Algorithmic Targeting for Opaque Selling in Vertical Markets

Xuefeng Peng
School of Management, University of Science and Technology of China, Hefei, China
pengxf@mail.ustc.edu.cn

Zhenxiao Chen (Corresponding author)
Faculty of Business, The Hong Kong Polytechnic University, Kowloon, Hong Kong
zhenxiao.chen@polyu.edu.hk

Qiao-Chu He
School of Business, Southern University of Science and Technology, Shenzhen, China
heqc@sustech.edu.cnn

Tingliang Huang
Haslam College of Business, University of Tennessee, Knoxville, TN, USA
thuang7@utk.edu

Abstract: Motivated by algorithmic targeting and data management, we explore a scenario where the seller holds an advantage over consumers regarding match-related information about products. The seller optimizes a product line consisting of two vertically differentiated products alongside an opaque product resulting from their mixture, strategically recommending these products to potential consumers. We model algorithmic targeting using an information design framework, and our investigation revolves around understanding how algorithmic targeting shapes consumer purchasing behaviors and influences market equilibrium. Furthermore, we explore the potential orchestration between algorithmic targeting and opaque selling, facilitated by product-line design. These two closely related instruments coincide in ex-ante manipulating information while differing in their targeting objects. Interestingly, only when the basic products exhibit intermediate differentiation does the seller use both instruments. This is because, when the disparity between the two primary products is extreme (either too large or too small), algorithmic targeting makes opaque selling ineffective at increasing profits. However, when these differences are moderate, the two strategies can complement each other. Opaque selling enhances profitability by introducing intermediate product variety, enabling more nuanced market segmentation, while algorithmic targeting is more flexible in promoting the willingness-to-pay of a wider range of consumers. Furthermore, when conducting welfare analysis, the adoption of algorithmic targeting is found sometimes to reduce consumer surplus but can enhance overall social welfare, highlighting the need for careful regulatory oversight in this domain.

Key words: Algorithm and data management, Algorithmic targeting, Information design, New business model, Product line design

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1 Introduction

Data and analytics technologies have endowed tech firms with informational dominance about their customer profiles. They enjoy the privilege of collecting historical data, including how the customers previously searched, browsed, and bought, which helps them better tailor their future recommendations (Joglekar et al. 2022, Bimpikis et al. 2024). A controversial issue arising from firms' information advantage is *algorithmic targeting*, which refers to the use of committed algorithms to automate product recommendations aimed at specific consumer segments or individuals (e.g., Zhang and Lahiri 2023, Iyer and Ke 2024, Iyer et al. 2024). For instance, the online travel agency Priceline leverages its personalized display (e.g., pushing notifications and targeted advertising) via proprietary algorithms to deliver customized product recommendations for different consumer segments. Martin Brodbeck, Chief Technology Officer of Priceline, publicly stated: "The second area we focused on was personalization and product recommendations to our customers based on what they are searching for on our platform."[1] Such recommendations can target either a group of customers or a specific individual. Group recommendations involve segmenting customers into categories and providing standardized recommendations for each group. For example, Trip.com classifies users into Silver, Gold, or Platinum tiers and offers tailored recommendations for each level.[2] In contrast, the other approach focuses on more personalized, individual-level recommendations. For example, Priceline has introduced a feature called "*Just for You Recommendations*" that customizes suggestions based on users' unique interests.[3] Compared with traditional marketing, a salient advantage of algorithmic targeting is its ability to strategically manage information across different consumer groups. This approach leverages data-driven and rule-based mechanisms, which are often implemented through machine learning models or optimization algorithms, to personalize offerings based on specific consumer characteristics. A key feature of such algorithmic systems is their ability to credibly commit to tailored decision rules that govern information disclosure. This enables firms to flexibly reveal detailed information to certain consumer segments while pooling or withholding information from others. Such granular and credible control over information disclosure is difficult to achieve in traditional marketing environments.

When consumers are uncertain about their product preferences, being targeted by firms can help them discover options that align with their needs. However, studies indicate that firms may also exploit this uncertainty by fine-tuning the granularities of information provision, leading consumers to develop inaccurate beliefs about which products best match their needs (Shin and Yu 2021). This can result in customers purchasing products that are not ideally suited for them. Prior to the rise of algorithmic targeting, firms used strategies like product-line designs to achieve similar outcomes by controlling information. A related marketing tool is opaque selling (e.g., Geng 2016, Jiao et al. 2021, Fay and Gheibi 2024), which is prevalent in industries such as hospitality and retail. In this approach, firms sell opaque products, withholding the specific details until the payment is completed. For instance, as shown in Figure 1, Priceline's "*pricebreaker*"

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[1] Technology Magazine. Priceline: Data-driven dealmakers of travel. Accessed August 30, 2025, https://technologymagazine.com/company-reports/priceline-data-driven-dealmakers-travel.

[2] Trip.com. Trip.com's Loyalty Program. Accessed August 30, 2025, https://www.trip.com/customer/loyalty/.

[3] Priceline. Priceline's 2023 Summer Release: Introducing Our Trip Intelligence Suite. Accessed August 30, 2025, https://www.priceline.com/partner/v2/summer-release-2023.

offer is an opaque product where consumers see three potential hotels but learn the exact hotel only after payment.

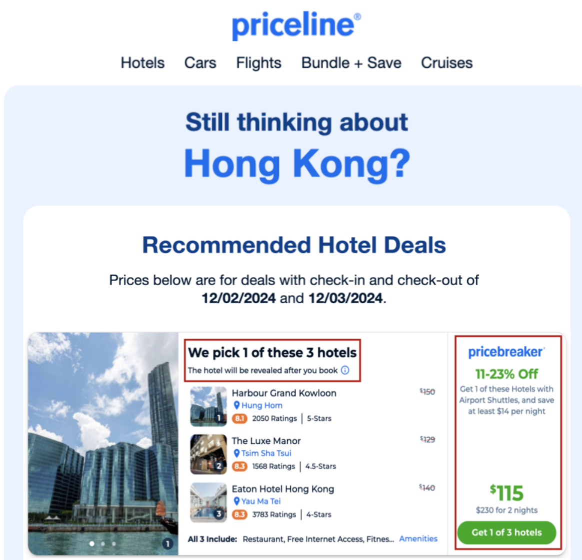


Figure 1 Priceline's combination of algorithmic targeting and opaque selling.

While both strategies involve information non-disclosure in matching consumers with products, algorithmic targeting induces randomization in consumers' types or beliefs, whereas opaque selling randomizes product types or features. Algorithmic targeting shapes consumers' beliefs about their preferences or the suitability of a product, whereas opaque selling influences choices by concealing product attributes, such as keeping the contents of an opaque product hidden until after purchase. Theoretically, prior research has shown that both algorithmic targeting (e.g., Trusov et al. 2016, Zhang and Lahiri 2023, Iyer and Ke 2024) and opaque selling (e.g., Jiang 2007, Fay and Xie 2008) can independently enhance firms' revenue through effective price discrimination. This raises an intriguing question: How do these strategies differ in their mechanisms, and can they be effectively integrated into new business scenarios? In practice, many technology firms already employ both methods to boost profitability. As shown in Figure 1, Priceline uses personalized targeting to recommend its opaque product to consumers. However, some firms remain concerned about the effectiveness of algorithmic targeting and its potential conflicts with existing marketing strategies. Despite the growing adoption of these approaches, the strategic interactions between them remain largely unexplored. This study seeks to address whether firms benefit more from combining these tools or focusing on optimizing a single, more impactful strategy to maximize profit. Moreover, with the growing adoption of algorithmic targeting, we aim to investigate its potential in business practices. By examining its unique features and mechanisms, we seek to understand how it differs from traditional marketing strategies and whether it can be effectively integrated into diverse business contexts, especially where conflicts with existing strategies arise. This analysis will shed light on whether algorithmic targeting enhances or undermines traditional approaches.

Our investigation focuses on understanding how algorithmic targeting influences consumer purchasing behaviors and market equilibrium. We consider two scenarios to comprehensively examine its potential impact. In a traditional business setting, a seller offers a product line containing high-quality and low-quality products in vertical markets. Here, algorithmic targeting serves as the sole tool to enhance market segmentation. Additionally, we explore a new business scenario where the seller expands the product line by introducing an opaque product resulting from the combination of existing ones. In this context, we investigate the potential orchestration between these two closely related but distinct instruments. Our research focuses on three primary aspects. Firstly, we investigate how the implementation of algorithmic targeting can influence consumers' purchasing decisions, the operational strategies of firms, and the dynamics of the market. Secondly, we examine, under different business scenarios, how algorithmic targeting interacts with other marketing strategies, such as opaque selling through product line design. Lastly, we analyze the implications of algorithmic targeting on firms' operations, its effects on consumer welfare, and its broader societal impact. To address these questions, we develop a stylized model that integrates both algorithmic targeting and opaque selling. In this model, the firm selects its algorithmic targeting and product line strategies, while consumers make purchase decisions based on the information and prices provided by the firm.

We model targeting policy using an information design framework such that a seller is able to disclose a consumer's idiosyncratic feature with tailored recommendations. The use of algorithmic targeting is found to broaden market coverage and encourage more purchases of the higher-margin product. In the new business scenario, we first rationalize opaque selling via convex preferences under complete information. Our findings align with existing literature, highlighting the value of opaque selling due to its price discrimination effect within a bundled product menu. When algorithmic targeting interacts with opaque selling, it may render opaque selling ineffective in boosting profits. This inefficacy is especially pronounced when the disparity between the two basic products (in terms of production cost) is too large or small. When these two instruments are implemented together, the seller strategically withholds information from low-segment consumers while fully disclosing it to intermediate-segment consumers who opt for opaque products. This information structure aims to enhance demand and profitability for the opaque product, which yields the highest marginal profit in the product portfolio. Furthermore, welfare analysis reveals that the seller can efficiently improve profit using algorithmic targeting, but consumer surplus may be compromised. While aggregate social welfare can benefit from this emerging technology, consideration should be given to regulations aimed at safeguarding consumers.

We also discuss the practical implications of opaque selling and algorithmic targeting, both independently and jointly. Opaque selling enhances price discrimination by introducing an intermediate product that primarily targets high-type consumers, effectively increasing profitability within this segment. However, it has limited impact on low-type consumers. In contrast, algorithmic targeting is highly versatile, influencing consumer beliefs across various segments and proving effective in diverse scenarios. Nevertheless, it requires careful management to mitigate intra-cannibalization and ensure profitability across product lines. When employed together, these two levers can work effectively in shaping consumer purchasing behaviors: opaque selling focuses on high-type consumers, while algorithmic targeting extends market reach to low-type consumers.

The rest of this paper is structured as follows. Section 2 provides a review of relevant literature. Section 3 presents the basic model setup. Section 4 examines a traditional business scenario where the seller offers only basic products in vertical markets, with algorithmic targeting serving as the sole marketing tool. Section 5 studies a new business scenario where opaque selling as a means to expand the product line is introduced, exploring its interaction with algorithmic targeting in determining the seller's optimal operational strategy. Section 6 discusses the implications of using opaque selling and algorithmic targeting independently and in combination. Section 7 conducts robustness checks on the main results under alternative setups. Section 8 provides a summary of the main conclusions.

2 Literature Review

Our work is closely related to two main literature streams: (1) algorithmic targeting in e-commerce and online market and (2) opaque selling in product line design.

2.1 Algorithmic Targeting in E-commerce and Online Market

Our research contributes to the growing literature examining how firms leverage consumer data to optimize algorithmic targeting within digital marketplaces. This approach often involves tailoring marketing efforts to deliver personalized recommendations to individual consumers using advanced algorithms (Zhang and Lahiri 2023, Iyer and Ke 2024, Iyer et al. 2024, Peng et al. 2025). Prior research underscores that targeting technology helps reduce search costs for consumers (Goldfarb and Tucker 2019) and enhance overall market efficiency (Goldfarb and Que 2023). Despite these benefits, concerns are mounting among consumers and regulators regarding the potential misuse of targeting technology. The central issue is that such targeting allows firms to discern consumers' actual needs, enabling them to implement price discrimination (Trusov et al. 2016, Baardman et al. 2023). Anticipating these challenges, recent studies explore how consumers may strategically respond to firms' targeting efforts (Wang et al. 2023, Li and Li 2023). However, these studies generally assume that consumers have perfect knowledge of their willingness to pay or match value for specific products. In reality, a common scenario in e-commerce is that consumers can only estimate this information after seeing product characteristics (Ichihashi 2020) or after experiencing the products themselves (Zou et al. 2020). Moreover, advancements in data analytics increasingly enable firms to understand consumer needs better than the consumers themselves. Addressing this emerging trend, our research considers a market where consumers have imperfect knowledge of their product fit. Using the framework of information design, we investigate how firms can control the flow of information to consumers, thereby influencing their purchasing decisions.

Our study contributes to the growing body of research on the application of information design in modeling targeted advertising and recommendation systems (Kamenica and Gentzkow 2011, Kamenica 2019). Within the e-commerce context, this framework investigates how platforms and firms can endogenously design information environments to shape consumer usage or purchasing behaviors (e.g., Iyer and Zhong 2022, Küçükgül et al. 2022, Gur et al. 2023, Ning et al. 2025). Our work is most closely related to the study by Ning et al. (2025), which also investigates strategic targeting within the framework of information design. However, their analysis focuses on a single-product setting, where strategic information pooling is employed to encourage consumer adoption of the focal product and enhance firm profitability. In contrast, we examine how strategic targeting influences consumer choice across a portfolio of products. In this multi-product context, we similarly demonstrate that targeted information provision can improve firm profits. More importantly, our study highlights a critical nuance: when designing optimal information strategies, sellers must carefully account for potential intra-product cannibalization effects. Therefore, our work extends this stream of literature by incorporating strategic targeting into a multi-product environment and uncovering new insights into the trade-offs firms face when managing informational influence across competing products.

2.2 Opaque Selling in Product Line Design

Opaque selling has emerged as an important area in product line design, garnering significant attention in the literature. Jiang (2007) and Fay and Xie (2008) are among the earliest works on opaque selling, showing how it segments consumers in horizontally differentiated markets. By offering an opaque product, sellers can target consumers with weak preferences, enhancing market efficiency through price discrimination. Building on this, Fay and Xie (2010) and Jerath et al. (2010) compare opaque selling with other selling strategies such as advance selling and last-minute sales. Further, Fay and Xie (2015) explore opaque selling as a mechanism to improve inventory management by reducing overall inventory costs. Similarly, Li et al. (2020) demonstrate that disclosing both inventory and preference information can boost customer satisfaction and ensure long-term success, despite short-term revenue losses. Given the uncertainty in product assignments, Elmachtoub and Hamilton (2021) further demonstrate that opaque selling works optimally when all consumers are homogeneously pessimistic. From a channel dynamics perspective, Fay and Gheibi (2024) examine opaque selling's role in retailer-manufacturer relationships, finding that it reduces double-marginalization inefficiencies. Most recently, Yin and Huang (2025) investigate the interaction between opaque selling and customization, finding them to be strategic complements.

The above studies have enhanced our understanding of opaque selling in horizontally differentiated markets, particularly its role in reducing mismatches through efficient price discrimination. Our research, however, shifts the focus to vertically differentiated markets, where consumer preferences vary substantially. In contrast to horizontal markets, where consumers show indifference towards component products, all consumers in vertical markets strictly prefer higher-quality components. This raises a key question: Can opaque selling apply effectively in vertical markets? Huang and Yu (2014) demonstrate that under standard settings (i.e., certain demand, ample capacity, and full rationality), opaque selling is suboptimal. However, under conditions of bounded rationality, opaque selling can be profitable, especially with dynamic strategies (Huang and Yin 2021). Zheng et al. (2019) further validate the profitability of opaque selling by considering salient thinking among consumers, where opaque goods serve as a context management tool. Moreover, He and Rui (2022) identify consumers' convex preference, characterized by diminishing marginal rates of substitution, as the mechanism that facilitates the necessary conditions for profitable opaque selling. Within the topic of inventory management, opaque selling has proven effective for offloading excess high-quality products (Zhang et al. 2015) and as a tool for inventory clearance (Ren and Huang 2022). Other research has extended its scope to specialized contexts, such as combating counterfeit goods (Gao and Wu 2023) and designing rarity for collectibles (Hu et al. 2024).

Our work contributes to this stream of literature by exploring how opaque selling can be integrated with other marketing strategies to jointly influence consumer purchasing behavior and enhance firm profitability. In particular, our study is closely related to the recent work by Yin and Huang (2025), which examines the interaction between opaque selling and product customization. Their analysis, centered on two product-side strategies, highlights that combining multiple product-line design tools can yield performance gains. Distinct from their focus, we investigate the interplay between product-line design and information disclosure. This allows us to reveal how firms can leverage both improved product-line structuring and belief manipulation to boost profits. To the best of our knowledge, this paper is among the first to systematically analyze the integration of algorithmic targeting with opaque selling in vertically differentiated markets. Therefore, our study offers insights into how opaque selling and, more broadly, other product line design methods can be effectively coordinated with informational levers to improve firms' performance in digital markets.

3 Basic Model

In this section, we introduce our basic model following the sequence of events. First, we describe the seller's product line design problem in Section 3.1. Next, we explain how the seller conducts algorithmic targeting by optimizing the recommendation algorithm in Section 3.2. Finally, we characterize how consumers make purchase decisions based on the seller's product portfolio and the recommendation information in Section 3.3.

3.1 Seller's Product Line Design

We begin by describing the main elements in the basic model, wherein a monopolist seller offers two vertically differentiated products to the consumer. The seller spends the production cost c_j to produce a type j product with the quality q_j, where $j \in \{l,h\}$. The high-quality and low-quality products are denoted as h and l, respectively. Following existing literature (e.g., Huang and Yu 2014, He and Rui 2022), we treat c_j and q_j as exogenous variables, and the seller can adjust the price p_j of different products. Without loss of generality, we assume $c_h > c_l$ and $q_h > q_l$, indicating that the high-quality product requires a higher production cost. Meanwhile, we normalize the production cost and the extrinsic value for analytical tractability by setting $q_h = 1$, $q_l = q$, $c_h = c$, and $c_l = 0$, where $0 < c < 1$ and $0 < q < 1$.

In addition to selling basic products with transparent types, the seller can offer consumers an alternative option in the form of opaque products, which randomly allocate between high-quality and low-quality products. When a consumer purchases the opaque product, they receive the high-quality product with a probability of $\lambda \in (0,1)$ and the low-quality product with a probability of $1-\lambda$. Consistent with previous studies (e.g., Zheng et al. 2019, Ren and Huang 2022), the seller determines the preannounced probability and cannot deviate from this commitment due to regulations or laws. We use the notation o to denote the opaque products, and the seller can sell a type j product to the consumer after introducing opaque selling, where $j \in \{l,o,h\}$. Intuitively, the production cost of one unit of opaque product can be expressed as $c_o \equiv \lambda c$. Correspondingly, the expected quality of the opaque product is $q_o \equiv \lambda + (1-\lambda)q$ (He and Rui 2022). We assume that, apart from production costs, selling and delivering both basic products and the opaque product does not incur extra costs for the seller. In Section 7.3, we demonstrate the robustness of the main results by accounting for the additional costs associated with selling the opaque product.

3.2 Seller's Algorithmic Targeting

Under the framework of information design, we model the seller's algorithmic targeting as the design of a recommendation system. Specifically, we capture algorithmic targeting by allowing the seller to strategically pool information for certain consumer segments while fully revealing it to others, reflecting the key functionality of this emerging technology. We assume that consumers are heterogeneous with respect to their valuation type, θ, which is uniformly distributed over the interval $[0,1]$. A higher θ represents a stronger preference for product quality and a greater inclination to pay for better offerings. At the outset, the seller chooses a recommendation algorithm $\sigma(m|\theta)$, which serves as a signaling rule between the consumer's type θ and the recommendation information m. Consistent with prior literature on targeting (e.g., Ichihashi 2020, Zhang and Lahiri 2023, Ning et al. 2025), we assume that consumers are initially unaware of their exact type and estimate θ based on the received recommendation. This assumption captures a growing phenomenon where advancements in data analytics allow firms to understand consumer preferences better than the consumers themselves. Moreover, since consumers often only realize their actual type or preferences after using a product (Zou et al. 2020), they heavily rely on the seller's recommendation to make purchase decisions. In this process, the seller first designs $\sigma(m|\theta)$, and then a type-θ consumer arrives. Upon receiving the recommendation m, the consumer updates belief $\mu(\theta|m)$ using Bayes' rule:

$$\mu(\theta|m) = \frac{\sigma(m|\theta)f(\theta)}{\int \sigma(m|\theta)f(\theta)d\theta}, \tag{1}$$

where $f(\theta)$ is the prior distribution of θ. Based on the posterior belief, the consumer makes a purchase decision according to the posterior expectation, denoted as $\tilde{\theta}_m \equiv \mathbb{E}(\theta|\mu, m)$. Recommendations can vary in form, such as personalized or group recommendations, and differ in their level of information granularity (Kong et al. 2024). Reflecting common practices in customer segmentation, we focus on a monotone partitional information structure (Dworczak and Martini 2019, Guo and Shmaya 2019), where recommendations take two main forms:

- Personalized recommendations with accurate information (***Policy A***): A unique recommendation is provided to each consumer, accurately reflecting their type θ. Given the recommendation, the posterior expectation is $\tilde{\theta}_m = \theta$.
- Group recommendations with range information (***Policy R***): A uniform recommendation is given to all consumers within a specified range $\theta \in [\underline{\theta}, \overline{\theta}]$. The posterior expectation for consumers in this group is $\tilde{\theta}_m = \frac{\underline{\theta}+\overline{\theta}}{2}$.[4]

The model's policies reflect real-world practices where firms adjust recommendation accuracy to meet strategic objectives. Personalized recommendations use cookies and historical data to analyze individual consumer profiles, delivering tailored suggestions, as seen in Priceline's "Just for You Recommendations" feature. In contrast, group recommendations categorize consumers into tiers, analyze information at the group level, and offer uniform suggestions for each group. For instance, Trip.com classifies users as Silver, Gold, or Platinum and provides tailored recommendations for each tier. Compared to personalized recommendations, group-based approaches are more likely to lead consumers to consider products that do not perfectly match their needs. By strategically adjusting the granularity (i.e., *policy A or R*) of its recommendation algorithm, sellers can optimize algorithmic targeting to shape consumer beliefs and influence purchasing behavior. In the main model, we assume both targeting strategies incur no additional costs for the seller, reflecting the efficiency of modern data analytics and recommendation systems. In Section 7.2, we demonstrate the robustness of the main results by incorporating the additional costs associated with *Policy A*.

[4] For example, a consumer with a \$1000 budget might receive a group-based recommendation (*Policy R*) showing laptops priced from \$800 to \$2000, anchoring their expected spending at \$1400. Under a personalized recommendation (*Policy A*), the seller would directly suggest laptops priced around \$1000, aligning exactly with the consumer's budget.

3.3 Consumers' Purchasing Decisions

Previous studies have identified several mechanisms driving the profitability of opaque selling in vertically differentiated markets, as summarized in Table 1. In the basic model, we focus on a single-period scenario, excluding considerations like bounded rationality and inventory management. To explain the profitability of opaque selling, we adopt the convex preference framework from He and Rui (2022) to model consumer utility. We shall explore a setup involving bounded rationality in Section 7.1, where the key findings remain robust.

Table 1 Summary of opaque selling in vertically differentiated markets.

	Existing literature	Main feature
Bounded rationality (Section 7.1)	Huang and Yu (2014) Huang and Yin (2021)	Anecdotal reasoning in a dynamic setting
	Zheng et al. (2019)	Salient thinking in a static setting
Convex preference (basic model)	He and Rui (2022)	Diminishing marginal utility in a static setting
Inventory management	Zhang et al. (2015)	Excess capacity in a static setting
	Ren and Huang (2022)	Inventory clearance in a dynamic setting

We assume that each consumer in the market purchases at most one unit of the product, selecting the option that yields the highest nonnegative payoff. For simplicity, we assume that when indifferent between options, a consumer weakly prefers the higher-quality product. Consumers who choose not to make a purchase derive a utility of zero, denoted as n. A key feature of our model is the integration of both a linear component (U^L) and a convex component (U^C) into the consumer utility function (U). Under complete information, the decision problem for a type-θ consumer, considering whether and which product to purchase from the seller, can be formulated as:[5]

$$\max_{j\in\{l,o,h,n\}} U(\theta, j) = \begin{cases} \alpha U^C + (1-\alpha)U^L, & j \in \{l,o,h\}, \\ 0, & j = n, \end{cases} \tag{2}$$

where $\alpha \in [0,1]$ represents the degree of preference convexity. Consistent with prior literature (e.g., Moorthy 1988, Zheng et al. 2019), the linear utility component is defined as:

$$U^L(\theta, p_j, q_j) \equiv \theta q_j - p_j, \quad j \in \{l,o,h\}, \tag{3}$$

which is standard in operations management and marketing literature, capturing the baseline price-quality trade-offs. To illustrate preference convexity, we consider a normative utility maximization problem in

[5] When the actual θ is unknown, the consumer forms a posterior belief $\tilde{\theta}_m$ based on the seller's recommendation m. The utility function then uses $\tilde{\theta}_m$ in place of θ.

microeconomics, where consumers, heterogeneous in wealth, select an option from a feasible consumption set to maximize their utility. In vertically differentiated markets, consumers' type θ typically represents their wealth or budget.[6] Depending on the value of θ, consumers choose a product offered by the seller. Thus, in our model, each consumer's consumption set consists of three options $j \in \{l, o, h\}$. The following definition and lemma summarize the concept of preference convexity and introduce our choice of utility function U^C.[7]

DEFINITION 1. A preference relation $\succeq$ on a consumption set X is convex if, for any $x \in X$, the upper contour set $\{y \in X \mid y \succeq x\}$ is convex.

LEMMA 1. *If a utility function represents preference relation $\succeq$, then this utility function is (strictly) quasiconcave if and only if $\succeq$ is (strictly) convex. The following utility function represents such strict convex preference in the basic model:*

$$U^C(\theta - p_j, q_j) \equiv (\theta - p_j)q_j, \quad j \in \{l, o, h\}. \tag{4}$$

This quasiconcave utility function captures how consumers evaluate their choices by considering the utility derived from the *main product* (quantified by q_j) and the remaining budget available for the *composite good* (measured by $\theta - p_j$).[8] The term "composite good" is an economic abstraction that captures all other goods in the budget aside from the main product. It reflects what must be given up, along the budget constraint, to consume more of the main product. Although the term does not necessarily imply multiple goods, it can be treated as a single representative good to simplify demand analysis. This formulation allows the joint consumption of the main product and the composite good to be captured by a Cobb-Douglas utility function over two goods, enabling the model to incorporate diminishing marginal utility within our single-purchase context.

To better illustrate this idea, consider a consumer planning a vacation. The utility function $(\theta - p_j)q_j$ reflects the combined influence of the main product's quality (e.g., a hotel) and the quality of composite goods (e.g., dining, transportation, and leisure activities), which is positively related to the remaining budget $\theta - p_j$. The utility is maximized when the budget is optimally balanced between the hotel and other expenditures, avoiding extremes such as spending the entire budget on the hotel ($p_j = \theta$) or exclusively on other commodities ($p_j = q_j = 0$). In this sense, convex preferences reflect consumers' "variety-seeking" behavior in their consumption. This behavior aligns with the principle of diminishing marginal utility, which

[6] This is one of the most common observations in literature investigating vertically differentiated markets: an increase in θ corresponds to the purchase of higher-quality products, reflecting the tendency of wealthier consumers to prefer higher-quality goods.

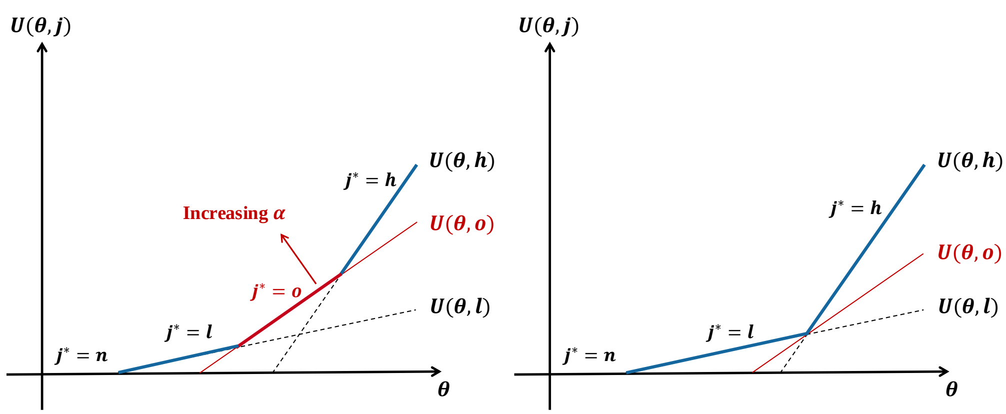
[7] For further discussion on preference convexity, refer to microeconomics textbooks, such as (Jehle 2001, p. 11).

[8] While we currently use a unified parameter θ to flexibly map to either willingness-to-pay (in the linear utility) or budget (in the convex utility), we can also adopt the more traditional interpretation of θ as either willingness-to-pay for quality or as a budget parameter. For example, if θ reflects willingness-to-pay, the remaining budget can be modeled as a non-decreasing function $g(\theta)$. This alternative yields the same qualitative insights as our current formulation.

highlights the consumer's desire for balance: hotels, dining, transportation, and leisure activities cannot perfectly substitute for one another, even though they serve related purposes. Moreover, this utility function serves as a simplified yet tractable variant of the Cobb-Douglas utility function, widely employed to represent convex preferences. Prior studies, such as Shaked and Sutton (1982) and Bolton and Bonanno (1988), have demonstrated its applicability in vertically differentiated markets.[9] Additional technical details on the choice of U^C are discussed in the proofs. Section EC.1 in the E-companion extends the analysis to consider more generalized utility forms, demonstrating that the key insights of the model remain robust.

To summarize, our model integrates both linear and convex components to characterize consumer utility in a unified framework. While each component has been individually explored in prior studies on opaque selling, our approach is distinct in introducing a weighting parameter α, which captures the extent of convexity in consumer preferences. This parsimonious formulation allows us to flexibly model varying degrees of variety-seeking behavior, thereby enriching the analysis of how preference convexity influences product choice under opaque selling. This dimension has received limited attention in the existing literature. We formalize this insight in the following proposition.

PROPOSITION 1. *Given a pair of basic products with prices* (p_l, p_h)*, it is profitable for the seller to introduce the opaque selling strategy if and only if consumers exhibit convex preferences* $(\alpha > 0)$*. Furthermore, the number of consumers purchasing the opaque product increases in the degree of preference convexity.*



(a) Market segmentation when $\alpha > 0$ (b) Market segmentation when $\alpha = 0$

Figure 2 How preference convexity influences consumer utility $U(\theta, j)$ and market segmentation.

The findings are depicted in Figure 2, illustrating how market segmentation equilibrium varies in the degree of preference convexity. This result echoes prior literature, which shows that, in the absence of excess capacity (Zhang et al. 2015), bounded rationality (Zheng et al. 2019), or convex preferences (He and

[9] For example, Shaked and Sutton (1982) adopt $U = u_k(t - p_k)$ to model the utility of a type-t consumer purchasing a product k, where u_k represents product quality and p_k its price.

Rui 2022),[10] opaque selling cannot be a profitable strategy for sellers. More importantly, by incorporating both linear and convex components, our model captures a broader spectrum of consumer preferences. The weight parameter α governs the relative contribution of the convex utility term. A higher α reflects stronger convex preferences, which align with empirically observed behaviors such as variety-seeking or aversion to extreme allocations. As α increases, the opaque product becomes more attractive, offering a balanced trade-off between quality and price while avoiding extreme outcomes. Therefore, unlike prior studies that assume purely linear or convex utility forms, our hybrid utility formulation offers a novel framework to examine how varying degrees of preference convexity influence consumer choices in the context of opaque selling.

Timeline. The sequence of events is depicted in Figure 3.

1. **Product Line Design:** The seller designs the vertical product line by setting the prices (p_l, p_h) for the basic products. After incorporating opaque selling, the seller also sets the price p_o and the mixing probability λ for the opaque product.

2. **Algorithmic Targeting:** The decision of algorithmic targeting can be characterized by specific thresholds related to θ and the information policy (A or R) within each interval. In a traditional business scenario, consumers either do not purchase any product ($j = n$) or purchase one of the basic products ($j \in \{l, h\}$). This creates three market segments, with the information structure represented by two thresholds (θ_l, θ_h). In a new business scenario, an additional threshold θ_o is introduced for the opaque product.[11]

3. **Consumer Purchases:** After the consumer's type θ is determined by nature, the recommendation information m is generated. The consumer updates the belief about θ and makes a purchase decision.

A summary of the main model nomenclature is provided in E-companion Section EC.2.

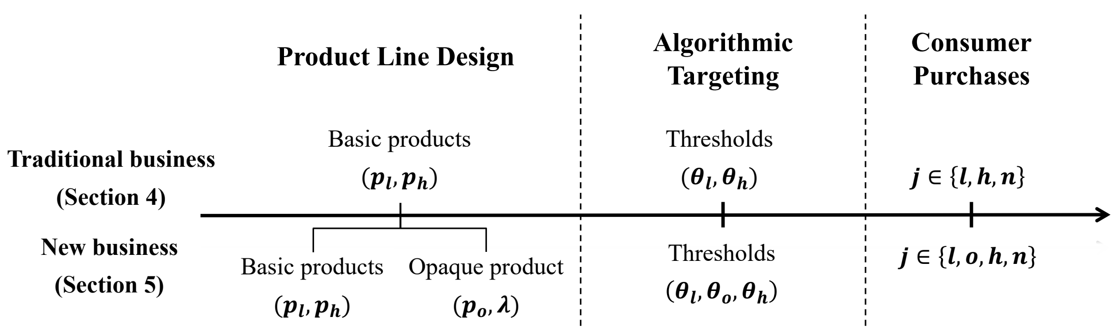


Figure 3 Sequence of events.

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[10] Indeed, the linear form $(\theta q - p)$ serves as a simplified approximation of a more general utility function to facilitate the study of product differentiation and pricing in vertically differentiated markets. While analytically tractable, it lacks strictly convex preferences due to its linear indifference curve. Section 3.1 of He and Rui (2022) shows this limitation is usually negligible but crucial for modeling opaque selling.

[11] The sequential order of product line design and algorithmic targeting does not affect the results because the seller makes both decisions without knowing the type of each arrived consumer. In practice, the design of the recommendation algorithm may precede or follow the product line design, depending on the firm's existing analysis system.

4 Traditional Business Scenario

In traditional selling, the seller provides the basic (i.e., high-quality and low-quality) products to consumers. The market will be segmented into three parts: non-purchase market n, low-end market l, and high-end market h. The equilibrium market segmentation is thus characterized by two thresholds θ_l and θ_h. The demand for product l is determined by the difference $(\theta_h - \theta_l)$, while the demand for product h is $(1 - \theta_h)$. Because the recommendation to customers can take two forms (A or R), and there are three market segments in equilibrium, the information scheme can be further refined by specifying the recommendation form in each segment. Table 2 summarizes the information schemes we have discussed in this section. For example, *ARR* represents the situation wherein the seller provides the no-purchase consumers with accurate information while pooling information for the other two types of consumers. Other possible structures (e.g., *AAR*) are strictly dominated by the information structures in the table, and the specific proofs are relegated to Section EC.3.2 in the E-companion. We start by analyzing the case of complete information, where the seller discloses accurate information to all consumers (i.e., *AAA*).

Table 2 Notation of different information policies (traditional selling).

	Case	Structure	Descriptions
Traditional Business	a	*AAA*	Accurate information for all consumers
	b	*ARR*	Pooling information for segment l and h
	c	*ARA*	Pooling information for segment l

4.1 Complete Information Benchmark

Complete information represents traditional mass marketing approaches where firms disseminate full product information to all consumers. Examples include TV commercials, catalog distributions, and banner ads that showcase the entire product range without differentiation. This is a classic example of John Wanamaker's famous quote: "Half my advertising spend is wasted; the trouble is, I do not know which half."[12] Such campaigns were commonly used before the advent of consumer-level data analytics, relying on broad exposure to prompt self-selection among heterogeneous consumers. The information structure corresponds to the *AAA* case, and we denote it by superscript a. When the seller provides a pricing scheme (p_l^a, p_h^a), the market cutoffs are derived as: $\theta_l^a = \frac{p_l^a - p_l^a(1-q)\alpha}{q}$ and $\theta_h^a = \frac{p_h^a - p_l^a}{1-q} + p_l^a\alpha$. The seller's optimization problem, aiming to maximize profit, can be expressed as:

$$\max_{p_h^a, p_l^a} \Pi = (p_h^a - c)(1 - \theta_h^a) + p_l^a(\theta_h^a - \theta_l^a). \tag{5}$$

[12] Forbes. Wanamaker Was Wrong – The Vast Majority Of Advertising Is Wasted. Accessed August 30, 2025, https://www.forbes.com/sites/georgebradt/2016/09/14/wanamaker-was-wrong-the-vast-majority-of-advertising-is-wasted/?sh=1595be7f483b.

Solving this optimization problem, we can obtain the optimal pricing $(p_l^{a^*}, p_h^{a^*})$ for these two products. This equilibrium strategy, consisting of product-line and information design, is recorded as $\{(p_l^{a^*}, p_h^{a^*}), AAA\}$. In turn, the market cutoffs $(\theta_l^{a^*}, \theta_h^{a^*})$ can be derived. The detailed values are shown in Section EC.3.1 in the E-companion. Given the equilibrium prices and market cutoffs, the market segmentation holds under the condition that $0 \le \theta_l^{a^*} \le \theta_h^{a^*} \le 1$, which is satisfied when the cost c is below the threshold defined by $c \le \frac{(1-q)(2-\alpha(2-q))}{2-2\alpha(1-q)}$. That is, when the production cost of the high-quality product exceeds this threshold, the equilibrium degenerates into a two-interval form, where no customer purchases the high-quality product.

4.2 Algorithmic Targeting

Algorithmic targeting enables the seller to accurately reveal or pool information for specific consumers. We use the complete-information case as the primary benchmark. Alternatively, one could consider the no-information case as the benchmark, in which the seller pools information across the entire consumer segment. In both cases, the value of algorithmic targeting lies in its ability to strategically pool information for certain consumer segments while fully disclosing it for others. For the remainder of the analysis, we focus on how strategic information disclosure enabled by algorithmic targeting can improve the seller's performance relative to the complete-information benchmark. The seller selects one of two strategies based on the marginal profit of the two basic products. These strategies are denoted as *ARR* (with superscript b) and *ARA* (with superscript c), with equilibrium outcomes expressed as $\{(p_l^{b^*}, p_h^{b^*}), ARR\}$ and $\{(p_l^{c^*}, p_h^{c^*}), ARA\}$, respectively.

PROPOSITION 2. *Compared to the complete-information benchmark, strategically pooling information expands market coverage and increases profit. In traditional selling, when the production cost of the high-quality product is low, the seller adopts the strategy* $\{(p_l^{b^*}, p_h^{b^*}), ARR\}$. *Otherwise, the optimal strategy shifts to* $\{(p_l^{c^*}, p_h^{c^*}), ARA\}$. *Detailed equilibrium results are presented in Table 3.*

Table 3 The optimal strategy in the presence of algorithmic targeting.

Condition	Pricing Strategy	Information Structure
$c < \frac{1-q-\alpha+q\alpha}{1-\alpha+q\alpha}$	$p_l^{b^*} = \frac{cq}{2(1-q)(1-\alpha)},\ p_h^{b^*} = \frac{c+(1-q)(1-\alpha)-c\alpha(1-q)}{2(1-q)(1-\alpha)}$	*ARR*
$c \ge \frac{1-q-\alpha+q\alpha}{1-\alpha+q\alpha}$	$p_l^{c^*} = \frac{q}{2(1-\alpha+q\alpha)},\ p_h^{c^*} \ge 1-\frac{q}{2}$	*ARA*

Proposition 2 indicates that the seller always provides accurate information for the non-purchasing market while pooling information for the low-end market. For the high-end market, the seller customizes the information disclosure based on marginal profits. When the high-quality product is more profitable (i.e., $c < \frac{1-q-\alpha+q\alpha}{1-\alpha+q\alpha}$), the seller pools information in the high-end market. This strategy strengthens consumers' beliefs about their type θ, thereby expanding the high-end market. On the other hand, when the cost exceeds this threshold, the low-quality product becomes more profitable. In such cases, the seller fully discloses information for the high-end market and sets a higher price $p_h^{c^*}$, leading all consumers in this segment to switch from purchasing the high-quality product to the low-quality product. In summary, strategically pooling information within a specific market segment can boost demand in that segment but may reduce it in others, resulting in an *intra-cannibalization* effect. This trade-off is crucial in shaping the seller's information policy decisions. Building on the equilibrium results, we further analyze the impact of algorithmic targeting on consumer surplus and social welfare in the E-companion. The findings suggest that while algorithmic targeting may reduce consumer surplus, it consistently increases overall social welfare, as the gain in the seller's profit outweighs the loss in consumer surplus. For a detailed discussion, see Corollary EC.2 in the E-companion.

5 New Business Scenario

In this section, we study algorithmic targeting in new business scenarios, which refer to the situation wherein the consumer's purchasing choice expands beyond the basic products. As a typical example, opaque selling is the paper's focus. By this means, we examine whether algorithmic targeting can still play a role as the product line has already expanded in new business models. With opaque selling, the seller offers an additional opaque product indexed by o. The price of the opaque product is p_o and the mixing probability of high-quality products is λ. The market will be segmented into four parts: non-purchase market n, low-end market l, opaque selling (intermediate) market o, and high-end market h. The equilibrium market segmentation is thus characterized by three thresholds θ_l, θ_o, and θ_h. The demand for low-quality, opaque, and high-quality products are $(\theta_o - \theta_l)$, $(\theta_h - \theta_o)$, and $(1 - \theta_h)$, respectively. Consistent with how we characterize the information scheme in Section 4, we employ Table 4 to summarize the information schemes we have discussed. For instance, *ARAA* represents the situation wherein the seller pools information for the low-type consumers while revealing accurate information for other consumers. Other possible structures (e.g., *AARR*) are strictly dominated by the information structures in the table, and their discussions are relegated to Section EC.3.2 in the E-companion. We start with the case of complete information (i.e., *AAAA*).

Table 4 Notation of different information policies (opaque selling).

	Case	Structure	Descriptions
Opaque	d	*AAAA*	Accurate information for all consumers
Selling	e	*ARAA*	Pooling information for segment l

5.1 Complete Information Benchmark

The complete information structure corresponds to the *AAAA* case, and we denote it by the superscript d. When the seller conducts a product line design (p_l, p_h, p_o, λ), the market thresholds are derived as: $\theta_l^d = \frac{p_l(1-p_l\alpha(1-q))}{q}$, $\theta_o^d = \frac{p_l+p_l\alpha(q-1)+p_o(\alpha(q-1)(\lambda-1)-1)}{\lambda(q-1)}$, and $\theta_h^d = p_o\alpha + \frac{p_h-p_o}{(1-q)(1-\lambda)}$. The corresponding optimization problem is expressed as:

$$\max_{p_h^d, p_l^d, p_o^d, \lambda^d} \Pi = (p_h - c)(1-\theta_h^d) + (p_o^d - \lambda^d c)(\theta_h^d - \theta_o^d) + p_l^d(\theta_o^d - \theta_l^d). \tag{6}$$

Solving the optimization problem, we can obtain the optimal design $(p_l^{d^*}, p_h^{d^*}, p_o^{d^*}, \lambda^{d^*})$ and this equilibrium strategy is recorded as $\{(p_l^{d^*}, p_h^{d^*}, p_o^{d^*}, \lambda^{d^*}), AAAA\}$. The market cutoffs $(\theta_l^{d^*}, \theta_o^{d^*}, \theta_h^{d^*})$ can be derived accordingly. The detailed values are shown in Section EC.3.1 in the E-companion.

5.2 Algorithmic Targeting

The optimal algorithmic targeting strategy in conjunction with opaque selling is more nuanced compared to traditional selling. Both levers can improve market segmentation, but in equilibrium, the seller may implement only one of them. For instance, if the seller implements only algorithmic targeting without introducing opaque selling (by setting $\lambda = 0$ or 1), the optimal strategy becomes the one described in Proposition 2. In the following, we characterize the seller's optimal strategy when both algorithmic targeting and opaque selling are available.

PROPOSITION 3. *When the seller is able to strategically pool information and introduce opaque selling, it consistently adopts the pooling strategy. However, opaque selling is implemented only if the disparity between the two basic products is at an intermediate level ($\tilde{c} < c < \overline{c}$). When these conditions are met, the seller combines both levers, and the optimal strategy is $\{(p_l^{e^*}, p_h^{e^*}, p_o^{e^*}, \lambda^{e^*}), ARAA\}$. The corresponding market segmentation satisfies $0 < \theta_l^{e^*} < \theta_o^{e^*} < \theta_h^{e^*} < 1$. The thresholds $\tilde{c}$ and $\overline{c}$ are functions of both q and α, and their closed-form expressions are provided in the E-companion.*

Opaque selling emerges only when the production cost of the high-quality product, c, falls within an intermediate range. To better understand this result, we examine how the optimal mixing probability λ^* varies with c. When the cost is sufficiently low (i.e., $c < \tilde{c}$), the high-quality product becomes more profitable for the seller. In this case, the equilibrium mixing probability is $\lambda^* = 1$, meaning the opaque product consists entirely of the high-quality item. Conversely, when the cost is sufficiently high (i.e., $c > \overline{c}$), the seller strongly favors the low-quality product. The resulting equilibrium is $\lambda^* = 0$, and the opaque product includes only the low-quality item. At intermediate cost levels, the seller adopts the strategy $\{(p_l^{e^*}, p_h^{e^*}, p_o^{e^*}, \lambda^{e^*}), ARAA\}$, which combines algorithmic targeting and opaque selling. In this equilibrium, the seller pools information for lower-type consumers while fully disclosing product information for higher-type segments. This strategy expands overall market coverage and enhances demand for the opaque product, while full disclosure in higher segments mitigates the risk of intra-product cannibalization.

The ARAA structure maps closely to industry practices in algorithmic targeting, where firms strategically pool information for low-valuation consumers while fully disclosing it to high-valuation ones. For example, Trip.com segments users into different tiers, with high-tier members receiving personalized hotel and activity suggestions. In contrast, entry-level users often see more standardized offerings labeled with heuristic cues such as "Best for Budget-Conscious Travelers" or "Popular Choice for Budget Travelers." Similarly, Expedia Group's One Key and Booking.com's Genius programs also provide higher-tier users with more exclusive recommendations.[13] These practices reflect our model's prediction that firms may withhold or aggregate information for low-type consumers to shape favorable beliefs and encourage engagement, while deploying fine-grained personalization for consumers with higher valuations.

This proposition identifies the conditions under which the seller finds it optimal to combine opaque selling with algorithmic targeting. In all other cases, the seller's optimal strategy reverts to one without opaque selling, as characterized in Proposition 2. In the following proposition, we shall identify the seller's optimal strategy under different market conditions and analyze how it evolves in response to changes in key exogenous parameters.

PROPOSITION 4. *Depending on consumer preferences and product characteristics, the seller chooses among three strategies to maximize profit:*

- *When $c < \tilde{c}(q,\alpha)$: The optimal strategy is $\{(p_l^{b*}, p_h^{b*}), ARR\}$. The seller offers only the low- and high-quality products; opaque selling is not employed.*
- *When $\tilde{c}(q,\alpha) < c < \bar{c}(q,\alpha)$: The optimal strategy is $\{(p_l^{e*}, p_h^{e*}, p_o^{e*}, \lambda^{e*}), ARAA\}$. The seller offers all three products: low-quality, opaque, and high-quality.*
- *When $c > \bar{c}(q,\alpha)$: The optimal strategy is $\{(p_l^{c*}, p_h^{c*}), ARA\}$. The seller offers only the low-quality product and excludes both high-quality and opaque options.*

The thresholds satisfy: $\tilde{c}(q,\alpha)$ decreases with both q and α, whereas $\bar{c}(q,\alpha)$ decreases with q but increases with α. When $\bar{c}(q,\alpha) < \tilde{c}(q,\alpha)$, the optimal strategy is $\{(p_l^{b*}, p_h^{b*}), ARR\}$ when $c < \tilde{c}(q,\alpha)$ and $\{(p_l^{c*}, p_h^{c*}), ARA\}$ otherwise.

To interpret this result, it is helpful to revisit the insights from Proposition 2. The strategies $\{(p_l^{b*}, p_h^{b*}), ARR\}$ and $\{(p_l^{c*}, p_h^{c*}), ARA\}$ are optimal when the seller aims to extract profit primarily from the high- and low-quality products, respectively. When the high-quality product's production cost is sufficiently low ($c < \tilde{c}(q,\alpha)$), the seller adopts the $\{(p_l^{b*}, p_h^{b*}), ARR\}$ strategy to boost demand for the high-quality product and increase profitability. Conversely, when c is large, the seller finds it more profitable to withdraw from offering the high-quality option and instead adopts the $\{(p_l^{c*}, p_h^{c*}), ARA\}$ strategy, which emphasizes

[13] Expedia Group. Expedia Group Announces 'One Key,' a Groundbreaking New Loyalty Program That Rewards Every Traveler. Accessed August 30, 2025, https://www.expedia.com/newsroom/expedia-group-announces-one-key-a-groundbreaking-new-loyalty-program-that-rewards-every-traveler/.

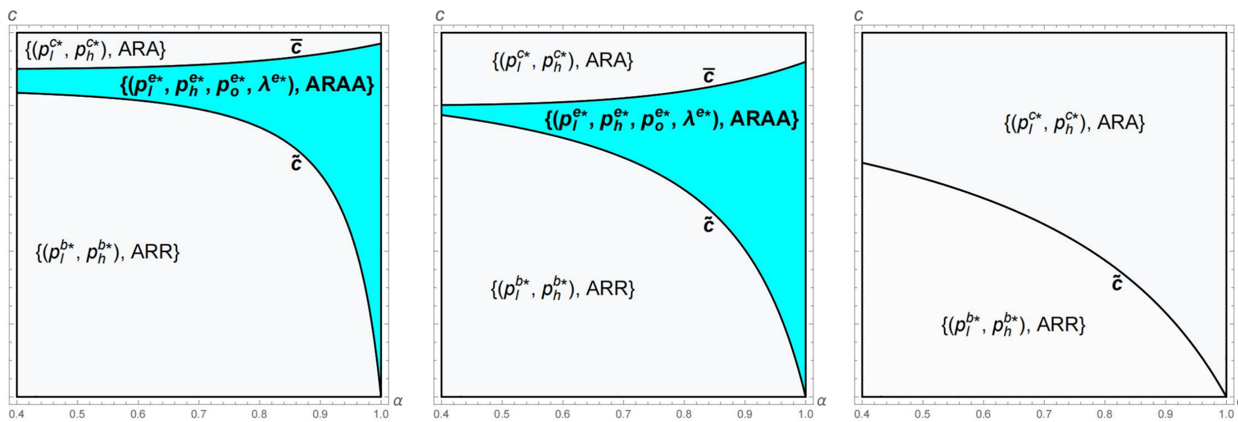
the low-quality product. The strategy $\{(p_l^{e*}, p_h^{e*}, p_o^{e*}, \lambda^{e*}), ARAA\}$, which involves offering the opaque product with a mixing probability λ, emerges only when the cost c lies within an intermediate range. Notably, this hybrid strategy degenerates to the other two when λ approaches 1 or 0. Specifically, if $\lambda = 1$, the opaque product consists solely of the high-quality option, aligning with $\{(p_l^{b*}, p_h^{b*}), ARR\}$; if $\lambda = 0$, the opaque product includes only the low-quality version, consistent with $\{(p_l^{c*}, p_h^{c*}), ARA\}$.

These dynamics are illustrated in Figure 4. Subfigures (a) and (b) show how the optimal strategy transitions from $\{(p_l^{b*}, p_h^{b*}), ARR\}$ to $\{(p_l^{e*}, p_h^{e*}, p_o^{e*}, \lambda^{e*}), ARAA\}$ and eventually to $\{(p_l^{c*}, p_h^{c*}), ARA\}$ as c increases. The economic intuition is that rising production costs of the high-quality product prompt the seller to shift focus from high- to low-quality offerings to maintain profitability. The proposition further shows how the two cost thresholds, $\tilde{c}(q,\alpha)$ and $\bar{c}(q,\alpha)$, vary with q and α. To understand the effect of low-quality product's quality q, we can fix (c,α) and compare strategy choices across the three subfigures. The general pattern remains consistent: as the quality of the low-end product improves, the optimal strategy transitions from $\{(p_l^{b*}, p_h^{b*}), ARR\}$ to $\{(p_l^{e*}, p_h^{e*}, p_o^{e*}, \lambda^{e*}), ARAA\}$ and eventually to $\{(p_l^{c*}, p_h^{c*}), ARA\}$. In other words, higher values of q and c both diminish the relative appeal of the high-quality product, encouraging the seller to adopt strategies centered on low-quality options. Thus, these two parameters shape strategic transitions in similar ways. Further analysis in the E-companion reveals that when q is sufficiently large, we may have $\bar{c}(q,\alpha) < \tilde{c}(q,\alpha)$. In this case, the intermediate regime supporting opaque selling disappears, and the seller never finds it optimal to use the *ARAA* strategy. The intuition is that with high q, mixing in the low-quality product alone can be highly profitable, leaving no incentive to combine it with the high-quality alternative. This special case is illustrated in Figure 4(c). The degree of preference convexity α also plays a critical role. As shown in Proposition 1, a higher α increases the opaque product's attractiveness to consumers. Consequently, higher values of α broaden the range of conditions under which the strategy involving opaque selling becomes optimal. This effect is clearly illustrated by the comparison between Figures 4(a) and (b).

In the E-companion, Figure EC.2 visualizes how the seller's maximum profit varies with production cost c, corresponding to the three scenarios $(q = \frac{1}{16}, \frac{1}{8}, \frac{1}{4})$ in Figure 4. The general pattern confirms that lower production costs c and/or higher quality q lead to greater profits. Finally, the E-companion also examines how algorithmic targeting affects consumer surplus and social welfare in the presence of opaque selling. As with the case without opaque selling, algorithmic targeting may reduce consumer surplus but consistently enhances social welfare, since the gain in seller profit outweighs the consumer loss. For detailed results, see Corollary EC.3.

6 Values of Opaque Selling and Algorithmic Targeting

This section first evaluates the effect of opaque selling or algorithmic targeting separately and then considers their combined value. To facilitate the discussion, we summarize the equilibrium results across different business scenarios. Figure 5 (a) illustrates the seller's optimal strategy selection when no lever, one lever,

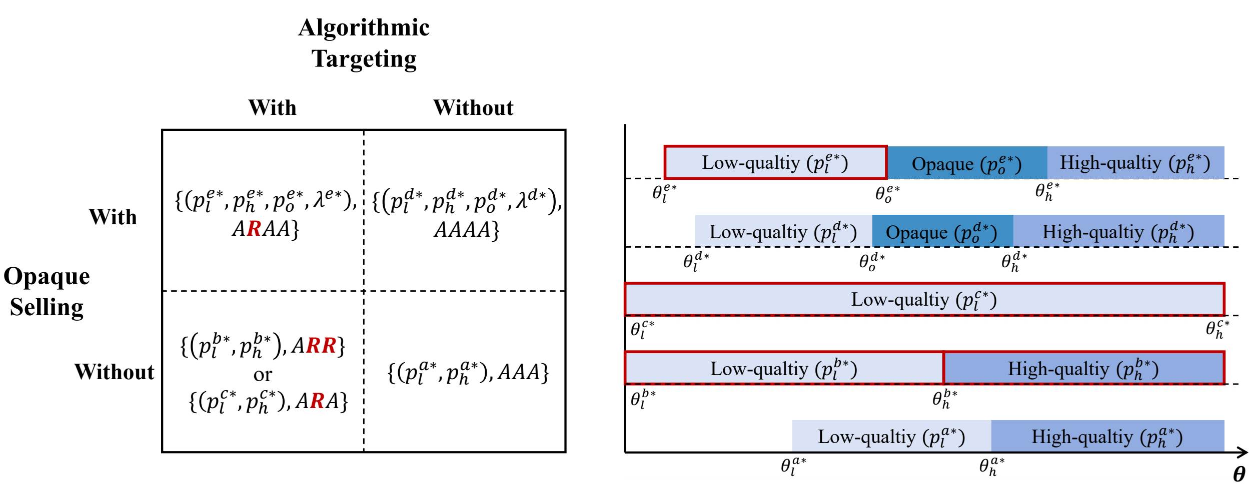


(a) $q = 1/16$ (b) $q = 1/8$ (c) $q = 1/4$

Figure 4 Seller's optimal strategy under various conditions.

Note: The figure maps the firm's optimal strategy across the parameter space (α, c), with panels (left to right) showing decreasing quality differentiation $(q = \frac{1}{16}, \frac{1}{8}, \frac{1}{4})$. Green regions indicate adoption of both opaque selling and algorithmic targeting.

or both levers are available. Figure 5 (b) presents a comparison of market segmentation outcomes across these cases. In brief, opaque selling primarily enables price discrimination by expanding the product line to include an intermediate product aimed at high-type consumers. Algorithmic targeting influences consumer beliefs about product preferences, driving higher sales of the higher-margin product. Regarding the strategy adoption, algorithmic targeting is consistently employed, while opaque selling is used selectively, depending on the characteristics of the basic products. Below, we discuss these findings in more detail.



(a) Summary of seller's optimal strategy (b) Summary of market segmentation

Figure 5 Equilibrium results across different business scenarios.

Note: The red bold box indicates that the seller pools information within this range; please refer to the upper index in each subfigure for cross-referencing details.

6.1 Effect of Opaque Selling

To evaluate the value of opaque selling, we compare case a with case d, isolating its effect from algorithmic targeting. Additionally, we compare cases b and c with case e to assess its incremental value when combined with algorithmic targeting.

PROPOSITION 5. *Opaque selling expands the seller's product line by introducing an intermediate product, which helps enhance price discrimination, particularly among high-type consumers. The seller should adopt opaque selling when the disparity between the basic products is intermediate.*

Opaque selling is particularly effective for high-type consumers by offering a bundled intermediate product, allowing the seller to charge higher prices to those who previously purchased high-quality products. Specifically, under opaque selling, the equilibrium price for the high-quality product is higher ($p_h^{d^*} > p_h^{a^*}$), and this effect persists with algorithmic targeting (as seen by comparing case e with cases b and c). Conversely, the equilibrium price for the low-quality product decreases ($p_l^{d^*} < p_l^{a^*}$). This mechanism enables effective price discrimination in the high-end market, enhancing profitability. However, opaque selling may reduce profitability in the low-end market due to the lower price of the low-quality product. Proposition 3 outlines that opaque selling is only viable when the disparity between the basic products falls within an intermediate range. Outside this range, the seller may adjust the mixing probability λ^* to either 0 or 1, actually removing the opaque product from the market and using algorithmic targeting solely.

6.2 Effect of Algorithmic Targeting

Algorithmic targeting shapes consumer beliefs across a broader range of types by strategically pooling information. To evaluate its impact, we compare cases ARR (b) and ARA (c) with full information benchmark (case AAA: a), isolating the effect of algorithmic targeting (i.e., cases b and c) from opaque selling. Additionally, we compare case ARAA (e) with full information benchmark (AAAA: case d) to assess the incremental value of algorithmic targeting (i.e., case e) when combined with opaque selling. The mechanism and conditions for adopting algorithmic targeting are summarized in the following proposition.

PROPOSITION 6. *Algorithmic targeting shapes consumers' beliefs about product preferences, increasing the purchase of the higher-margin product within the existing product portfolio. This strategy proves effective in either the low-end or high-end market, depending on profitability conditions, and the seller should always adopt it to enhance profitability.*

Although algorithmic targeting does not expand the seller's product line by introducing new products, it significantly benefits the seller by increasing purchases of the higher-margin product within the existing portfolio. This advantage holds whether or not the seller adopts opaque selling. Comparing case a with cases b and c, algorithmic targeting can effectively target either low-type or high-type consumers, depending on profitability conditions. When the low-quality product is more profitable (case c), algorithmic targeting encourages more consumers to purchase the low-quality product. Conversely, when the high-quality product is more profitable (case b), algorithmic targeting motivates more consumers to purchase the high-quality product. When combined with opaque selling (case e vs. case d), algorithmic targeting and opaque selling influence different consumer segments. Specifically, the seller strategically pools information to influence low-type consumers and expand the low-end market, while opaque selling enhances profitability in the high-end market. However, indiscriminately withholding information across all consumers can lead to intra-cannibalization within the product portfolio (as discussed in Proposition 2). This explains why the seller provides accurate information for selected consumer segments. Therefore, strategic information obfuscation, particularly for low-end consumers, is essential to balance demand and marginal profitability across products.

To understand why strategically pooling information can effectively expand the demand for specific products, consider case b. Figure 6 illustrates market segmentation under two scenarios: (i) algorithmic targeting with pooling information and (ii) traditional marketing with complete information disclosure. The withdrawal of algorithmic targeting refers to reverting to non-algorithmic, full-disclosure strategies. Take a consumer with $\theta_l^{b^*}$ as an example. Under algorithmic targeting, this consumer forms a posterior belief $\tilde{\theta}_m = (\theta_l^{b^*} + \theta_h^{b^*})/2$, as the seller pools information within this range. This belief leads the consumer to purchase the low-quality product, as it offers higher utility than no purchase, i.e., $U(\tilde{\theta}_m, l) \geq U(\tilde{\theta}_m, n)$. Without targeting, however, the consumer knows their actual type $\theta_l^{b^*}$ and chooses not to purchase, as $U(\theta_l^{b^*}, l) < U(\theta_l^{b^*}, n)$. This shift also explains why consumers with $\theta \in (\theta_l^{b^*}, \tilde{\theta}_l^{b^*})$ transition from purchasing the low-quality product to no purchase: their expectations about θ drop from $\tilde{\theta}_m = (\theta_l^{b^*} + \theta_h^{b^*})/2$ to lower levels. Similarly, the demand for the higher-margin product (i.e., the high-quality product) decreases when targeting is removed. Consumers with $\theta \in (\theta_h^{b^*}, \tilde{\theta}_h^{b^*})$ downgrade from purchasing the high-quality product to the low-quality one because their expectations about θ also fall. These findings highlight how strategic pooling of information encourages lower-type consumers to form higher beliefs, thereby increasing their likelihood of purchasing higher-quality products. Notably, this mechanism is particularly effective in converting no-purchase consumers into buyers of the low-quality product. As observed in cases b, c, and e, the seller should always pool information in the low-end market to expand market coverage.[14] In summary, algorithmic targeting for low types implies strategically pooling consumers towards whom information is disclosed, which boosts their overconfidence and increases willingness-to-pay by "*feeling good about themselves*."

The findings in this section offer several insights. By examining how prices are influenced by opaque selling, we show that its underlying mechanism allows for price discrimination, particularly targeting higher-type consumers. Additionally, opaque selling appears to be effective only when the disparity between basic

[14] In contrast, opaque selling expands the market by lowering the price of the low-quality product, whereas algorithmic targeting achieves this by inducing low-type consumers to form higher beliefs about their types.

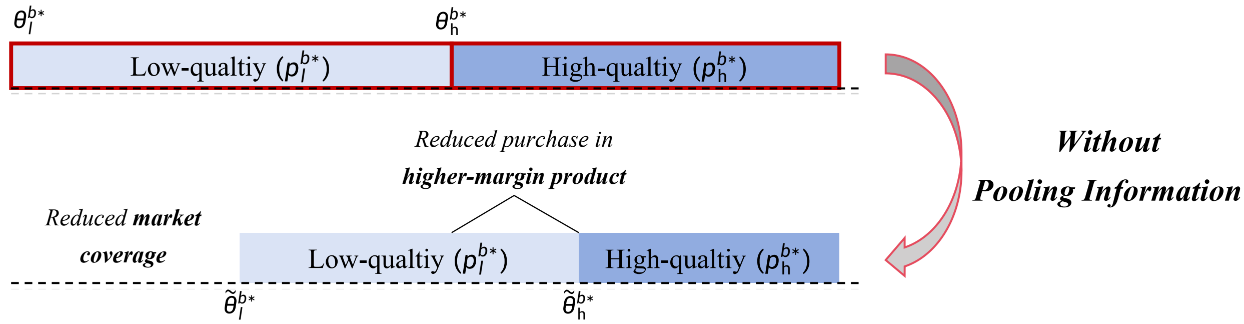


Figure 6 Impact of algorithmic targeting on market segmentation in case *b*.

products is at an intermediate level. These insights may also apply to broader methods in product line design, suggesting that the introduction of new products is often constrained by their market positioning and the existing products available. Furthermore, our work shifts the focus from single-product pricing to the role of algorithmic targeting within a product portfolio. While prior research typically examines how algorithmic targeting can increase the price of a single product, we highlight its potential to enhance market segmentation and boost the sales of high-margin products across an entire portfolio.

From a practical perspective, our findings offer guidance for firms considering the use of opaque selling and algorithmic targeting. The comparison of these two strategies suggests that firms should always use algorithmic targeting, while the adoption of opaque selling depends on the characteristics of the basic products. Algorithmic targeting, being a flexible and robust tool, can effectively influence consumer preferences in either low-end or high-end markets, improving profitability. However, it comes with the risk of intra-cannibalization, which requires careful strategic information disclosure to balance demand and profitability across products. When applied together, opaque selling and algorithmic targeting can help shape consumer purchasing behaviors more effectively: opaque selling primarily targets high-type consumers, while algorithmic targeting focuses on low-type consumers, thus expanding market reach.

7 Extensions

7.1 Bounded Rationality

This section examines how algorithmic targeting interacts with opaque selling under the assumption of bounded rationality. In this stream of literature, Huang and Yu (2014) and Huang and Yin (2021) characterize consumers' boundedly rational behavior through the anecdotal reasoning framework. This framework suggests that in multi-period sales, consumers in a focal period cannot observe the actual mixing probability and instead estimate it based on the purchasing behaviors of past consumers. Similarly, in a single-period setup, Elmachtoub and Hamilton (2021) adopt a similar notion, assuming that consumers cannot accurately observe the mixing probability. Building on this literature, we study bounded rationality within a simplified framework. Instead of using convex preferences (as in Equation 2), the decision problem for a type-θ consumer, determining whether and which product to purchase, is revised as:

$$\max_{j\in\{l,o,h,n\}} U(\theta, j) = \begin{cases} \theta q_l - p_l, & j = l, \\ \theta q_o^\gamma - p_o, & j = o, \\ \theta q_h - p_h, & j = h, \\ 0, & j = n. \end{cases} \tag{7}$$

The expected quality of the opaque product is $q_o \equiv \lambda q_h + (1-\lambda)q_l$. Consumers' estimation of its quality is $q_o^\gamma \equiv \min\{\gamma\lambda q_h + (1-\gamma\lambda)q_l, q_h\}$, where $\gamma > 0$ reflects the degree of bounded rationality.[15] Consumers are fully rational when $\gamma = 1$. For $\gamma < 1$, they underestimate the probability of receiving a high-quality product, while for $\gamma > 1$, they overestimate it. Maintaining the other assumptions of the model, we analyze the value of algorithmic targeting under this bounded rationality framework, following the sequence in Section 5. Consistent with Proposition 3, we examine whether opaque selling and algorithmic targeting can coexist under the bounded rationality setup.

PROPOSITION 7. *In the bounded rationality setup, the seller adopts algorithmic targeting across all market conditions, while opaque selling is employed only when the disparity between the two basic products is at an intermediate level, which is consistent with the findings in Proposition 3. The key difference is that the two cost thresholds for implementing opaque selling now depend on q and γ.*

Under bounded rationality, consumers tend to overestimate the quality of the opaque product, enabling the seller to charge a higher price and extract greater profit. As in Proposition 3, opaque selling is optimal only when the disparity between the low- and high-quality products is moderate. When the production cost c is either too low or too high, the optimal mixing probability becomes either 0 or 1, and the opaque product is thus excluded from the optimal strategy.

7.2 Additional Costs of Personalized Recommendation

The basic model assumes zero costs for implementing various information policies, reflecting the efficiency of modern data management and recommendation systems. However, in practice, personalized targeting could demand greater resources and incur higher expenses for the seller. In this section, we introduce an additional cost, denoted as c_a, for conducting personalized targeting to evaluate the robustness of our primary findings. Under traditional selling, such costs do not affect the design or economic value of algorithmic targeting, as the seller pools information for all consumers. In the new business scenario, however, the cost of personalized targeting directly influences whether the seller adopts the strategy $\{(p_l^{e^*}, p_h^{e^*}, p_o^{e^*}, \lambda^{e^*}), ARAA\}$, as this approach requires personalized targeting for high-type consumers.

[15] An implicit assumption $\gamma\lambda \le 1$ ensures that the overestimated probability does not exceed one.

PROPOSITION 8. *Higher costs of personalized targeting (Policy A) increase the likelihood of the seller pooling information. Compared with Proposition 3, the seller still chooses among three strategies, but the viability of* $\{(p_l^{e^*}, p_h^{e^*}, p_o^{e^*}, \lambda^{e^*}), ARAA\}$ *narrows. Specifically, this strategy is adopted only when* $\tilde{c}_a < c < \overline{c}_a$*, where the thresholds satisfy* $\tilde{c} < \tilde{c}_a < \overline{c}_a < \overline{c}$.

This finding highlights that the inclusion of additional costs for personalized targeting affects only the quantitative viability of integrating algorithmic targeting with opaque selling. Intuitively, personalized recommendation becomes infeasible when the costs are prohibitively high ($c > \overline{c}_a$), aligning with established principles in the information disclosure literature (Guo and Shmaya 2019). In such cases, the seller has a stronger incentive to pool information across consumers. In the E-companion, Figure EC.3 illustrates how the optimal strategy shifts with the inclusion of c_a. As expected, the seller is more likely to adopt the strategies $\{(p_l^{b^*}, p_h^{b^*}), ARR\}$ and $\{(p_l^{c^*}, p_h^{c^*}), ARA\}$, as these involve more frequent pooling of consumer information.

7.3 Additional Costs for Selling Opaque Products

The basic model assumes that selling opaque products incurs no additional costs for the seller. However, in practical scenarios, activities such as logistics, packaging, and marketing may introduce extra expenses. To account for this, we introduce an additional cost, denoted as c_p, associated with selling opaque products to consumers. When delivering opaque products involves additional costs, the seller is more inclined to rely on the basic products, making strategies that include opaque selling less attractive.

PROPOSITION 9. *Additional costs for selling opaque products alter the seller's strategy under the new business scenario: while the seller still chooses among three strategies only if* c_p *is not too large, the viability of* $\{(p_l^{e^*}, p_h^{e^*}, p_o^{e^*}, \lambda^{e^*}), ARAA\}$ *diminishes.*

In the traditional business scenario, the effect is straightforward: when selling opaque products is costless, the seller introduces them unconditionally to extend the product line. This facilitates effective price discrimination among high-type consumers. However, when additional costs are involved, the seller must weigh these costs against the gains to decide whether to offer opaque products. Therefore, the seller is more likely to adopt strategies $\{(p_l^{b^*}, p_h^{b^*}), ARR\}$ and $\{(p_l^{c^*}, p_h^{c^*}), ARA\}$, as these strategies exclude the introduction of opaque product.

8 Conclusion

This paper studies how algorithmic targeting shapes consumers' purchasing decisions, firms' operational strategies, and market dynamics. We focus on a scenario where the seller holds an advantage over consumers regarding match-related product information. The seller optimizes a product line comprising two vertically differentiated products and an opaque product resulting from their combination, strategically recommending these offerings to potential consumers. We examine two representative scenarios to comprehensively explore the potential of algorithmic targeting. In the traditional business scenario, the seller offers only basic products in vertical markets, with algorithmic targeting being the sole marketing tool. Additionally, we investigate a new business scenario where, in addition to the two basic products, the seller expands the product line with an opaque product resulting from their combination. In this context, we explore the potential orchestration between these two closely related but distinct instruments.

We adopt an information design framework to model algorithmic targeting. In the traditional scenario, the seller leverages information design to promote the higher-margin product. When opaque selling is introduced, its value arises from price discrimination within the bundled product offering. The interactions between algorithmic targeting and opaque selling depend on the characteristics of the basic products. When the differences between the two basic products are too extreme, algorithmic targeting renders opaque selling ineffective in boosting profits. However, when these differences are moderate, the two strategies can complement each other: opaque selling increases profits by introducing an intermediate product variety for more refined market segmentation, while algorithmic targeting promotes consumers' willingness-to-pay by inducing them to feel good about themselves. The seller uses targeted information disclosure to influence consumer behavior, withholding information from low-type consumers while fully disclosing it to intermediate-type consumers who choose the opaque product. Our work offers actionable insights for both regulators and businesses. By analyzing diverse scenarios, we demonstrate the effectiveness of algorithmic targeting in enhancing firm profitability, either independently or in combination with other approaches.

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References

Baardman, Lennart, Setareh Borjian Boroujeni, Tamar Cohen-Hillel, Kiran Panchamgam, Georgia Perakis. 2023. Detecting customer trends for optimal promotion targeting. *Manufacturing & Service Operations Management*, 25 (2), 448-467.

Bimpikis, Kostas, Yiangos Papanastasiou, Wenchang Zhang. 2024. Information provision in two-sided platforms: Optimizing for supply. *Management Science*, 70 (7), 4533-4547.

Bolton, Patrick, Giacomo Bonanno. 1988. Vertical restraints in a model of vertical differentiation. *The Quarterly Journal of Economics*, 103 (3), 555-570.

Dworczak, Piotr, Giorgio Martini. 2019. The simple economics of optimal persuasion. *Journal of Political Economy*, 127 (5), 1993-2048.

Elmachtoub, Adam N, Michael L Hamilton. 2021. The power of opaque products in pricing. *Management Science*, 67 (8), 4686-4702.

Fay, Scott, Shahryar Gheibi. 2024. The effect of probabilistic selling on channel dynamics in supply chains. *Manufacturing & Service Operations Management*, 26 (2), 632-645.

Fay, Scott, Jinhong Xie. 2008. Probabilistic goods: A creative way of selling products and services. *Marketing Science*, 27 (4), 674-690.

Fay, Scott, Jinhong Xie. 2010. The economics of buyer uncertainty: Advance selling vs. probabilistic selling. *Marketing Science*, 29 (6), 1040-1057.

Fay, Scott, Jinhong Xie. 2015. Timing of product allocation: Using probabilistic selling to enhance inventory management. *Management Science*, 61 (2), 474-484.

Gao, Yuetao, Yue Wu. 2023. Regulating probabilistic selling of counterfeits. *Management Science*, 69 (8), 4498-4517.

Geng, Xin. 2016. Opaque selling in congested systems. *Operations Research Letters*, 44 (6), 737-741.

Goldfarb, Avi, Verina F Que. 2023. The economics of digital privacy. *Annual Review of Economics*, 15 (1), 267-286.

Goldfarb, Avi, Catherine Tucker. 2019. Digital economics. *Journal of Economic Literature*, 57 (1), 3-43.

Guo, Yingni, Eran Shmaya. 2019. The interval structure of optimal disclosure. *Econometrica*, 87 (2), 653-675.

Gur, Yonatan, Gregory Macnamara, Ilan Morgenstern, Daniela Saban. 2023. Information disclosure and promotion policy design for platforms. *Management Science*, 69 (10), 5883-5903.

He, Ying, Huaxia Rui. 2022. Probabilistic selling in vertically differentiated markets: The role of substitution. *Production and Operations Management*, 31 (11), 4191-4204.

Hu, Ming, Taojie Qin, Shreyas Sekar. 2024. Pricing and rarity design of blind boxes with random items. *Working paper*, Available at SSRN 4929281.

Huang, Tingliang, Zhe Yin. 2021. Dynamic probabilistic selling when customers have boundedly rational expectations. *Manufacturing & Service Operations Management*, 23 (6), 1597-1615.

Huang, Tingliang, Yimin Yu. 2014. Sell probabilistic goods? A behavioral explanation for opaque selling. *Marketing Science*, 33 (5), 743-759.

Ichihashi, Shota. 2020. Online privacy and information disclosure by consumers. *American Economic Review*, 110 (2), 569-595.

Iyer, Ganesh, T Tony Ke. 2024. Competitive model selection in algorithmic targeting. *Marketing Science*, 43 (6), 1226-1241.

Iyer, Ganesh, Yunfei Jesse Yao, Zemin Zachary Zhong. 2024. Precision-recall tradeoff in competitive targeting. *Working Paper*, Haas School of Business, Berkeley, CA.

Iyer, Ganesh, Zemin Zhong. 2022. Pushing notifications as dynamic information design. *Marketing Science*, 41 (1), 51-72.

Jehle, Geoffrey Alexander. 2001. *Advanced microeconomic theory*. Pearson Education India.

Jerath, Kinshuk, Serguei Netessine, Senthil K Veeraraghavan. 2010. Revenue management with strategic customers: Last-minute selling and opaque selling. *Management Science*, 56 (3), 430-448.

Jiang, Yabing. 2007. Price discrimination with opaque products. *Journal of Revenue and Pricing Management*, 6 118-134.

Jiao, Yifan, Christopher S. Tang, Jingqi Wang. 2021. Selling virtual items in free-to-play games: Transparent selling vs. opaque selling. *Service Science*, 13 (2), 53-76.

Joglekar, Nitin, Edward G Anderson Jr, Kyungmin Lee, Geoffrey Parker, Ettore Settanni, Jagjit Singh Srai. 2022. Configuration of digital and physical infrastructure platforms: Private and public perspectives. *Production and Operations Management*, 31 (12), 4515-4528.

Kamenica, Emir. 2019. Bayesian persuasion and information design. *Annual Review of Economics*, 11 249-272.

Kamenica, Emir, Matthew Gentzkow. 2011. Bayesian persuasion. *American Economic Review*, 101 (6), 2590-2615.

Kong, Guangwen, Jingjing Weng, Yang Zhang. 2024. Advice provision in the pandemic: The impact of information granularity on social protection. *Working paper*, Available at SSRN 4914620.

Küçükgül, Can, Özalp Özer, Shouqiang Wang. 2022. Engineering social learning: Information design of time-locked sales campaigns for online platforms. *Management Science*, 68 (7), 4899-4918.

Li, Qing, Christopher S Tang, He Xu. 2020. Mitigating the double-blind effect in opaque selling: Inventory and information. *Production and Operations Management*, 29 (1), 35-54.

Li, Xi, Krista J. Li. 2023. Beating the algorithm: Consumer manipulation, personalized pricing, and big data management. *Manufacturing & Service Operations Management*, 25 (1), 36-49.

Moorthy, K Sridhar. 1988. Product and price competition in a duopoly. *Marketing science*, 7 (2), 141-168.

Ning, Z Eddie, Jiwoong Shin, Jungju Yu. 2025. Targeted advertising as implicit recommendation: Strategic mistargeting and personal data opt-out. *Marketing Science*, 44 (2), 390-410.

Peng, Xuefeng, Feng Tian, Stefanus Jasin. 2025. Statistical vs. operational model selection: The value of model misspecification in algorithmic hiring. *Working paper*, Available at SSRN 5363579.

Ren, Hang, Tingliang Huang. 2022. Opaque selling and inventory management in vertically differentiated markets. *Manufacturing & Service Operations Management*, 24 (5), 2543-2557.

Shaked, Avner, John Sutton. 1982. Relaxing price competition through product differentiation. *The Review of Economic Studies*, 49 (1), 3-13.

Shin, Jiwoong, Jungju Yu. 2021. Targeted advertising and consumer inference. *Marketing Science*, 40 (5), 900-922.

Trusov, Michael, Liye Ma, Zainab Jamal. 2016. Crumbs of the cookie: User profiling in customer-base analysis and behavioral targeting. *Marketing Science*, 35 (3), 405-426.

Wang, Qiaochu, Yan Huang, Stefanus Jasin, Param Vir Singh. 2023. Algorithmic transparency with strategic users. *Management Science*, 69 (4), 2297-2317.

Yin, Zhe, Tingliang Huang. 2025. Probabilistic selling with customization? A theoretical analysis. *Production and Operations Management*, 34 (9), 2891-2909.

Zhang, Zelin, Kissan Joseph, Ramanathan Subramaniam. 2015. Probabilistic selling in quality-differentiated markets. *Management Science*, 61 (8), 1959-1977.

Zhang, Zhe, Atanu Lahiri. 2023. Fairness in algorithmic targeting: An economic analysis. *Working Paper*, Available at SSRN 4538553.

Zheng, Quan, Xiajun Amy Pan, Janice E Carrillo. 2019. Probabilistic selling for vertically differentiated products with salient thinkers. *Marketing Science*, 38 (3), 442-460.

Zou, Tianxin, Bo Zhou, Baojun Jiang. 2020. Product-line design in the presence of consumers' anticipated regret. *Management Science*, 66 (12), 5665-5682.