Supplier Selection Criteria under Heterogeneous Sourcing Needs: Evidence from an Online Marketplace for Selling Production Capacity

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Supplier selection is critical in the sourcing process: retailers evaluate candidate suppliers across multiple attributes, including price, quality, speed, and service, to locate an ideal supply chain partner. While related theoretical research requires prior knowledge of retailers' preferences across attributes, little empirical evidence about the criteria has been drawn from actual sourcing decisions. Capitalizing on an innovative online marketplace where manufacturers sell production capacity, our research reveals the relative importance assigned by retailers to over twenty supplier attributes including price, product quality, speed in multiple phases from ordering to delivery, and various ancillary services. Our research enables a direct connection between theoretical models and business practices and solidifies existing survey studies by removing reporting bias and increasing representative samples. Using various machine learning approaches, we discover that speed and price attributes are considered the most important, followed by quality, and finally, service offerings. We further investigate how supplier selection criteria are adjusted based on order sizes and product features. We reveal that, as the order size increases, price and quality attributes become more important while speed and service attributes plummet in importance. Furthermore, we find that retailers attach a higher value to speed and service attributes with trendy innovative products, but care more about the price dimension with long-life-cycle functional products. Based on these findings regarding supplier selection criteria, we provide investment guidelines for suppliers by quantifying the economic value associated with each non-price attribute. Also, to enable more efficient information disclosure, we recommend that online platforms consolidate their service menus by removing services with low enrollment rates and low impact on deal formation.

Key words: supplier selection criteria, marketplace design, B2B platform

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1. Introduction

In the context of a globalized economy, the activity of selecting suppliers has emerged as a pivotal aspect of sourcing, drawing significant attention within the operations management field (Ho et al. 2010). A previous study (Talluri 2002) suggests a general preference for suppliers that can offer rapid production speeds, superior quality, and competitive pricing. However, the exact hierarchy of these attributes is not well-defined. While survey research often underscores the primacy of quality (e.g., Dickson 1966, Weber et al. 1991), theoretical frameworks tend to prioritize cost or profit optimization, viewing quality considerations as constraints (e.g., Hong et al. 2005). The incorporation of service dimensions in manufacturing underscores the increasing relevance of service quality in supplier selection, potentially offsetting deficits in other areas (Guajardo et al. 2012). Our study seeks to directly assess retailer sourcing decisions within a major online marketplace, aiming to elucidate the relative importance attributed to supplier features such as price, quality, speed, and services in sourcing agreements. Furthermore, we examine the dynamics of retailer preference in relation to order size and product categorization, revealing nuanced adjustments in selection criteria.

Leveraging a unique dataset from a Chinese business-to-business (B2B) online marketplace encompassing a variety of industries, our empirical analysis distinguishes itself. This online marketplace, which specializes in the sale of production capacity rather than finished goods, allows for the isolation of supplier characteristics central to sourcing decisions, unimpeded by the attributes of the end products. This platform is closely related to the concept of "Made on the Internet", which reflects the significant transformation in global B2B e-commerce, where platforms facilitate the digital sourcing of goods. The global B2B e-commerce market, valued at \$7,432.12 billion in 2022 and projected to reach \$36,107.63 billion by 2031 (Straits Research 2023), underscores the rising importance of online marketplaces like the one we examine in China. These platforms not only provide new opportunities for small-scale retailers, such as those on Shopify, to import goods globally and overcome traditional geographic sourcing barriers, but they also feature standardized user interface designs that help retailers make informed decisions using a standardized supplier attributes menu. Additionally, these platforms include both supplier self-reported measures and platform-validated measures, which help mitigate retailer risk, making this concept very popular and attractive. Our research delves into the dynamics of supplier selection within these digital platforms, providing crucial insights for optimizing their design and enhancing the supplier–retailer matching processes.

With a primary focus on the economically substantial apparel sector (boasting an annual revenue of \$900 billion), our findings are further corroborated within the textile and knitwear sectors. The applicability of our insights regarding supplier selection criteria extends beyond the apparel industry, offering potential optimization strategies for underutilized capacity on B2B platforms across diverse retail goods. Our dataset comprises 21,249 transactions between 440 suppliers and a vast number of retailers, recorded from September 2017 to June 2018. For each transaction, we meticulously documented the selected supplier, order volume, timing specifics, and all potential suppliers' attributes. These 18 attributes span four critical dimensions: price, quality (encompassing both self-reported assessments *Quality Level* and retailer evaluations *Accuracy Rate for Description of*

Goods), speed (including production lead times *Lead Time Rate*, delivery velocity *Issue Rate*, and responsiveness *Response Rate*), and service (including payment terms *Sell on Credit*, return and exchange policies *Free Return*, *Replacement in 7 Days*, *Replacement in 15 Days*, *Return with No Reason in 15 Days*, and guarantees relating to timeliness *Shipping in 48 Hours*, *Delivery Guarantee*, *Platform-Endorsed Delivery Guarantee*,*Compensation If Out of Stock* and quality *Quality Guarantee*, *Material Guarantee*, and *Buyer Right Guarantee*).[1]

Our analysis utilizes gradient-boosted decision trees (GBDT) to quantitatively assess the impact of each supplier attribute on its attractiveness to retailers. The robustness of our findings is further validated through six supplementary machine learning and econometric methodologies. Initial results highlight speed and price as attributes of paramount importance to retailers, followed by quality and service provisions. Notably, our investigation reveals adjustments in supplier selection criteria that depend on order size and product types. Subsample analyses indicate a diminishing significance of speed and service attributes with escalating order sizes, whereas the relevance of price and quality considerations intensifies. Drawing on product classification theory (Fisher 1997), we observe a prioritization of speed and service by retailers dealing in trendy, innovative goods, as opposed to those trading in durable, functional items, who favor cost and quality.

Our research enhances the understanding of sourcing behavior and decision-making in the context of the "Made on Internet" concept, providing practical insights for both suppliers and online B2B platforms. Suppliers receive strategic guidance on prioritizing attributes that enhance their appeal to retailers. We provide investment recommendations to quantify the price premiums achievable through incremental improvements in non-price attributes. The most economically significant attributes identified are the speed attribute *Lead Time Rate*, indicative of production speed, and the quality attribute *Accuracy Rate for Description of Goods*, a quality metric derived from buyer feedback. For instance, a 1% enhancement in the *Lead Time Rate* commands a 3.78% price premium when the order quantity is under 300 units, whereas a similar improvement in the quality attribute *Accuracy Rate for Description of Goods* results in a 0.45% price premium.

For online B2B platforms, our study pinpoints the critical attributes to be prominently displayed to retailers, aiding in user interface optimization and enhancing the platform's effectiveness in deal matching. The crucial role of these platforms in facilitating digital matchmaking through effective information disclosure is underscored. With the increasing shift towards servitization in the manufacturing sector, the importance of service aspects in online B2B marketplaces has grown, reducing

[1]We recognize our focus on observable attributes, given their pivotal role in guiding buyer decisions within online marketplaces, where direct interaction and physical product examination are generally not feasible. It is acknowledged that additional supplier characteristics assessed during in-person interactions, such as reliability, communication effectiveness, and cultural compatibility, fall outside the scope of this dataset.

retailers' risk concerns and emphasizing suppliers' unique value in ancillary services. However, an excessive number of service attributes can lead to information overload, which impairs decision-making processes and reduces the quality of decisions (Malhotra 1982). Our analysis reveals that many service attributes currently offered are underutilized by suppliers and ranked low in importance by retailers. We recommend that platforms streamline their service offerings by either eliminating low-impact services or consolidating those with overlapping functions. We also propose the introduction of an "essential service package" for suppliers, which simplifies decision-making for both suppliers and retailers by focusing on high-impact service attributes.

Our study significantly advances the academic discourse on supplier selection by leveraging real-world transaction data from an online B2B marketplace to quantitatively analyze supplier attributes across price, speed, quality, and service dimensions. We elucidate how retailers prioritize these attributes and adjust their criteria based on variables such as order size and product type, thereby enriching existing survey-based literature and advancing empirical understanding in B2B settings, building upon foundational works by Dickson (1966) and Ho et al. (2010). Furthermore, our research lays the groundwork for future analytical explorations within the supply chain domain by establishing a ranking of supplier attributes that refine existing theoretical models or inspire new ones, particularly by advocating for treating quality as a constraint rather than an objective. Employing advanced analytical techniques, including GBDT and various robust methodologies, our findings not only validate the importance of these attributes but also quantify the trade-offs and economic values associated with them. This approach enhances the precision and applicability of analytical supply chain studies and enriches the strategic deployment of supply chain analytics.

The remainder of this paper is organized into seven sections: Section 2 contextualizes our study within existing literature and outlines its contributions; Section 3 introduces our empirical setting and dataset; Section 4 details the criteria for supplier selection and its variability; Section 5 addresses the robustness of our findings; Section 6 discusses the managerial implications for suppliers and platform design; and Section 7 concludes with a summary of our research, its limitations, and avenues for future inquiry.

2. Literature Review

In this section, we delve into the procurement literature to elucidate retailer assessment of supplier attributes and studies focusing on purchasing decisions for online platforms.

2.1. Supplier Evaluation in Procurement Literature

Theoretical models within procurement literature have extensively explored the complexities of supplier selection, focusing on the trade-offs between various supplier attributes to optimize costs and profits. Employing a diverse array of analytical techniques – ranging from constrained optimization

(Hong et al. 2005), multi-objective programming (Narasimhan et al. 2006), the analytic hierarchy process (Chan and Kumar 2007), to data envelopment analysis (Weber and Desai 1996) – these studies have significantly contributed to our understanding of how quality and price impact supplier selection. However, they often overlook the increasingly important service-related attributes. Moreover, the nuanced interplay and relative weighting of these attributes in the selection process have not been fully elucidated. Through an in-depth analysis of large-scale, real-world sourcing decisions, our research not only uncovers but also systematically ranks the importance of supplier attributes, including those pertaining to service. This innovative study not only enriches theoretical frameworks but also significantly enhances practical strategies for supplier selection, providing a comprehensive perspective on the multifaceted criteria that influence procurement decisions in today's complex marketplace.

While empirical evidence directly reflecting real-world transaction dynamics remains rare, insights from survey-based literature have shed light on the pivotal roles played by various supplier attributes. Seminal research by Dickson (1966) pinpointed quality and timely delivery as paramount in purchasing decisions, placing price in a secondary position relative to factors such as performance history, warranty terms, and production capabilities. Following this trajectory, subsequent analyses by Weber et al. (1991) and Kar and Pani (2014) have consistently highlighted price, delivery, and quality as the trifecta of attributes most valued by retailers. Our study draws parallels with Arbuthnot et al. (1993), which, through a survey of small apparel retailers in a traditional setting, echoes these priorities. However, despite a broad agreement on the critical nature of these attributes, discrepancies in their relative importance persist across various studies. Moreover, concerns of response bias loom large, suggesting a potential misalignment between what purchasing managers claim to prioritize and their actual decision-making behaviors. The choice modeling experiment conducted by Verma and Pullman (1998) underscores this point, revealing a practical predilection for price over quality, contrary to verbal assertions. This discrepancy underscores the limitations of relying on self-reported data. Addressing these challenges, our research leverages extensive, real-world transaction data from an online B2B marketplace, offering a nuanced and accurate depiction of retailer preferences in supplier selection. By grounding our analysis in the concrete behaviors observed in large-scale sourcing activities, our approach not only mitigates the biases inherent in survey literature but also enriches our understanding of the strategic considerations that guide real-world purchasing decisions.

The scarcity of empirical research on real-world supplier selection primarily stems from a dearth of detailed sourcing data. Existing studies in supply chain management have focused on the impact of supply chain partnerships on firm performance, relying on firm-level databases such as Compustat's customer segment data (Serpa and Krishnan 2017), Bloomberg's supply chain databases

(Osadchiy et al. 2015), and Factset Revere data (Wang et al. 2021). While informative, these sources primarily capture outcomes of supplier selection processes without delving into the specifics of supplier attributes or the wide range of candidates considered by firms. A comprehensive understanding of supplier selection mechanisms necessitates a closer examination beyond firm-level interactions to include detailed evaluations of candidate suppliers' attributes.

In this context, Schmitt and Van Biesebroeck (2013) and Bray et al. (2019) emerge as pioneering empirical investigations utilizing component-level data to analyze the influence of geographical proximity on supplier choices. Despite their contributions, these studies fall short of capturing supplier attributes such as price, quality, and service, nor do they accommodate variations in selection criteria that may arise from differing retailer production requirements. Our research fills a critical gap by utilizing extensive transaction-level data enriched with detailed information on supplier attributes across four key dimensions – price, speed, quality, and service – and examining sourcing decisions across various order sizes and product types. This study not only addresses an important void in empirical research but also provides statistically robust and broadly applicable insights into the factors that influence supplier selection. Consequently, our study greatly enhances our understanding of the complex decision-making processes that retailers navigate in selecting suppliers.

Context-wise, the growing body of literature on online platforms has extensively explored buyer preferences in business-to-consumer (B2C) and consumer-to-consumer (C2C) markets (Lewis et al. 2006, Gefen and Carmel 2008, Cui et al. 2020). However, research investigating the preferences of business buyers, such as retailers, within B2B marketplaces remains limited. While Cui et al. (2021) examines the B2B market, their work focuses specifically on the price attribute in supplier quotes. Our study builds upon previous research by examining four critical attribute dimensions – price, speed, quality, and service – and analyzing their relative importance in B2B market sourcing decisions. Unlike prior work that often concentrates on the attributes of finished products, our research focuses on production capacity. This focus allows us to isolate supplier characteristics that are central to sourcing decisions, free from the influence of the end product's attributes.

2.2. Information Disclosure and Decision-Making in Online Sourcing

Information disclosure plays a pivotal role in B2B marketplaces, particularly in how it influences the supplier-retailer matching process. Traditional studies often focus on information sharing within buyer-seller relationships (Huang et al. 2018, Guan et al. 2020), but our research delves into the unique dynamics of online B2B interactions. When suppliers strategically disclose only partial information, information asymmetry becomes a critical issue, posing significant challenges to effective matching (Constantinides et al. 2018, Tadelis and Zettelmeyer 2015). To address this, our study adopts a multifaceted approach to assess supplier attributes, including platform-verified, buyer-verified, and self-reported data. This method aims to mitigate the adverse effects of information asymmetry by ensuring a more transparent and trustworthy presentation of supplier capabilities.

Conversely, our research also tackles the issue of information overload, which arises when suppliers share too much information. Excessive data can overwhelm retailers, reducing the quality of their decisions due to increased cognitive burden (Malhotra 1982, Lee and Lee 2004). Malhotra (1982) showed that when presented with more than 15 attributes, individuals begin to experience the detrimental effects of information overload. This is particularly evident in the platform we study, when retailers are faced with evaluating 18 different supplier attributes across four dimensions: price, speed, quality, and service. Such a scenario likely induces overload, potentially compromising decision effectiveness. To counteract this, we propose an "Essential Service Package," which streamlines the attribute menu by consolidating or eliminating excessive service attributes. This approach not only simplifies decision-making for retailers but also helps suppliers by identifying the most economically valuable and relevant attributes to offer. Ultimately, by addressing both information asymmetry and overload, our study aids in refining the attribute selection process, thus enhancing the functionality of online platforms and fostering more effective matches between suppliers and retailers.

3. Data

In this section, we describe the research background, the sample and variable preparation, and the characteristics of the dataset.

3.1. Background

We first introduce the B2B sourcing platform that grants us valuable observations for research. This platform features over 10,000 manufacturers selling their unused production capacity across various industries. We focus on the apparel sector, the platform's largest category, accounting for more than half of all transactions. We first describe the platform's transparency and authentication measures, which are essential in online sourcing environments. We then discuss the platform's benefits for suppliers and retailers, followed by an exploration of the promising business concept "Made on the Internet."

The platform streamlines and enhances the supplier-retailer matching process, promoting efficiency and transparency (Figure 1). First, the platform determines which supplier attributes to disclose, drawing from a combination of sources: self-reported documents from suppliers (verified by government and third-party agencies), retailer feedback, and electronic transaction records. These attributes cover four important categories: price, speed, quality, and service. We detail them in Section 3.2. Second, the platform conducts a rigorous vetting process on qualified manufacturers, including document evaluation and ongoing monitoring to ensure data accuracy (penalties are imposed for false claims). Next, the platform offers a wide array of service attributes and allows suppliers to strategically choose which to invest in as part of their service packages. Retailers can then leverage this comprehensive set of attributes to identify and select suitable suppliers. Finally, following transactions, the platform updates supplier attributes based on delivery performance and retailer feedback. Notably, during the observation period, the platform did not charge fees to either suppliers or retailers, potentially mitigating distortions in supplier selection criteria. The design of the platform's user interface is particularly unique; it standardizes the information that suppliers can disclose, thereby simplifying the comparison process for retailers. Suppliers must carefully select and disclose the right attributes to attract retailers and secure transactions. This standardized and transparent information generates ideal datasets for researchers, enabling them to evaluate all supplier candidates during the transaction period and estimate the relative importance of each supplier attribute. The integration of both objective and subjective supplier attributes enhances the validity of measurements, significantly improving the robustness of our analyses.

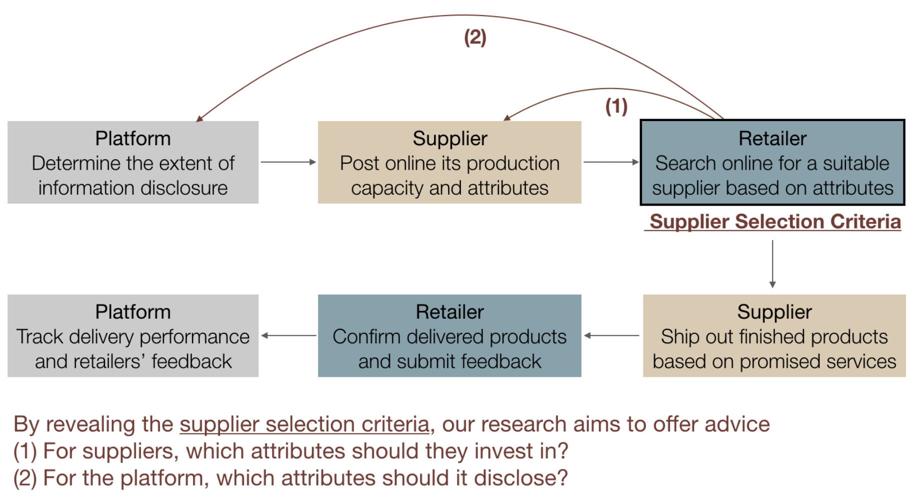

Figure 1 **Process Flow of the B2B Online Marketplace**

Suppliers benefit from the platform by eliminating intermediary business and optimizing production capacity management. They can post distinct production capacities for each product type, allowing them to sell excess capacity at the production-line level during off-season periods. By specifying unique attributes for each product type, suppliers can effectively manage their production capabilities. For example, they may offer short lead times and high-quality guarantees for t-shirt manufacturing if they possess numerous production lines and skilled workers. Conversely, they might indicate longer lead times and refrain from providing quality guarantees for women's dresses if their tailors have limited experience. In our study, 64.2% of suppliers offered capacity for one product type, while 35.8% offered two or more types. This flexibility enables suppliers to optimize their production management through the B2B online sourcing marketplace, catering to their specific strengths and idle resources. To enhance sales performance within this platform, understanding the attributes most valued by retailers is critical. By revealing supplier selection criteria, our research aims to offer practical advice for suppliers: which attributes should they invest in to become more attractive to retailers?

Retailers benefit from the platform's disruption of traditional sourcing models, enjoying previously unavailable advantages such as low minimum order quantities, fast lead times, and transparent supplier information. These features streamline inventory management and enable rapid product testing. The platform offers responsive and lean sourcing options for retailers, with a minimum order quantity of thirty units and a typical order size of several hundred, significantly lower than industry norms. This flexibility allows retailers to test new products and manage inventory more effectively. Moreover, the average one-week manufacturing lead time provides fast production channels, benefiting smaller retailers who often lack access to such short lead times. The platform simplifies the sourcing process by offering easy access to extensive supplier information, allowing retailers to efficiently find ideal suppliers with minimal search costs. However, an excessive amount of supplier information may overwhelm retailers, potentially hindering decision-making and reducing the effectiveness of supplier-retailer matching. To avoid the information overload issue and streamline the matching process, the platform should prioritize disclosing the specific supplier attributes deemed most valuable by retailers. By revealing the supplier selection criteria, our research aims to offer advice for the platform: which attributes should it disclose?

The B2B marketplace that sells production capacity is rapidly aligning with the innovative "Made on the Internet" concept, signaling a promising future trend in sourcing. By providing a streamlined and transparent platform that benefits both suppliers and retailers, this online marketplace has the potential to become a leading sourcing channel in the near future. This potential is reflected in the growth of the global B2B online market, valued at $7,432.12 billion in 2022 and projected to reach $36,107.63 billion by 2031 (Straits Research 2023). Notably, platforms like Shopify can also source products on this platform and import goods globally, facilitating a seamless integration of supply chains and expanding market reach.

3.2. Data Preparation and Variable Construction

Our dataset from the online B2B platform encompasses a detailed record of transactions spanning from September 2017 to June 2018. We focused our analysis on the apparel industry and further validated our findings in the textile and knit industries, where results remained consistent. Our final dataset encompasses 21,249 transactions involving 440 suppliers offering 808 apparel production options, each transaction includes detailed supplier attributes, allowing us to study supplier selection criteria. To ensure the relevance and reliability of our data, we limited our analysis to suppliers with a healthy stream of transactions linked to their current online profiles, thereby excluding manufacturers with small transaction numbers on their e-commerce pages. These could be new players who have recently posted their production capacity online, or those with less appealing production offerings.

For each transaction recorded, we observe key elements such as the retailer's identity, the timing of the order placement, the product type, and the order size. This dataset allows us to reconstruct the decision environment for each transaction and evaluate all candidate suppliers selling the same product type during the retailer's selection process. Apparel retailers typically determine an optimal order size based on market predictions and financial status, then search the platform to identify the best-fit supplier by comparing factors such as price, quality, lead time, and service. The detailed tracking information in our data enables us to precisely assess how retailers adjust their supplier selection criteria based on the order size and product type.

Given the platform's flexibility, suppliers can set distinct lead times across various order size buckets: 0 (30-299 units), 1 (300-799 units), 2 (800-1,499 units), and 3 (1,500+ units). We calculate the number of transactions per supplier-product-bucket combination to represent the outcome of the supplier selection process. Additionally, we repeat our analyses using transaction volume as the outcome variable to ensure the robustness of our findings, as detailed in Section 5.

The most critical information covered in each transaction is the detailed attributes of each supplier, which fall into four dimensions: price, quality, speed, and service. These dimensions are consistent with survey literature and respond to the trends of a service-based economy. The inclusion of these categories allows us to capture the nuances of supplier offerings and their alignment with retailer preferences, which vary by product category and order size. This detailed information on supplier attributes, defined in Table 1, aids us in understanding how preferences shift given different order types. We elaborate on each of the four categories in the following paragraphs.

Quality. The platform provides two measures to characterize the quality dimension: the supplier-specified *Quality Level* (i.e., 0 (low), 1 (medium), or 2 (high)) and the platform-calculated *Accuracy Rate for Description of Goods* based on previous retailers' feedback. Suppliers report their quality levels, while the platform-generated rating validates a supplier's self-reported quality. Together, these two measures help retailers evaluate a supplier's quality. Alternatively, we repeat our analyses using the online reviews left by retailers as the quality measure in Section 5, and our primary conclusions stay consistent.

Table 1 Descriptions of Supplier Attributes and Features

Dimension	Supplier Attributes and Feature Controls	Explanation
Quality	*Quality Level*	The self-reported quality level of the product: high, medium, or low.
	Accuracy Rate for Description of Goods	Retailer-rating of the accuracy of the product description.
Speed	*Lead Time Rate*	A rating for the manufacturing speed.
	Response Rate	A platform-generated rating for measuring the supplier's speed in responding to customer requests.
	Issue Rate	A platform-generated rating for measuring the supplier's speed in shipping out finished products.
Service	*Sell on Credit*	Whether the retailer can make a purchase on credit for at most 30 days.
	Free Return	Whether the supplier covers the logistic insurance: if yes, an insurance company will cover the logistic fees for the retailer to return the goods.
	Replacement in 7 Days	Whether the supplier agrees to replace the damaged products when the damage is not man-made: the retailer should make a request within 7 days after confirmation.
	Replacement in 15 Days	Whether the supplier agrees to replace the damaged products when the damage is not man-made: the retailer should make a request within 15 days after confirmation.
	Return with No Reason in 15 Days	Whether the supplier allows the retailer to return the products unconditionally within 15 days if the products are still in good condition.
	Quality Guarantee	Whether the supplier guarantees the product quality to be consistent with the samples: if inconsistent, the supplier is required to compensate the retailer.
	Material Guarantee	Whether the supplier guarantees that the products are manufactured using the promised materials: if not, the supplier is required to compensate the retailer.
	Buyer Right Guarantee	Whether the supplier guarantees to pay an up to 400-dollar (currency converted) deposit to the retailer if the supplier breaks the contract: this guarantee is endorsed by the platform.
	Delivery Guarantee	Whether the supplier guarantees to ship the products within the agreed time window: if not, the supplier is required to compensate the retailer.
	Platform Delivery Guarantee	Whether the supplier guarantees to ship the products within the agreed time window: if not, the supplier is required to compensate the retailer. This guarantee is endorsed by the platform and enables convenient compensations compared to the Delivery Guarantee.
	Shipping in 48 Hours	Whether the supplier agrees to ship the products within 48 hours after the products are manufactured, i.e., the lead time is reached.
	Compensation If Out of Stock	Whether the supplier promises to compensate the retailer if the products cannot be delivered on time.
Price	*Price*	Unit price of the product.
Feature	*Product Category*	The categorization of the product type used in the apparel industry.
	Stage Time	The duration that the supplier-product combination has been presented on the platform.
	Experience Time	The duration that the supplier has been presented on the platform.

Speed. Suppliers' speed is assessed using supplier-specified production lead time, which is the total time required to manufacture an order; and two other platform-generated ratings, namely, the *Response Rate* and the *Issue Rate*. These two ratings summarize the speed of the supplier's response to retailer requests and the shipment of finished goods, respectively. These three speed metrics correspond to different stages in the production process: 1) the communication stage captured by the *Response Rate*, 2) the manufacturing stage captured by the lead time, and 3) the shipping stage captured by the *Issue Rate*. All attributes, except price and lead time, signal a more desirable supplier with higher values. We thus perform a transformation on lead time to follow the convention of other attributes. Recall that the supplier-specified production lead time can vary across the order size buckets. We construct a *Lead Time Rate* measure for each supplier-product-bucket combination. Specifically, the *Lead Time Rate* is calculated as

$$\text{Lead Time Rate} = 1 - \frac{\text{Lead Time}}{\text{Maximum lead time within the product-bucket group}}.$$

Intuitively, a *Lead Time Rate* of 0 indicates that the supplier is the slowest among all suppliers manufacturing the product type in the same bucket size, and a *Lead Time Rate* close to 1 indicates that the supplier is competitive along the lead time dimension.

Service. To mitigate common trust and risk issues in online marketplaces, the B2B platform we study provides a comprehensive list of escrow services and guarantees, in addition to the platform-generated supplier ratings, as shown in Table 1. Suppliers can customize their service offerings, such as quality guarantees, for each product type. For example, when manufacturing t-shirt-related products, a supplier can ensure a high-quality guarantee if they have more experienced workers for handling this type of product. Conversely, the same supplier can choose not to offer a quality guarantee for manufacturing women's dresses if they have tailors with limited experience in that product type. This service attribute's value is 1 if a supplier offers it for the product type, and 0 if a supplier does not.

Price. Price is also considered a critical attribute that shapes the retailer's purchasing decision. To protect deal privacy, we use a proxy price to capture the relative price competitiveness of each production option, rather than the actual transacted price. From the online wholesale platform managed by the same company, we retrieve the average price of the same type of product from the same supplier. We acknowledge that this price is likely different from the final price in the deal. However, this price should be close to the transacted price and positively correlated with it. Thus, the proxy price serves well to capture price competitiveness and reflect the importance of price in choosing a supplier.

We also observe control variables at the supplier-product level, such as product categories, *Stage Time* (the duration a supplier-product combination has been on the platform), and *Experience Time* (the duration a supplier has been on the platform). Controlling for product categories isolates the variations in supplier attributes that might be specific to different types of products. Including stage time in the model accounts for the maturity of the product. Products that have been available for a longer time may have more established reputations and have accumulated more reviews, which could influence their selection by retailers. Similarly, controlling for experience time distinguishes the impacts of a supplier's long-term presence and accumulated expertise from their specific attributes. Additionally, our data includes order size and product type, which allow us to further investigate how supplier selection criteria might vary according to these specific factors. The summary statistics of all variables are presented in Table 2.

Table 2 Summary Statistics (808 Supplier-Product Pairs)

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Number of Transactions	56.245	62.320	2	10	29	74	222
Order Size Bucket (Categorical: 0, 1, 2, 3)	0.926	–	–	–	–	–	–
Quality Level (Categorical: 0, 1, 2)	2.423	–	–	–	–	–	–
Accuracy Rate for Description of Goods	0.037	0.011	0.010	0.030	0.040	0.040	0.230
Lead Time Rate	0.806	0.176	0.000	0.767	0.850	0.930	1.000
Response Rate	0.150	0.099	0.010	0.070	0.130	0.220	0.760
Issue Rate	0.156	0.114	0.010	0.060	0.130	0.250	0.610
Sell on Credit (Dummy)	0.458	–	–	–	–	–	–
Free Return (Dummy)	0.061	–	–	–	–	–	–
Replacement in 7 Days (Dummy)	0.031	–	–	–	–	–	–
Replacement in 15 Days (Dummy)	0.107	–	–	–	–	–	–
Return with No Reason in 15 Days (Dummy)	0.020	–	–	–	–	–	–
Quality Guarantee (Dummy)	0.089	–	–	–	–	–	–
Material Guarantee (Dummy)	0.285	–	–	–	–	–	–
Buyer Right Guarantee (Dummy)	0.728	–	–	–	–	–	–
Delivery Guarantee (Dummy)	0.747	–	–	–	–	–	–
Platform Delivery Guarantee (Dummy)	0.089	–	–	–	–	–	–
Shipping in 48 Hours (Dummy)	0.002	–	–	–	–	–	–
Compensation If Out of Stock (Dummy)	0.028	–	–	–	–	–	–
Price (CNY)	27.330	25.794	1.000	6.000	20.000	40.000	200.000
Stage Time (Day)	54.82	29.907	0	28	64	82	90
Experience Time (Year)	3.167	2.210	0	1	3	5	15

3.3. Characteristics of the Data in Studying Supplier Selection Criteria

Our dataset is a valuable resource for studying supplier selection criteria, as it is sourced directly from the supplier selection process, provides comprehensive information for tracing the process, and delivers detailed data for deep insights and statistically robust findings.

First, the data are generated from the actual supplier selection process. A large pool of candidate suppliers necessitates a sophisticated selection mechanism for retailers. The platform standardizes attributes for suppliers, ensuring consistent information disclosure. This is a significant improvement over many offline sourcing scenarios where manufacturers have considerable leeway in how they present their bidding documents or proposals and may engage in in-person interactions that remain unobservable by researchers. Such consistency not only facilitates a more transparent and informed selection process for retailers but also significantly enhances the accuracy of our quantitative analysis.

Second, the dataset allows researchers to observe all supplier attributes and outcomes in the selection process. Unlike datasets like FactSet and Bloomberg, which typically provide only selection outcomes, it documents the specific attributes retailers consider when making selections. We can identify available candidate suppliers based on product type and the time frame during which retailers search online for suppliers. We also manage to observe all attributes of the candidate suppliers and the chosen supplier, which enables us to recover the selection process and outcomes.

Third, the substantial number of supplier-retailer pairs allows us to reveal supplier selection criteria with generalizable findings. Compared to supply chain data obtained from a single company, the online platform enables us to study sourcing decisions across a wide range of suppliers and retailers, significantly enhancing the statistical power of our analysis relative to other empirical studies on supplier selection. Additionally, the dataset's granularity and the volume of observations permit a nuanced understanding of how supplier selection criteria vary with different ordering needs, such as transaction volume and product types.

Finally, we discuss how the design of the data generation mechanism removes endogeneity concerns from our research. Endogeneity usually arises from three sources: omitted variables, reverse causality (or "simultaneity"), and measurement error. *First*, we minimize the potential omitted variable bias in our analysis because the online platform traces all influential attributes and outcomes, and researchers observe the full information that retailers utilize to make decisions. *Second*, simultaneity is not an issue in our study because, by design, the attributes are revealed first, and then the selection happens based on the attributes. In other words, our explanatory variables are generated before the outcome variable. Hence, the causality direction is from the suppliers' attributes to the orders placed by the retailers. *Third*, measurement error is rare in our dataset, given that all attributes and outcomes information is directly sourced from the marketplace database. We also investigate any outlier data points to ensure no system recording or measurement errors appear in our sample.

4. Empirical Analysis

In this section, we first describe our empirical methodology and then perform the analysis to reveal the supplier selection criteria.

4.1. Methodology

To determine the importance of supplier attributes in attracting business deals, we use a machine learning method called GBDT (gradient-boosted decision trees). This method is suitable for ranking and quantifying the importance of attributes, including price, quality, speed, and service offerings, based on their impact on attracting orders for suppliers, which aligns with our research agenda. We also conduct robustness checks using various alternative machine learning and econometric approaches, with detailed results and model comparisons available in Section 5.

GBDT is an ensemble model built on top of many regression decision trees. The ensemble is based on gradient boosting, which enhances the prediction gradually by reducing the residual. Each subsequent tree improves predictions on observations that are not well captured by previous trees. In most cases, GBDT outperforms linear and machine learning models and frequently wins many data mining challenges. GBDT offers notable advantages, including but not limited to the ability to handle missing values, relax distribution and functional form assumptions to capture complex non-linear relationships, and deliver high predictive accuracy (Ye et al. 2009). Building upon the study of Bastani and Bayati (2020), which explores feature selection and embedded regularization in optimization methods, our research applies GBDT to examine the relative importance and economic value of supplier attributes on B2B online platforms. Our work extends existing insights that use machine learning to address operations-related questions, such as product demand prediction, emergency department wait time estimation, and clinical trial outcome prediction (Ferreira et al. 2015, Ang et al. 2015, Bertsimas et al. 2016).

The most appealing feature of GBDT, in contrast to other machine learning methods, is its ability to quantify the relative importance of each attribute in determining the outcome variable (Sun et al. 2022). Specifically, the relative importance is a score generated by the GBDT that indicates how useful or valuable each attribute is in constructing the boosted decision trees within the model. The more an attribute is used to make key decisions in the decision trees, the higher its relative importance.[2] GBDT explicitly calculates the relative importance of each attribute, allowing for ranking and comparison across all attributes. Importantly, the relative importance of all attributes sums to 100%. Consequently, we can interpret an attribute's relative importance as the percentage contribution it makes towards determining the outcome variable.

To select the optimal hyperparameters for our GBDT model, we employ a hyperparameter tuning process using a 10-fold cross-validation strategy. This approach identifies the best hyperparameters that fit the model well and avoids overfitting, as model performance is evaluated on unseen data (Arlot and Celisse 2010). We first define the search space for each hyperparameter. Then, we conduct a 10-fold cross-validation for each candidate set of hyperparameters to acquire reliable performance metrics. More details of our hyperparameter tuning process are included in Appendix A of the online supplements. By evaluating performance metrics across all hyperparameter sets, we achieve the optimal hyperparameters. Specifically, we select 10,000 trees, which provides a robust learning framework. The maximum tree depth is set to 4, balancing the complexity of variable interactions with computational tractability, which is crucial given the substantial number of attributes in our supplier selection dataset. Furthermore, we determine that a shrinkage parameter of 0.1 enables nuanced learning within our model.

[2]For a single decision tree, the influence is calculated as the amount of improvement in the performance measure through each attribute split point, weighted by the number of observations the split point carries. The importance is then averaged across all of the decision trees generated from the model. We refer readers to the book *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* for more information on how importance is calculated in boosted decision trees.

4.2. Empirical Results: Importance of Supplier Attributes

We present the relative importance of supplier attributes in Figure 2, highlighting the dimension to which each attribute belongs using different symbols. To simplify the figure, we include only attributes with a relative importance of 0.5 or greater, i.e., attributes that contribute more than 0.5% to the importance in determining the number of orders. We obtain the confidence intervals for the relative importance by performing 10-fold cross-validation. The narrow confidence intervals shown in Figure 2 reinforce the robustness of the measured relative importance of each attribute.

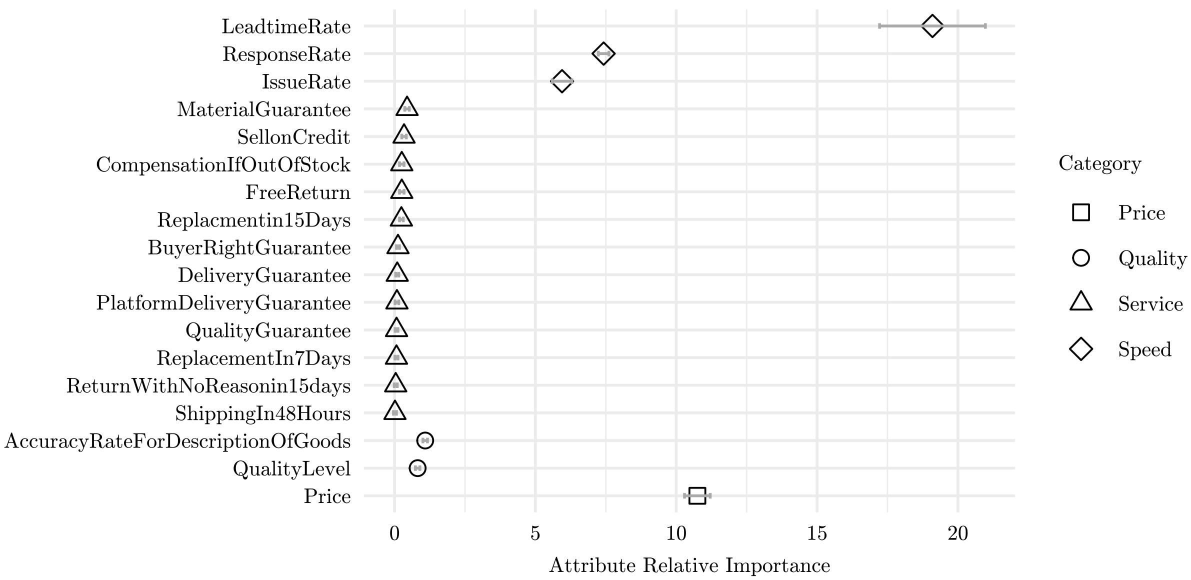

Figure 2 Relative Importance of Supplier Attributes

Note. The confidence interval of the relative importance is represented by the bar around the point estimate. The depicted relative importance in the figure sums to less than 100% because attributes with minimal importance have been excluded for visual clarity, and control variables, such as product category, also contribute to the number of transactions.

In the full-sample analysis, the most critical attribute influencing the number of transactions is the speed attribute, *Lead Time Rate*. It is followed in importance by price and the other speed-related attributes, *Response Rate* and *Issue Rate*. Our model specifically indicates that *Lead Time Rate* comprises approximately 20% of the importance, with price explaining 11%. This emphasis on speed and price signals a strategic adaptation by retailers to evolving consumer behaviors. Retailers must excel in rapid responsiveness to capture fleeting customer interest, particularly in contemporary markets characterized by short attention spans. Similarly, competitive pricing strategies are essential for customer acquisition and retention in dynamic marketplaces where alternative choices abound. Note that the relative importance of speed is not always greater than price. We discuss the change in supplier selection criteria under different order sizes and product types in the following sections, with analyses of stratified samples.

Among the speed metrics evaluated by retailers, *Lead Time Rate* – a measure of production speed – is prioritized due to its direct impact on the overall supply chain efficiency, emphasizing the critical role of manufacturing in the operational timeline. This is followed by *Response Rate*, which measures the speed of supplier responsiveness to retailer inquiries, and *Issue Rate*, indicating the promptness of shipping finished products. This hierarchy underlines that, while communication and shipping are essential, the core manufacturing process demands the greatest time investment, aligning with the operational complexities associated with different product stages. Retailers value *Lead Time Rate* the most, highlighting the importance of rapid production capabilities and responsiveness to market demands. *Response Rate* is also crucial, reflecting the importance of quick and efficient communication in establishing a supplier's reliability and service quality. *Issue Rate*, while essential, is seen as less critical than the ability to quickly produce and respond, suggesting that timely delivery, though important, is secondary to the effectiveness of production and communication processes. For suppliers, understanding these retailer priorities allows them to focus on improvements that align with what retailers value most, enhancing their attractiveness and competitive position in the marketplace.

Compared to speed and price, retailers assign less importance to quality attributes, specifically, the self-reported *Quality Level* and the platform-generated *Accuracy Rate for Description of Goods*. Although managers consistently claim in surveys that quality is the most crucial factor when deciding supply chain partners, our results demonstrate that quality is not as salient in retailers' selection criteria compared to price and speed. This divergence between stated and revealed preferences is corroborated by the findings of Verma and Pullman (1998), who similarly demonstrate a practical prioritization of price over quality, contrary to managers' verbal assertions of quality being the top priority. The relative importance of the quality dimension obtained from this platform implies that retailers account for quality attributes by setting a minimum requirement instead of desiring the best quality available, similar to the qualification screening documented in procurement literature (i.e., Wan and Beil 2009). For theoretical work, this finding justifies modeling quality as a secondary factor (for example, in the constraints) instead of equally important as price and speed.

Service offerings, as a set of supplier attributes, have a low impact on retailers' selection. While the platform emphasizes service offerings by providing suppliers with a broad selection of auxiliary services, these offerings have minimal importance as predictors of supplier attractiveness. Each individual service attribute holds a relative importance of less than 1%. Moreover, even when considered collectively, service attributes remain the least important factor compared to speed, price, and quality, as evidenced in Figure 3. Given the low importance of various service attributes, the platform should consolidate or eliminate some to enhance the effectiveness of information disclosure. We elaborate further on this implication in Section 6.

Attribute Importance by Order Size

To identify the impact of order volume on retailers' selection criteria, we now elaborate on the importance of attributes by order size. The platform allows suppliers to specify varying lead times based on the four order size buckets: 30-299 units, 300-799 units, 800-1,499 units, and 1,500+ units. Following the platform categorization, we quantify the importance of supplier attributes in each bucket and then visualize the changes in supplier selection criteria as order size increases (see Figure 3). The narrow confidence intervals in Figure 3 reinforce the robustness of the relative importance across the four dimensions.

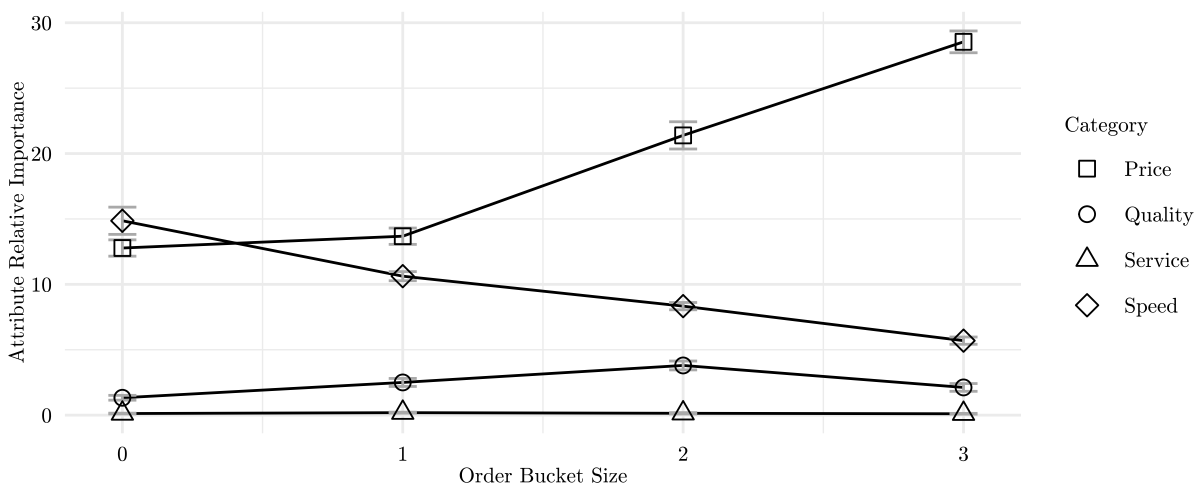

Figure 3 Attribute Importance by Order Size
Note. The confidence interval of the relative importance is represented by the bar around the point estimate. Order size bucket: 0 (30-299 units); 1 (300-799 units); 2 (800-1,499 units); and 3 (1,500+ units).

Figure 3 reveals a nuanced interplay between order size and the relative importance of price and speed in supplier selection. As order quantity increases, the importance of the speed dimension demonstrably declines. Conversely, price transcends speed to become the most critical supplier attribute for larger orders. This prioritization of speed for small-quantity orders reflects retailers' need to hedge against uncertainties in customer demand. Responsive suppliers enable retailers to rapidly diversify their product portfolios and cater to a broader range of on-season market segments through smaller, more frequent orders. However, with large order quantities, even marginal price differences translate into significant cost savings or expenses. This compels retailers to prioritize lower prices, outweighing the benefits of faster delivery times for bulk orders. For instance, fast fashion retailer Zara frequently places small, quick orders from its suppliers, emphasizing speed to capture fast-changing fashion trends; whereas electronics manufacturer Apple negotiates on price for large component orders to reduce production costs.

The importance of quality in the supplier selection process increases with the order size, as shown in Figure 3, despite not being as critical as speed and price. This shift in priority can be attributed to significant financial risks and the potential for reputational damage from poor quality in large quantities. Substantial orders involve larger financial commitments, where quality issues can result in hefty losses due to the difficulty and expense of sourcing replacements swiftly, thus missing crucial market opportunities (Oke and Gopalakrishnan 2009). Moreover, for large-scale distributions, the impact of defective products on a brand's reputation can be severe and wide-reaching. For instance, in the automotive industry, Toyota prioritized quality over speed and cost following massive recalls in 2010 that tarnished its reputation for reliability. Similarly, in consumer electronics, Samsung emphasized enhancing quality controls after the Galaxy Note 7 recall in 2016, which was necessitated by safety issues due to battery defects. Both cases illustrate how major corporations prioritize quality in large orders to mitigate extensive financial and reputational risks.

The importance of service attributes in the supplier selection process, while consistently ranked at the bottom, is more pronounced for relatively small orders. The relative importance of service decreases from 0.21% to 0.15% as bucket size increases from 1 to 3. This phenomenon can be attributed to two potential factors. First, retailers placing small orders may exhibit higher levels of risk aversion, leading them to place greater emphasis on risk-mitigating service guarantees. Second, the capped compensation provided by service guarantees may adequately justify the potential losses incurred for small orders, but may not be sufficient for larger orders. Consequently, retailers placing larger quantities may not prioritize service guarantees to the same extent as those placing smaller orders. For example, retailers on e-commerce platforms like Etsy may prioritize delivery guarantees and flexible return policies from suppliers to mitigate risks. Conversely, larger retailers like Walmart or Best Buy might focus less on these service attributes, given their capacity to absorb the impact of supply chain failures.

Attribute Importance by Product Type (Functional or Innovative)

According to Fisher (1997), it is essential in supply chain management to align product types with the appropriate supply chain design. Fisher (1997) suggests classifying products into two categories based on their demand patterns: functional and innovative. We apply this framework to categorize observed orders. Functional orders, such as those for basic apparel items like t-shirts, polo shirts, and hoodies, exhibit stable and predictable demand, long product life cycles, lower contribution margins, and minimal need for end-of-season markdowns. In contrast, innovative orders, including trend-driven apparel items like women's dresses, blouses, skirts, and cardigans, tend to have more unpredictable demand patterns, shorter life cycles, higher contribution margins, and a greater potential for significant end-of-season markdowns. This classification draws upon consultations with fashion industry experts who have 15 to 20 years of experience in the apparel industry, including factory owners and retail directors of famous fashion brands.

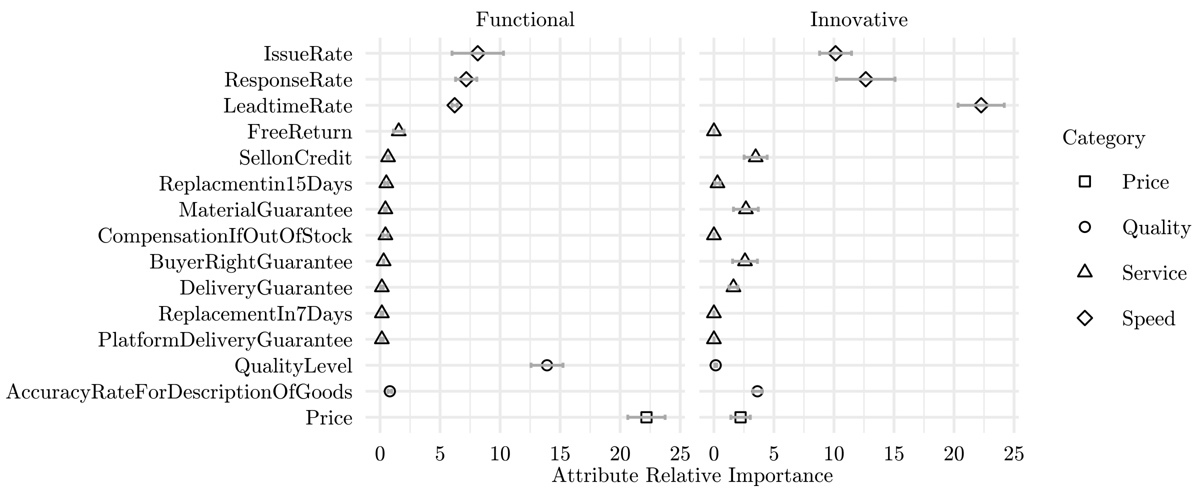

Figure 4 Attribute Importance by Product Type (Functional or Innovative)
Note. Categorization is based on Fisher (1997) into orders for functional products and for innovative products.

As shown in Figure 4, we observe that the respective importance of price and *Lead Time Rate* shift position for different product types. For innovative products, *Lead Time Rate* explains over 20% of the importance in determining the number of suppliers' attracted orders, while price explains only about 2%. However, with functional products, the importance rank between the two attributes flips, with price and *Lead Time Rate* explaining 22% and 6%, respectively. This shift in attribute importance aligns with business strategies tailored to these two different product types. Retailers require a responsive supply chain for trendy, innovative products, thus placing a higher value on speed. Conversely, when manufacturing more mature, functional items, cost efficiency becomes paramount, leading retailers to prioritize the price attribute.

Figure 4 reveals a clear distinction in how retailers prioritize quality for functional versus innovative products. *Quality Level*, the second most important attribute for functional products, accounting for approximately 13% of its importance in determining the number of transactions, appears less important when selecting suppliers of innovative products. This difference likely stems from the inherent nature of the products themselves. Functional products, with extended lifecycles and frequent usage, necessitate high quality as a critical attribute. In contrast, innovative products prioritize adaptability to rapidly changing trends, which may render quality less essential. Additionally, retailers' perception of risk associated with quality reporting for each product category may contribute to this difference. Functional products expose suppliers to the risk of accumulating negative feedback if they exaggerate *Quality Level* due to their long lifecycles. This incentivizes truthful reporting of *Quality Level* to maintain a positive long-term reputation with retailers. Conversely, the shorter lifecycles of innovative products create less incentive for truthful reporting, potentially leading suppliers to exaggerate *Quality Level* to secure more deals.

Our analysis further reveals a heightened emphasis on specific service attributes for innovative products. These attributes include *Sell on Credit* and three guarantee services. *Sell on Credit*, allowing retailers up to 30 days of deferred payment, becomes particularly attractive due to the inherent uncertainty surrounding the demand for trendy products. This service empowers retailers to experiment with a wider variety of products within budgetary constraints. The relatively short selling window for innovative products also amplifies the importance of the *Material Guarantee*, *Buyer Right Guarantee*, and *Delivery Guarantee*. The *Material* and *Buyer Right Guarantees* safeguard retailers by ensuring products align with advertised materials or by providing compensation for any discrepancies. Similarly, the *Delivery Guarantee* mitigates the risk of missing out on sales opportunities for trendy products by offering compensation for late deliveries.

In conclusion, our study sheds light on the relative importance of various attributes influencing retailers' supplier selection criteria. Our analysis reveals that *Lead Time Rate* and price emerge as the most critical supplier attributes, while quality and service offerings generally hold less weight in retailer decision-making. Further analysis demonstrates that the relative importance of speed, price, and quality varies depending on order size or product type. These insights empower suppliers to gain a deeper understanding of retailer expectations and strategically tailor their offerings to enhance their competitiveness in the online marketplace. Additionally, our findings offer valuable insights for the platform, aiding in the optimization of user interfaces and enhancing its appeal.

5. Robustness Check

In this section, we conduct additional analyses to validate our results and improve the stability of our findings.

Alternative Machine Learning and Econometric Approaches. We evaluate several alternative machine learning and econometric methods as benchmarks for our GBDT approach, including *Linear Regression, Logistic Regression, Decision Tree, Random Forest, Extreme Gradient Boosting (XGBoost), and K-Nearest Neighbours (KNN).* Our main takeaways remain the same across different methods: as order size increases, the importance of price escalates, whereas the importance of speed attributes diminishes. We observe minor inconsistencies between matching learning approaches and traditional econometrics methods, which we believe are due to the following two facts: 1) machine learning methods, such as GBDT, are more complex ensemble methods with high flexibility, and thus can capture non-linear relationships by integrating multiple decision trees; and 2) machine learning models, specifically complex ones like GBDT, often outperform traditional approaches with larger datasets (Lehrer and Xie 2022). We present the detailed results in Table B.1 of Appendix B in the online supplements. We evaluate the performance of each method using Mean Absolute Error (MAE), Mean Square Error (MSE), and Score on Testing Data (STD). Lower values of MAE and MSE, and a higher value of STD imply higher accuracy of a model. Table 3 shows that GBDT produces the highest STD and the lowest MSE and MAE. Thus, we conclude that GBDT is the best-performing and most suitable approach for our study.

Table 3 Model Comparison

Model	STD	MSE	MAE
Linear Regression	0.08	1803.01	27.71
Logistic Regression	0.18	2490.45	25.30
Decision Tree	0.71	569.36	13.83
Random Forest	0.96	81.41	3.41
XGBoost	0.61	773.41	17.98
GBDT	**0.97**	**64.79**	**1.54**
KNN	0.69	602.03	13.88

Note. MAE (Mean Absolute Error) and MSE (Mean Square Error) measure the average and variance of the residuals, respectively, while STD (Score on Testing Data) indicates how well a model fits a given dataset. Lower values of MAE and MSE, and a higher value of STD imply a more accurate model.

Alternative Industries. To investigate the applicability of our findings across various sectors, we conduct the same analyses on two additional industries: textile (sample size 3,913) and knit (sample size 5,054). Appendix C in the online supplements indicates that our main takeaways remain consistent. Price and speed attributes remain at the top of the supplier attributes list, and as the order size increases, the importance of price displays an increasing trend, while the importance of speed decreases.

Alternative Outcome Variable. Although a high *Number of Transactions* can imply greater supplier attractiveness, it may not necessarily correspond to higher *Transaction Volume* if most orders are small. To strengthen the robustness of our findings, we therefore employ *Transaction Volume* as an alternative outcome variable. This analysis validates the results of our main model. Detailed results and further discussions are included in Appendix D in the online supplements.

Alternative Variable Construction for Quality. Our primary analysis utilizes supplier-specified quality metrics, such as the *Quality Level* and the *Accuracy Rate for Description of Goods*. However, the *Accuracy Rate for Description of Goods* may not always align with actual product quality. To address this limitation and strengthen our quality measure, we incorporate online reviews alongside the original metrics. Results of this analysis, presented in Appendix E in the online supplement, strengthen our primary model's findings.

Omitted Variable: Supplier Location To mitigate the potential for omitted variable bias in our research, we control for supplier location in analysis. Suppliers in the same location often face similar market conditions, such as labor costs, rental expenses, transportation logistics, and access to resources. Additionally, co-located suppliers may experience peer pressure to offer comparable services. We include the specific location as a control variable in our mode, and the results of this analysis are consistent with our main findings. More details of this analysis and additional procedures we take to minimize the risk of omitted variable bias are presented in Appendix F in the online supplements.

6. Managerial Implications and Practical Recommendations

In this section, we initially explore how suppliers can leverage our findings to guide their investment choices regarding various attributes. Following that, we investigate how online marketplaces can utilize our results to optimize information disclosure, which fosters efficient pairings between suppliers and retailers.

6.1. For Suppliers, Here are the Attributes to Invest

To assist suppliers' investment decisions regarding attribute enhancement, we quantify the economic value of quality, speed, and service attributes. This valuation is determined by calculating the substitution effect of each attribute with respect to price. In essence, if a supplier improves a speed or quality attribute by 1% or offers a service warranty, we assess the additional percentage of price premium they can impose without compromising their appeal to retailers.

Table 4 presents the price substitution estimates of supplier attributes across four order size buckets. To simplify the table, we rank the attributes by the magnitude of their price substitution effects and report only those attributes with significant estimates. Specifically, the reported coefficients evaluate the economic value of supplier attributes based on the effects of changes in product price. Generally, the price substitution effect of supplier attributes decreases with bucket size. This finding aligns with our intuition and findings in Section 4.2: as retailers become more price-sensitive with larger order sizes, the economic value of other supplier attributes declines.

The speed and quality dimensions contribute the most valuable supplier attributes across all four bucket sizes. The *Lead Time Rate* and the *Accuracy Rate for Description of Goods* are, in particular, two high-value investments for suppliers. For example, when the order size is smaller than 300 units, suppliers with a 1% quicker *Lead Time Rate* can charge a 3.781% price premium and yet still maintain the same attractiveness to retailers.

In addition to speed and quality attributes, several service attributes have significant economic value. As discussed in Section 4.2, when the order size is relatively small, retailers focus on speed attributes and are more willing to pay a price premium to obtain products faster. This emphasis ascribes significant economic value to speed attributes and related service guarantees, such as *Shipping in 48 Hours*, *Delivery Guarantee*, and *Platform-Endorsed Delivery Guarantee*. For instance, retailers will pay 22.6% more if a supplier offers the *Shipping in 48 Hours* service for orders between 30 and 299 units. Retailers also value the *Compensation If Out of Stock* service, which ensures that the chosen supplier will deliver the final goods on time, confirming retailers' emphasis on the

Table 4 The Economic Value of Attributes

Order Size Bucket 0: 30–299 units			**Order Size Bucket 1: 300–799 units**		
Attribute	Dimension	Price Substitution	Attribute	Dimension	Price Substitution
Lead Time Rate	Speed	3.781*** (1.213)	Accuracy Rate for Description of Goods	Quality	6.627*** (0.695)
Return with No Reason in 15 Days	Service	1.970*** (0.491)	Response Rate	Speed	3.714*** (0.189)
Platform Delivery Guarantee	Service	1.480*** (0.455)	Lead Time Rate	Speed	2.673*** (0.709)
Compensation If Out of Stock	Service	0.709*** (0.149)	Compensation If Out of Stock	Service	1.645*** (0.488)
Accuracy Rate for Description of Goods	Quality	0.452*** (0.094)	Issue Rate	Speed	0.772*** (0.135)
Issue Rate	Speed	0.407*** (0.175)	Delivery Guarantee	Service	0.770*** (0.110)
Free Return	Service	0.378*** (0.144)	Replacement in 7 Days	Service	0.652*** (0.187)
Sell on Credit	Service	0.353*** (0.129)	Sell on Credit	Service	0.340*** (0.133)
Shipping in 48 Hours	Service	0.226*** (0.122)	Return with No Reason in 15 Days	Service	0.322*** (0.135)
Num. of Obs.		11,167	Num. of Obs.		4,026

Order Size Bucket 2: 800–1,499 units			**Order Size Bucket 3: 1,500+ units**		
Attribute	Dimension	Price Substitution	Attribute	Dimension	Price Substitution
Accuracy Rate for Description of Goods	Quality	0.720*** (0.024)	Lead Time Rate	Speed	1.006*** (0.048)
Lead Time Rate	Speed	0.590*** (0.024)	Accuracy Rate for Description of Goods	Quality	0.410*** (0.025)
Buyer Right Guarantee	Service	0.073*** (0.010)	Quality Guarantee	Service	0.090*** (0.013)
Platform Delivery Guarantee	Service	0.057*** (0.010)	Free Return	Service	0.056*** (0.012)
Free Return	Service	0.054*** (0.010)	Platform Delivery Guarantee	Service	0.042*** (0.013)
Material Guarantee	Service	0.023*** (0.010)	Replacement in 15 Days	Service	0.040*** (0.012)
Quality Guarantee	Service	0.017*** (0.010)	Sell on Credit	Service	0.021*** (0.012)
Num. of Obs.		2,520	Num. of Obs.		3,536

Note. This table includes only the supplier attributes with significant price substitution effects, and the rankings of the supplier attributes are based on the estimated values of the substitution effects, from higher to lower. We generate the standard errors with bootstrapping and use *** to indicate statistical significance at 0.01 level.

turnover of on-demand fashion apparel products. Moreover, retailers pay more attention to *Quality Guarantee* when the order size is larger, consistent with the increasing importance of quality attributes shown in Figure 3. The *Quality Guarantee* service merits a 9% price premium when the order quantity exceeds 1,500 units. Furthermore, retailers appreciate the *Sell on Credit*, *Free Return*, *Replacement in 7 Days*, *Replacement in 15 Days*, and *Return with No Reason in 15 Days* services, although their value decreases as order size increases. Retailers recognize these services for reducing financial burdens and risk concerns.

Understanding the economic implications of each supplier attribute is crucial for making strategic investment decisions, particularly when financial resources are limited. This approach is invaluable for suppliers navigating budget constraints, as it enables them to allocate resources more effectively.

By investing in attributes that significantly boost their appeal to retailers, suppliers enhance their market attractiveness and strengthen their competitive position. Prioritizing investments based on the attributes most valued by retailers allows suppliers to not only meet but exceed market expectations, thereby securing a more robust foothold in the industry. This focused strategy ensures that suppliers are not just participants but also leaders in their market, driving innovation and excellence through informed, strategic decisions. For instance, suppliers like Intel and Samsung have strategically prioritized quality in their component manufacturing processes to ensure reliability and performance, recognizing that these attributes directly influence large-scale procurement decisions by major technology companies. This example underscores the benefits of targeted attribute enhancements in strengthening market positions and building lasting business relationships.

6.2. For the Platform, Here are Attributes to Disclose

As we discussed in 3.1, the platform facilitates information disclosure to optimize supplier-retailer pairings. The platform faces a dual challenge in designing an effective attribute menu: it must create a menu that informs retailers effectively while also being cost-efficient for suppliers to maintain. Presenting an excessive number of attributes, currently totaling 18, may lead retailers to experience information overload, which can impair their decision-making capabilities. This overload not only hinders the efficiency of the marketplace but also escalates the costs for suppliers, who may invest in less impactful attributes. On the other hand, a well-curated set of attributes streamlines the decision-making process, enhancing the platform's functionality and the competitiveness of its users. Therefore, it is critical to refine the attribute selection, aiming to reduce unnecessary expenditures for suppliers while simplifying the decision-making process for retailers. This strategic curation is essential for maintaining a competitive edge in the marketplace, ensuring that the platform remains a valuable tool to effectively match suppliers and retailers.

We prioritize the refinement of service attributes. There are two main reasons for this: Firstly, they constitute a significant portion of the current menu (12 out of 18). However, as demonstrated in Section 4, not all service attributes are essential to the supplier selection process. Secondly, some service options offer overlapping functionalities. For example, *Free Return*, *Replacement in 7 Days*, *Replacement in 15 Days*, and *Return with No Reason in 15 Days* are all related to return and replacement, while *Shipping in 48 Hours*, *Delivery Guarantee*, and *Platform-Endorsed Delivery Guarantee* are all associated with shipping and delivery. To address these issues, we systematically analyze both supplier adoption rates and retailer preferences for each service attribute, leading to the development of an essential service package tailored to meet the needs of both parties effectively. We present our findings and recommendations to the platform, advocating for a streamlined service attribute menu. The platform has recognized the validity of our approach and has implemented the essential service packages we proposed, which are discussed in detail in the following paragraphs.

In Figure 5, we plot service attribute importance against its corresponding supplier enrollment rate across four bucket sizes. To enhance readability, we have labeled only the three most important services for retailers and the three most frequently offered services by suppliers. Figure 5 underscores a key takeaway: the platform offers many redundant services. These services, clustered as non-labeled points in the bottom left corner of each panel, represent attributes with the least importance to retailers and the lowest enrollment by suppliers. By presenting this data visually, we emphasize the need to streamline the service attribute menu. Eliminating or consolidating these redundant services will address issues of inefficiency in supplier and retailer matching caused by information overload, ensuring that only pertinent and impactful attributes are listed on the platform.

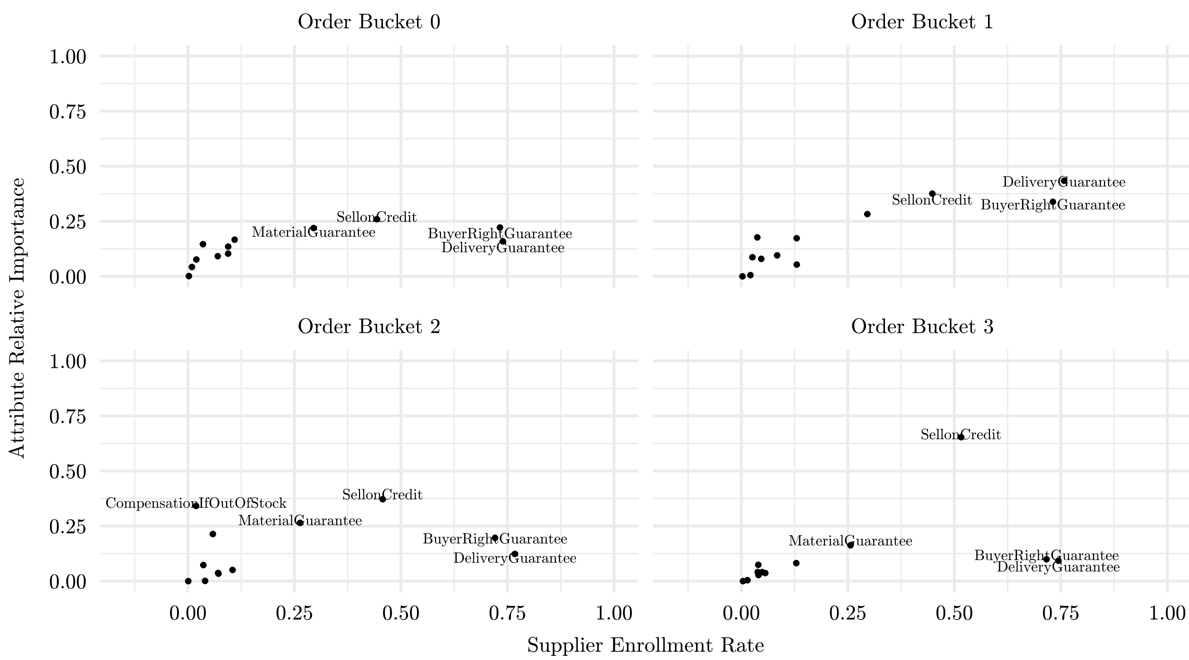

Figure 5 Attribute Importance versus Enrollment

Note. The three most important services for retailers and the three most popular services chosen by suppliers are labeled.

We devise an "Essential Service Package" tailored for each order bucket to guide platform information disclosure. Figure 5 reveals that services with the highest importance do not necessarily coincide with the most frequently adopted services. Therefore, only service attributes that demonstrate both high importance to retailers and high supplier enrollment rates are included in these packages. Additionally, we recognize that high enrollment rates do not necessarily guarantee significant economic benefits for suppliers. Consequently, we prioritize the incorporation of service attributes that deliver substantial economic value when offered. Offering these essential services enables suppliers to charge an additional price premium within specific order sizes, while maintaining attractiveness to retailers. Similar to our methodology in Table 4, we quantify the economic value of each service attribute within the packages by estimating its substitution effect relative to price attributes. Table 5 presents the identified essential service packages, along with their associated economic value. The numbers in the table represent the percentage increase in price premium that a supplier can charge without impacting their attractiveness to retailers when offering a specific service. Table 5 also indicates that the price substitution effect of service attributes decreases with the bucket size. This finding conforms with our findings in Section 4.2: as retailers become more price-sensitive with large order sizes, the economic value of other attributes decreases.

Table 5 The Economic Value of a Refined Service Package

Selected Services	Order Bucket 0	Order Bucket 1	Order Bucket 2	Order Bucket 3
Buyer Right Guarantee	–	–	0.073	–
Delivery Guarantee	1.480	0.770	0.057	0.042
Sell on Credit	0.353	0.340	–	0.021
Material Guarantee	–	–	0.023	–
Free Return	0.378	–	0.054	0.056
Quality Guarantee	–	–	0.017	0.090
Compensation If Out of Stock	0.709	1.645	–	–
Refined Service Package Total	2.920	2.755	0.224	0.209

Note. The numbers in the table indicate the additional percentage of price premium a supplier can charge without losing their attractiveness to retailers if they provide the corresponding service. The "-" in the table indicates that the service attribute is not recommended for the specific order size bucket.

The positive impact of a reduced attribute package on supplier selection has been confirmed in practice. After the platform implemented our recommendation to remove redundant service attributes, a new dataset with fewer attributes was obtained. This dataset comprises 29,361 transaction records from 167 buyers, involving decisions based on 13 supplier attributes, significantly fewer than the 18 attributes in our main dataset. These attributes include price, quality, speed, and refined service attributes (Table 5). We conducted a comparative analysis using three key indicators to assess supplier performance: retailer ratings, order size buckets, and repurchase rates. Retailer ratings serve as proxies for the accuracy of supplier selection predictions, reflecting retailer satisfaction and demonstrating the effectiveness of supplier-retailer matches. Order size buckets gauge the quality of decision-making concerning supplier profitability, with larger order sizes indicating greater potential revenue and profitability for suppliers. Lastly, repurchase rates measure the durability of supplier-retailer relationships. A higher repurchase rate, which is the percentage of buyers who have repeatedly purchased the same product from the same supplier, signifies more enduring relationships. These metrics collectively evaluate the overall success and sustainability of supplier and retailer matching quality on the platform.

Our findings in Table 6 reveal an increase in buyer satisfaction when decisions are made using a streamlined set of attributes, suggesting higher accuracy in supplier selection predictions. Additionally, transactions involving a reduced attribute lead to larger order sizes, suggesting more profitable supplier and retailer relationships. However, we observed that the repurchase rate remains unchanged following the streamlining of service attributes. This suggests that refining the service menu does not necessarily enhance the durability of supplier-retailer relationships. This is consistent with expectations, as building long-term, mutually trusted relationships between suppliers and retailers involves more than just simplifying the decision-making process. It requires consistent quality, reliability, and effective communication. Consequently, we conclude that reducing the number of attributes in supplier selection not only improves the accuracy of the matching process but also enhances decision quality for retailers searching for suppliers. This streamlined attribute menu contributes to improved reputations and financial outcomes for suppliers. With a more efficient attribute menu, the platform can disclose information more effectively, benefiting both suppliers and retailers. This optimization helps maintain the platform's competitiveness and positions it as a potential leader in the sourcing market in the foreseeable future.

Table 6 Comparison Analysis of Full and Reduced Attribute Lists

Variables	Full Attributes	Reduced Attributes	Difference
Mean Rating	4.818	4.952	0.134***
Mean Order Size Bucket	0.964	1.317	0.353***
Mean Repurchase Rate	0.275	0.253	-0.022 (Not significant)

Note. *** indicates significance level of 0.001.

7. Conclusion

Our analysis enables us to quantify and summarize the most crucial criteria for supplier selection. Utilizing the GBDT model, this study reveals that price and speed attributes hold greater importance than quality and service attributes. The significance of supplier attributes varies across different orders, with clear trends emerging upon stratifying samples by order size and product type. As order size increases, the impact of speed and service attributes diminishes, while the importance of price and quality attributes grows. Furthermore, we discover that services and a crowd-sourced quality index carry more weight for trendy, innovative products, while price and self-reported quality are vital for long-life-cycle functional products. Suppliers aiming to enter emerging digital B2B marketplaces can now leverage these insights more effectively to streamline implementation and optimize operations through focused marketing and product offerings that best address market demands.

The extensive observations from the online B2B marketplace provide a unique opportunity to augment existing survey and theoretical literature. We complement survey work by extracting precise and consistent preferences for supplier attributes from large-scale retailers' purchasing decisions. Specifically, the comprehensive dataset enables us to access the same information retailers do, creating an ideal environment for examining supplier selection criteria and processes. Furthermore, the rich detail and segmentation within the dataset allow us to explore how supplier selection criteria adapt according to order size and product type. Based on our findings, theoretical research can integrate these quantified preferences as numerical weights into optimization or simulation frameworks, thereby enhancing their practical relevance for supply chain management. Additionally, our results lay the groundwork for analyzing a wider range of market data, as digital B2B marketplaces, Internet of Things (IOT), and big data collection and analysis continue to expand in academia and industry.

Our findings also yield valuable insights for business practitioners. With limited budgets, suppliers can identify the most rewarding attributes to invest in by using our estimated economic value for each attribute. The quantified price substitution offers guidance on the extent of the price premium suppliers can charge while maintaining their attractiveness to retailers. Alternatively, suppliers can retain the same pricing but increase transaction volume by enhancing product attributes. For online platforms, there is a clear opportunity to optimize their attribute menus by focusing on attributes that hold high value for retailers and are economically feasible for suppliers. We advise platforms to streamline their service menus by removing or consolidating redundant or low-importance services. Implementing an "Essential Service Package" for each order size bucket, which includes services that deliver substantial economic benefits, can enable suppliers to charge a premium while maintaining attractiveness. Furthermore, platforms could benefit from adopting adaptive information displays that tailor attribute visibility based on retailer preferences and order specifics, enhancing decision-making efficiency and encouraging suppliers to prioritize their most impactful attributes.

When interpreting our results, it's important to acknowledge potential limitations. Our focus on actual purchasing decision data from an online sourcing marketplace within the apparel industry might influence the external validity of our findings. Nevertheless, our research has broader implications, particularly for sectors characterized by intense competition, easy market entry, fast-paced supply chains, demand volatility driven by trends and technology, and a need for supply chain adaptability in response to modern retail environments. Additionally, our stratified analysis indicates that our insights may generalize to offline sourcing settings, particularly when considering durable goods, long-life-cycle products, and large order sizes. Our findings hold particular relevance for the expanding B2B sourcing marketplace domain and the "Made on the Internet" concept. Future research can deepen these insights by investigating the distinct decision-making dynamics inherent to B2B and B2C marketplaces. A valuable approach would be to contrast the emphasis on cost and performance typically found in B2B purchases with the potential prioritization of convenience and experiential value in B2C platforms. This analysis could shed further light on how platform type influences decision-making processes, including concepts such as rationality and bounded rationality, ultimately advancing our understanding of supplier selection. As online B2B marketplaces proliferate and corporations enhance their data collection and analysis capabilities, our research lays the groundwork for future studies aimed at optimizing supplier matching and providing retailers with prioritized criteria for supplier selection.

References

Ang, Erjie and Kwasnick, Sara and Bayati, Mohsen and Plambeck, Erica L and Aratow, Michael (2015) Accurate emergency department wait time prediction. *Manufacturing & Service Operations Management* 18(1):141–156.

Arbuthnot, Jeanette Jaussaud and Slama, Mark and Sisler, Grovalynn (1993) Selection criteria and information sources in the purchase decisions of apparel buyers of small retailing firms. *Journal of Small Business Management* 31(2):12.

Sylvain Arlot and Alain Celisse (2010) A survey of cross-validation procedures for model selection. *Statistics Surveys* 4:40–79.

Bastani, Hamsa and Bayati, Mohsen (2020) Online decision making with high-dimensional covariates. *Operations Research* 68(1):276–294.

Bertsimas, Dimitris and O'Hair, Allison and Relyea, Stephen and Silberholz, John (2016) An analytics approach to designing combination chemotherapy regimens for cancer. *Management Science* 62(5):1511–1531.

Bray, Robert L and Serpa, Juan Camilo and Colak, Ahmet (2019) Supply chain proximity and product quality. *Management science* 65(9):4079–4099.

Chan, Felix TS and Kumar, Niraj (2007) Global supplier development considering risk factors using fuzzy extended ahp-based approach. *Omega* 35(4):417–431.

Constantinides, Panos and Henfridsson, Ola and Parker, Geoffrey G (2018) Introduction—platforms and infrastructures in the digital age. *Information Systems Research* 29(2):381–400.

Cui, Ruomeng and Li, Jingyun and Li, Meng and Yu, Lili (2021) Wholesale price discrimination in global sourcing. *Manufacturing & Service Operations Management* 23(5):1096–1117.

Cui, Ruomeng and Li, Meng and Li, Qiang (2020) Value of high-quality logistics: Evidence from a clash between sf express and alibaba. *Management Science* 66(9):3879–3902.

Dickson, Gary W (1966) An analysis of vendor selection systems and decisions. *Journal of Purchasing* 2(1):5–17.

Ferreira, Kris Johnson and Lee, Bin Hong Alex and Simchi-Levi, David (2015) Analytics for an online retailer: Demand forecasting and price optimization. *Manufacturing & Service Operations Management* 18(1):69–88.

Fisher, Marshall L (1997) What is the right supply chain for your product? *Harvard Business Review* 75:105–117.

Gefen, David and Carmel, Erran (2008) Is the world really flat? a look at offshoring at an online programming marketplace. *MIS Quarterly* 32(2):367–384.

Guajardo, Jose A and Cohen, Morris A and Kim, Sang-Hyun and Netessine, Serguei (2012) Impact of performance-based contracting on product reliability: An empirical analysis. *Management Science* 58(5):961–979.

Guan, Xu and Liu, Baoshan and Chen, Ying-ju and Wang, Hongwei (2020) Inducing supply chain transparency through supplier encroachment. *Production and Operations Management* 29(3):725–749.

Ho, William and Xu, Xiaowei and Dey, Prasanta K (2010) Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research* 202(1):16–24.

Hong, Gye Hang and Park, Sang Chan and Jang, Dong Sik and Rho, Hyung Min (2005) An effective supplier selection method for constructing a competitive supply-relationship. *Expert Systems with Applications* 28(4):629–639.

Huang, Song and Guan, Xu and Chen, Ying-Ju (2018) Retailer information sharing with supplier encroachment. *Production and Operations Management* 27(6):1133–1147.

Kar, Arpan Kumar and Pani, Ashis K. (2014) Exploring the importance of different supplier selection criteria. *Management Research Review* 37(1):89–105.

Lee, Byung-Kwan and Lee, Wei-Na (2004) The effect of information overload on consumer choice quality in an on-line environment. *Psychology & Marketing* 21(3):159–183.

Lehrer, Steven F and Xie, Tian (2022) The bigger picture: Combining econometrics with analytics improves forecasts of movie success. *Management Science* 68(1):189–210.

Lewis, Michael and Singh, Vishal and Fay, Scott (2006) An empirical study of the impact of nonlinear shipping and handling fees on purchase incidence and expenditure decisions. *Marketing Science* 25(1):51–64.

Malhotra, Naresh K (1982) Information load and consumer decision making. *Journal of Consumer Research* 8(4):419–430.

Narasimhan, Ram and Talluri, Srinivas and Mahapatra, Santosh K (2006) Multiproduct, multicriteria model for supplier selection with product life-cycle considerations. *Decision Sciences* 37(4):577–603.

Oke, Adegoke and Gopalakrishnan, Mohan (2009) Managing disruptions in supply chains: A case study of a retail supply chain. *International Journal of Production Economics* 118(1):168–174.

Osadchiy, Nikolay and Gaur, Vishal and Seshadri, Sridhar (2015) Systematic risk in supply chain networks. *Management Science* 62(6):1755–1777.

Schmitt, Alexander and Van Biesebroeck, Johannes (2013) Proximity strategies in outsourcing relations: The role of geographical, cultural and relational proximity in the european automotive industry. *Journal of International Business Studies* 44(5):475–503.

Serpa, Juan Camilo and Krishnan, Harish (2017) The impact of supply chains on firm-level productivity. *Management Science* 64(2):511–532.

Straits Research (2023) B2b ecommerce market share, size and forecast to 2031. retrieved on august 14th, 2024. URL https://straitsresearch.com/report/b2b-ecommerce-market.

Sun, Jiankun and Zhang, Dennis J and Hu, Haoyuan and Van Mieghem, Jan A (2022) Predicting human discretion to adjust algorithmic prescription: A large-scale field experiment in warehouse operations. *Management Science* 68(2):846–865.

Tadelis, Steven and Zettelmeyer, Florian (2015) Information disclosure as a matching mechanism: Theory and evidence from a field experiment. *American Economic Review* 105(2):886–905.

Talluri, Srinivas (2002) A buyer–seller game model for selection and negotiation of purchasing bids. *European Journal of Operational Research* 143(1):171–180.

Verma, Rohit and Pullman, Madeleine E (1998) An analysis of the supplier selection process. *Omega* 26(6):739–750.

Wan, Zhixi and Beil, Damian R (2009) RFQ auctions with supplier qualification screening. *Operations Research* 57(4):934–949.

Wang, Yixin and Li, Jun and Wu, Di and Anupindi, Ravi (2021) When ignorance is not bliss: An empirical analysis of subtier supply network structure on firm risk. *Management Science* 67(4):2029–2048.

Weber, Charles A and Current, John R and Benton, WC (1991) Vendor selection criteria and methods. *European Journal of Operational Research* 50(1):2–18.

Weber, Charles A and Desai, Anand (1996) Determination of paths to vendor market efficiency using parallel coordinates representation: a negotiation tool for buyers. *European Journal of Operational Research* 90(1):142–155.

Ye, Jerry and Chow, Jyh-Herng and Chen, Jiang and Zheng, Zhaohui (2009) Stochastic gradient boosted distributed decision trees. *Proceedings of the 18th ACM conference on Information and knowledge management*, 2061–2064.