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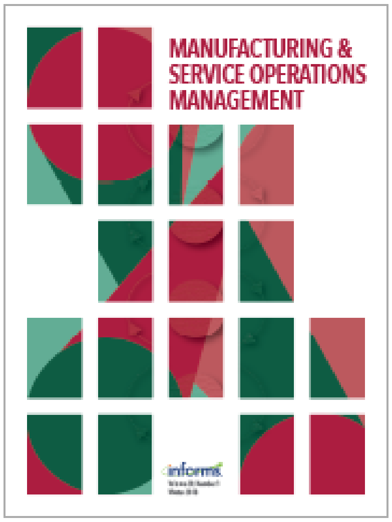

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AI and Procurement

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Abstract. ***Problem definition*:** In this research, we study how buyers' use of artificial intelligence (AI) affects suppliers' price quoting strategies. Specifically, we study the impact of automation—that is, the buyer uses a chatbot to automatically inquire about prices instead of asking in person—and the impact of smartness—that is, the buyer signals the use of a smart AI algorithm in selecting the supplier. ***Academic/practical relevance*:** In a world advancing toward AI, we explore how AI creates and delivers value in procurement. AI has two unique abilities: automation and smartness, which are associated with physical machines or software that enable us to operate more efficiently and effectively. ***Methodology*:** We collaborate with a trading company to run a field experiment on an online platform in which we compare suppliers' wholesale price quotes across female, male, and chatbot buyer types under AI and no recommendation conditions. ***Results*:** We find that, when not equipped with a smart control, there is price discrimination against chatbot buyers who receive a higher wholesale price quote than human buyers. In fact, without smartness, automation alone receives the highest quoted wholesale price. However, signaling the use of a smart recommendation system can effectively reduce suppliers' price quote for chatbot buyers. We also show that AI delivers the most value when buyers adopt automation and smartness simultaneously in procurement. ***Managerial implications*:** Our results imply that automation is not very valuable when implemented without smartness, which in turn suggests that building smartness is necessary before considering high levels of autonomy. Our study unlocks the optimal steps that buyers could adopt to develop AI in procurement processes.

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Keywords: artificial intelligence • procurement • wholesale pricing • automation • smartness

> Forty-five percent of chief procurement officers are using, piloting, or planning to use AI.
>
> (Deloitte 2018, p. 32; HICX Solutions 2018, p. 4)

1. Introduction

Artificial intelligence (AI) is related to making machines or software mimic human behavior and intelligence and eventually supersede or augment human work. AI is becoming the new operational foundation of business and has transformed the very nature of companies—how they operate and how they compete (Iansiti and Lakhani 2020). AI has two unique capabilities: *automation* and *smartness*, which are associated with physical machines or software that replace manual work through automated processes or augment human work through smart decisions (Boute and Van Mieghem 2021). AI can automate simple, tedious, and repetitive tasks to perform them faster and cheaper. AI can also facilitate smarter control rules by continuously learning, reasoning, deciding, and acting to drive a business outcome. As AI enables companies to reach unprecedented levels of scale, scope, and learning speed, organizations around the world are eager to participate in this AI transformation. However, the rise of AI is posing new challenges for organizations to understand how it works, when it is the most powerful, and how to optimize their AI strategies.

AI has created new business opportunities and delivered value to organizations in numerous ways. For example, a chatbot is an AI application that can automate basic, repeatable, standardized interactions between customers and sellers. Specifically, chatbots such as IKEA's Anna use voice or texts to automate communications and create personalized customer experiences. The chatbot market size is predicted to expand from $250 million in 2017 to $1.34 billion in 2024

(Pise 2018), and the adoption of the chatbot feature is predicted to save businesses \$11 billion annually by 2023 (Hampshire 2018).

AI has also been applied to automate procurement tasks and assist strategic sourcing in business-to-business (B2B) markets, which is referred to as cognitive procurement (Loo and Santhiram 2018). Surveys reveal that 60% of companies use AI to automate the request-for-quotation process and 50% of companies use AI to recommend new suppliers (Tata Consultancy Services 2016).

> There are two ways in which AI can be used for smarter sourcing in procurement. The first is the automation … . For example, AI-powered … bots … . The second—and more important—use relates to AI-powered tools helping to rapidly collect, present and even analyse commodity, market, and supply intelligence to inform market strategies.
>
> —Nicholas Walden, Senior Director at The Hackett Group (HICX Solutions 2018)

On one hand, chatbots have been used to automate the request-for-quotation process in procurement by mimicking human interactions, thereby relieving workers from tedious and repeatable tasks. For example, SAP Ariba—an information technology services company in the United States—uses a procurement AI assistant to request price quotations and draft contracts. Chatbots have been shown to reduce labor costs by 39% for a global energy company by automating procurement processes (Papa et al. 2019). On the other hand, procurement managers can also use AI to identify potential suppliers, which is referred to as *AI recommendation*. Traditionally, procurement companies often identify potential suppliers based on their colleagues' recommendation, which is referred to as *human recommendation*. AI adds the component of smartness to procurement manager's supplier selection decisions by using its extraordinary capability to collect and analyze market information. To summarize, in the procurement context, automation helps buyers automatically inquire about prices instead of asking in person, and smartness aids buyers by using an AI algorithm to recommend suppliers.

Given that procurement is the core decision in B2B businesses, it is critical to study how AI creates and delivers value along its automation and smartness capabilities. We investigate how buyers' AI strategies affect suppliers' wholesale pricing decisions. Specifically, we study the effect of automation—that is, whether the buyer inquires about prices using an autonomous chatbot or in person. We also study the effect of smartness—that is, whether the buyer signals the use of AI recommendations in selecting suppliers.

In this study, we run a field experiment by collaborating with a trading company that operates on Alibaba's trading platform 1688 (1688.com), which is the largest domestic trading platform in China. It serves millions of buyers and suppliers who use an integrated chat program called Aliwangwang to communicate with each other. The trading company's procurement managers are required to quote prices from suppliers on 1688. We design a 3×3 field experiment. The procurement representatives are (1) a female human, (2) a male human, or (3) a chatbot, where the chatbot automatically sends inquiry messages without human involvement. The quoting messages indicate that the supplier is (1) not informed of any recommendation, (2) recommended by a peer, or (3) recommended by an AI algorithm. We test the effect of automation and smartness in procurement by comparing suppliers' wholesale price quotes across the aforementioned three buyer types and three recommendation conditions.

We find that when automation is not equipped with a smart control, it negatively affects the quoted wholesale price. Specifically, chatbot buyers receive a higher price quote than human buyers. This is because a supplier might believe that a chatbot buyer lacks the expertise in product specifics, and in turn, has a higher reservation price and a higher willingness to pay than human buyers. Moreover, a supplier does not have to lower his wholesale price in order to develop a professional relationship with a chatbot buyer. Consequently, the supplier prices discriminate against chatbot buyers. In addition, as a side finding, our results reveal that the wholesale prices quoted to male and female buyers are not significantly different.

We find that signaling the use of AI algorithms in selecting the supplier reduces the wholesale price for chatbot buyers, but it cannot reduce the price for human buyers. This is because, for chatbot buyers, suppliers believe in AI's capability to collect and learn from market information and in AI's complete influence on chatbot buyers' decisions, thereby changing their perception of chatbot buyers' reservation price and willingness to pay. However, human buyers are not machines. They are susceptible to their own judgment and heuristics, thereby making them reluctant to strictly follow algorithm-suggested decisions (Cui et al. 2015, Dietvorst et al. 2018, Ibanez et al. 2018, Tan and Staats 2020, Sun et al. 2021). Because of such *decision deviations*, suppliers may perceive that human buyers do not follow AI's recommendations, thereby ignoring these buyers' use of AI and not altering the wholesale price accordingly. In contrast, we find that the traditional recommendation without smart controls—that is, human recommendation—cannot reduce the price quotes for either chatbot buyers or human buyers. This allows us to tease out the effect of recommendation and attribute the overall effect of AI recommendation to the effect of smartness.

In summary, in the absence of smart controls, the buyer suffers from automation by receiving a higher wholesale price, whereas having smart controls leads to a lower wholesale price for these autonomous buyers. This implies that when automation is implemented without smart controls, it is not very valuable, which suggests that building smartness is necessary before implementing high levels of autonomy.

Last, we study the combined value of automation and smartness. We find that chatbot buyers aided by a smart recommendation system receive the lowest price quote among all conditions. In other words, AI delivers the most value when buyers use both automation and recommendation in price inquiry. This finding highlights the value of using autonomous agents aided by a smart recommendation system in procurement.

2. Literature Review

2.1. AI Automation and Recommendation

Prior research indicates that automation creates value in inventory replenishment (Van Donselaar et al. 2010) and financial services (Köhler et al. 2011, Luo et al. 2019, Acimovic et al. 2021). An application of automation is a chatbot, which helps human workers automate communications with consumers. Extant literature reveals that consumers often dislike communicating with a chatbot, despite the fact that automation can improve agents' productivity. We complement this literature by investigating suppliers' reactions to the procurement managers' usage of chatbot.

Prior research has also shown that AI's recommendations add value in various contexts, such as disease diagnosis (Leachman and Merlino 2017), wholesale pricing (Karlinsky-Shichor and Netzer 2019), and product recommendations (Häubl and Trifts 2000). For example, Karlinsky-Shichor and Netzer (2019) create an AI version of B2B salespersons' pricing decisions that mimics their past pricing behavior, which improves profits by 10%. However, human decision-makers often choose to rely on their own judgment, making them reluctant to strictly follow algorithm-instructed decisions. Such decision deviation behavior has been widely documented in the literature. For example, managers tend to use their own demand forecasts rather than forecasts provided by machines (Cui et al. 2015, Dietvorst et al. 2018); doctors prioritize tasks in a manner that deviates from system recommendations (Ibanez et al. 2018); workers pack orders in boxes larger than the size suggested by the system (Sun et al. 2021); and restaurant managers deviate from the routing rules that they are instructed to follow (Tan and Staats 2020). We add to this literature by studying suppliers' reactions when B2B buyers tell them that they (the suppliers) are recommended by AI algorithms.

Our paper is closely related to Boute and Van Mieghem (2021). The authors propose a framework that synthesizes automation and smartness for companies who transform operations digitally. They argue that having a smart control is necessary before high levels of autonomy are considered. Our paper follows this framework to study the value and synergies between automation and smartness in procurement processes. Our findings echo the insights of Boute and Van Mieghem in that we empirically show that automation, when implemented without smart controls, does not bring value and can even backfire, whereas smartness is valuable. Specifically, we find that automation causes suppliers to increase their wholesale prices, but AI recommendations can effectively lower the price quotes. Consequently, AI delivers the most value when automation and smartness are adopted in combination with each other.

2.2. Procurement and Wholesale Pricing

Procurement is a critical business decision. The literature has studied various mechanisms, such as inventory investment (Jain et al. 2014), information provision (Engelbrecht-Wiggans and Katok 2008), timing of auctions (Bimpikis et al. 2020), and trust (Fugger et al. 2019) to improve procurement effectiveness. We follow suit to study the integration of AI as a market mechanism to affect request-for-quotation outcomes.

The procurement outcome that we measure is the wholesale price charged by sellers. Wholesale pricing is one of the central topics of supply chain management (Cachon 2003, Cachon and Netessine 2006). In supply chains, the wholesale price that suppliers charge for downstream buyers is an important determinant of suppliers' profit margins and buyers' prices, which in turn affects profitability. A supplier may charge different wholesale prices to retailers based on, for example, buyer intermediation (Tunca and Zhu 2018), supplier–buyer relationships (Zhang et al. 2014), or buyers' race (Cui et al. 2020). We contribute to the literature by studying whether suppliers price against or in favor of chatbot buyers and, if so, which features of AI allow it to deliver the most value.

3. Research Hypotheses

We study how suppliers vary their wholesale prices to buyers with and without the use of AI on an online B2B platform. Before purchasing a product, buyers research its market price by asking for price quotes from suppliers. Suppliers then provide a price quote to buyers based on buyers' characteristics and the inquiry message. In this section, we develop a framework that predicts the effect of automation and smartness in procurement. We discuss whether suppliers price against or in favor of (1) buyers' autonomous characteristic—whether the buyer is a chatbot or human, (2) buyers' smartness characteristic—whether the buyer signals the use of AI recommendations in selecting suppliers, and (3) buyers' autonomous and smartness characteristics—whether the buyer is a chatbot with a smart control or a human without a smart control.

3.1. Effect of Automation

When deciding on a wholesale price to charge buyers in a B2B setting, a supplier's most pivotal consideration is the buyer's best alternative to a negotiated agreement (BATNA). BATNA refers to the most advantageous alternative action that the buyer can take if the negotiation reaches an impasse (Fisher and Ury 1981, Fisher et al. 2011, Pinkley et al. 1994). Consequently, the buyers' BATNA determines the suppliers' pricing strategy: buyers with a stronger BATNA have better outside options, and in turn, they have a lower reservation price and a lower willingness to pay (Korobkin 2014), which results in a lower wholesale price charged by suppliers.

We consider the scenario that the chatbot or human buyer asks for prices without providing any recommendation information to the supplier, that is, automation without smartness. Autonomous chatbots are an effective tool to automate repeated inquiries and preprogrammed responses. In our research context, a chatbot is used to automatically send inquiry messages to a group of suppliers, saving buyers' time spent in sending messages to each supplier personally. However, these traditional chatbots, when their main objective is to repeat tasks without smart controls, are not equipped to address the complex requirements of B2B suppliers, who expect in-depth communications and negotiations with buyers (Swanson 2015). We interviewed several highly experienced trading managers who confirm that procurement requires a significant level of professional knowledge in product specifics, such as product materials, size, functionality, and after-sales service, which preprogrammed chatbots might be less knowledgeable in.[1] Consequently, suppliers may believe that chatbots lack expertise in product specifics and, in turn, have a worse BATNA and thus a higher reservation price than human buyers.

Furthermore, because chatbots lack personal feelings and empathy, suppliers do not need to lower the wholesale price in order to develop a serious relationship with chatbot buyers (Dietvorst et al. 2018, Luo et al. 2019). Therefore, we expect that without smart controls, chatbot buyers will be price discriminated against and receive a higher price quote than human buyers.

Hypothesis 1 (Automation). *Without smart controls, chatbot buyers receive a higher wholesale price quote than human buyers.*

3.2. Effect of Smartness

In this section, we study the effect of having smartness in the process of wholesale price inquiries. Smartness means that the buyer uses AI recommendations to select suppliers. Without claiming the use of AI recommendations, suppliers would not be able to know and react to this. Therefore, in our research context, smartness is signaled to the suppliers. Specifically, when asking for a price quote, the buyer tells the supplier that the company was recommended to the buyer by AI's market search and data analysis. The supplier can use this information to update beliefs about the buyer and alter the offered wholesale price accordingly.

The information on the use of AI recommendations can be a key determinant for suppliers, because AI has an extraordinary capability to collect and learn from market information (Häubl and Trifts 2000). Knowing that the buyer has comprehensive knowledge of the market aided by AI, the supplier would believe that the buyer has a stronger BATNA—that is, a better walk-away option—and in turn would consider lowering the price. In addition to the capability of AI, suppliers would also evaluate whether the AI recommendations have a complete influence on buyers' decisions. If a buyer does not follow AI-generated recommendations, then the buyer's decisions will not heavily rely on AI, which suggests that the supplier could ignore the buyer's AI use.

We first consider the scenario where the procurement manager uses autonomous chatbots to ask for prices and signal that the supplier was selected by AI's market search. Because chatbots are machines programmed to follow the AI's recommendations, the supplier would believe in the thorough knowledge of the market gained by AI and the influence that AI has on the buyer. Therefore, we expect that chatbot buyers' use of AI recommendations will improve the supplier's perception of their BATNA, thereby reducing the supplier's wholesale price.

Next, we consider the scenario where the human buyer asks for prices in person and informs the supplier that the company was recommended by AI. Humans are not machines. They are susceptible to their own judgment and heuristics, thereby making them reluctant to strictly follow algorithms and rules. This is known as decision deviation (Cui et al. 2015, Dietvorst et al. 2018, Ibanez et al. 2018, Tan and Staats 2020, Sun et al. 2021). Such deviation behavior from algorithm-instructed decisions has been widely documented in the literature. For example, managers are shown to use human forecasts rather than algorithmic forecasts (Cui et al. 2015, Deloitte 2018); doctors are shown to prioritize tasks in a manner that deviates from system recommendations (Ibanez et al. 2018); workers are shown to pack orders in boxes larger than the system-recommended size (Sun et al. 2021); and restaurant managers are shown to deviate from the routing rules that machines instruct them to follow (Tan and Staats 2020). Given this widespread recognition that humans often deviate from algorithmic recommendations, we expect that suppliers would anticipate human buyers to not strictly follow AI recommendations.

To further confirm that decision deviations exist in procurement, we interviewed nine professional B2B suppliers with an average of 12 years of trading experience. In the interviews, we asked them to share whether they believe in AI recommendations' influence on a human buyer or a chatbot buyer. We summarize their quotes in Table EC.1 in the online appendix. Most suppliers indicate that they believe that such an AI recommendation can help chatbot buyers learn about market knowledge and can dictate their sourcing choices. However, eight of nine suppliers do not believe that a human buyer will follow AI recommendations because they think that human buyers would make their own judgment about the market and are likely to deviate from algorithms. Therefore, we expect that suppliers would assume that human buyers do not follow the AI's recommendations, thereby ignoring buyers' use of AI and not altering their perception on the human buyers' BATNA. In other words, the use of AI becomes ineffective in reducing the wholesale price quote for human buyers.

Hypothesis 2 (Smartness). (a) *Chatbot buyers, when informing suppliers that they are selected by smart AI algorithms, receive a lower wholesale price quote than chatbot buyers without AI recommendations.* (b) *Human buyers, when informing suppliers that they are selected by smart AI algorithms, receive a similar wholesale price quote as human buyers without AI recommendations.*

3.3. Automation and Smartness

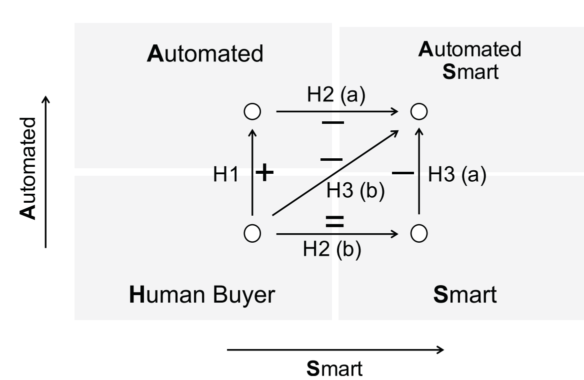
In this section, we study the effect of having both automation and smartness. We first discuss the effect of automation under smart controls. That is, we compare the difference between chatbot buyers with AI recommendations and human buyers with AI recommendations. When both human and chatbots are equipped with AI recommendations, the effect boils down to who would follow the AI's recommendations. According to Hypothesis 2(a), chatbots are programmed to follow the AI's recommendations. According to Hypothesis 2(b), human buyers may not fully follow the AI's recommendations because of their tendency to deviate from AI-instructed decisions. Therefore, suppliers will react to chatbot buyers' and ignore human buyers' use of AI recommendations. Taken together, when equipped with a smart control, suppliers would perceive that chatbot buyers have more comprehensive market knowledge, thereby a stronger BATNA with a lower reservation price than human buyers. We hypothesize this relation in Hypothesis 3(a).

Next, we study the difference between chatbot buyers with AI recommendations and human buyers without any recommendation. According to the previous theories, AI enables buyers to have comprehensive knowledge about the market and exerts a full influence on chatbot buyers. As a result, suppliers would perceive chatbot buyers with smartness to have a stronger BATNA and thus would offer them a lower wholesale price than human buyers without smartness. Therefore, we expect that the effect of AI is the strongest when both automation and smartness are in place.

Hypothesis 3 (Automation and Smartness). (a) *When informing suppliers that they are selected by smart AI algorithms, chatbot buyers receive a lower wholesale price quote than human buyers.* (b) *Chatbot buyers, when informing suppliers that they are selected by smart AI algorithms, receive a lower wholesale price quote than human buyers without AI recommendations.*

We summarize the effect of automation and smartness on suppliers' price decisions in Figure 1. We follow the framework of Boute and Van Mieghem (2021) to classify buyers' AI strategies into four groups: human buyer without the help of AI, automation enabled by chatbot buyers, smart control enabled by AI recommendations, and the joint application of automation and smartness. In this framework, Hypothesis 1 describes the pure effect of automation when we move from the *Human Buyer* zone to the *Automated* zone; Hypothesis 2 describes the effect of smartness on human buyers and chatbot buyers separately when we move from the *Human Buyer* zone to the *Smart* zone, and from the *Automated* zone to the

Figure 1. Framework of Automation and Smartness in Procurement



Notes. +, –, and = represent higher, lower, and similar price quotes, respectively. H1–H3 represent Hypotheses 1–3, respectively.

Automated+Smart zone, respectively; Hypothesis 3 describes the effect of automation under smartness when we move from the *Smart* zone to the *Automated+Smart* zone and the joint effect of automation and smartness when we move from the *Human Buyer* zone to the *Automated+Smart* zone.

4. Research Context

Alibaba Group launched 1688 in 1999, which is the largest domestic online B2B platform in China (Alibaba 2020a). This platform connects 30 million enterprise buyers and suppliers (China Daily 2019); the suppliers provide products in 49 major categories, including apparel, general merchandise, electronics, and car accessories (CNXtrans 2020). The 1688 platform has a built-in instant chat program called Aliwangwang that enables buyers to contact suppliers for product specifics and prices. Buying companies are permitted to embed autonomous chatbot features in Aliwangwang in order to automate communications.

On 1688, a supplier introduces company information on a profile page and lists product information on a product page. The supplier's profile page displays basic company information (e.g., name, location, membership status, and credibility) and trading performance on the platform (e.g., number of transactions, number of buyers, repeat purchase rate, and refund rate). Suppliers can pay to have an elite membership in order to obtain advantages in product promotion and exposure. A supplier's credibility has five levels. The product page displays product characteristics—for example, description, picture, price, and options—and transaction details—for example, number of reviews, review rating, and transaction volume in the past 30 days.

A buyer also has a personal profile that includes the buyer's name, gender, date of birth, location, photo, phone number, and email address. Buyers can search for a specific product and choose one from a list of suppliers displayed by the platform. The buyer can then view the supplier's profile and product details. The buyer sends a price quote to the supplier on Aliwangwang either through a personal message or using autonomous chatbots to automate the inquiry process. After receiving an inquiry from a buyer, the supplier chooses whether to follow up and how much to quote. After transaction details are settled, the buyer makes a payment, the supplier ships the order, and the transaction is completed.

5. Identification Design

We aim to study the effect of the buyer's usage of automation and smartness on the suppliers' price quoting strategy. We collaborate with a trading company that operates on 1688 to conduct a field experiment.

5.1. Study Design

In order to study the effect of automation, we design the sender who asks for the price quote to be a female human, a male human, or an autonomous chatbot. We identify the value of pure automation by comparing the price quote received by a chatbot buyer and a human buyer. In order to study the effect of smartness, we design the sender to signal that the supplier is recommended by AI or human peers, or to not signal any recommendation at all. We identify the value of AI recommendations by comparing the price quote received with AI recommendations and without any recommendation. We also introduce a treatment with human recommendations, in which the buyer signals that the supplier was recommended by a (human) peer, in order to disentangle the pure impact of having recommendations and the pure impact of having smart controls. If the effect of human recommendations is weak, we can attribute the overall effect of AI recommendations to smartness. Consequently, we use a 3×3 experiment design by considering three types of buyers (female buyer, male buyer, and chatbot buyer) and three recommendation conditions (no recommendation, human recommendation, and AI recommendation). We outline how our experiment design matches our AI framework in Figure EC.2 in the online appendix.

The company has multiple procurement representatives whose routine job is to keep track of market dynamics by collecting wholesale price information. The company also uses chatbots to assist in this task. In our study, the procurement representatives follow our scripts and guidelines when quoting wholesale prices from suppliers. The trading company asks for price quotes via three buying representatives: a female buyer, a male buyer, and a chatbot buyer. We tailor the messages to incorporate different recommendation conditions. Thereafter, we record and compare suppliers' responses. Table 1 summarizes the study design.

We select a sample of 3,960 products from 3,960 suppliers in the car accessories sector.[2] This sector, which is the backbone of China's industrial ascent (Hong and Einhorn 2018), has a large number of suppliers on 1688. Car-related products have also been studied to test price discrimination behavior in previous literature (Busse et al. 2017). In our sample, there are 14 product subcategories including, for example, automobile data recorders, car cameras, car MP3, vehicle displays, vehicle bluetooth headsets, vehicle bluetooth speakers, vehicle-mounted mobile holders, vehicle chargers, vehicle lockers, car vacuum cleaners, GPS locators, vehicle air purifiers, vehicle refrigerators, and vehicle-mounted inverters.[3] Each supplier usually sells a wide selection of products (e.g., a vehicle refrigerator in capacities of 6, 12, or 20 liters). From each supplier's listed products, we select a product

Table 1. Field Experiment Design

	Automation × recommendation condition								
	No recommendation			Human recommendation			AI recommendation		
Design	Chatbot	Female	Male	Chatbot	Female	Male	Chatbot	Female	Male
Planned sample size	440	440	440	440	440	440	440	440	440
Actual sample size	440	439	437	435	436	439	440	439	439

Notes. The planned sample size was 3,960—that is, 440 suppliers per treatment arm. The actual sample size is 3,944 after excluding unavailable listings.

model that is the most common and standard in the market. Suppliers are randomly assigned to one of the nine (3 × 3) treatment arms. Consequently, we obtain 1,320 suppliers per buyer type, 1,320 suppliers per recommendation condition, and 440 suppliers per treatment arm. This means that each supplier is quoted only once.

All our studied products are commodity products. Relative to noncommodities that are custom and unique, commodities are standard and basic goods. One might question that whether procuring standard commodities requires buyers to have extensive expertise in product specifics. Our interviews with several highly experienced trading managers confirm that buying commodity products also requires significant professional knowledge such as product materials, size, functionality, and after-sales service, which enables suppliers to exert in-depth communications and negotiations. Their exact interview quotes are summarized in Table EC.2 in the online appendix. On the other hand, when procuring noncommodity products, chatbots might be less knowledgeable in product specifics due to their uniqueness. Therefore, the estimated effect of automation for noncommodities products might be larger than the effect identified in our study.

In order to ensure that suppliers are randomly assigned to treatment arms, we conduct a randomization check across the following supplier characteristics: (1) membership status (i.e., the number of years that the supplier has been an elite member), (2) credibility (i.e., the supplier's credibility based on the Alibaba credit system), (3) number of transactions in the past 90 days, (4) number of buyers in the past 90 days, (5) repeat purchase rate in the past 90 days, (6) refund rate in the past 90 days, (7) listed price of the selected product, (8) trading volume of the selected product in the past 30 days; (9) number of reviews for the selected product, and (10) review rating for the selected product. Table 2 presents the summary statistics of these variables. Furthermore, the p-values in Table 3 are all larger than 0.05, which ensures the randomized assignment.

5.2. Study Procedure

Buyers' characteristics (male, female, or chatbot) are signaled by their names and profile pictures.[4] The buyers sent price inquiries to the selected suppliers during the period December 18, 2019, to January 20, 2020.[5] Each message asks for a price quote per unit for 1,000 units of the preselected product. The message content varies based on the recommendation conditions. In the "no recommendation" condition, the buyer includes the most basic information in the inquiry message without indicating any human or AI recommendation. In particular, all buyers in this condition sent a message that said, "Hello, I am [a procurement manager or a chatbot buyer]. We are interested in your product: [the specific product name and link of this product]. Could you please quote us your best price per piece for an order of 1,000 units?" The AI chatbot buyers disclose their machine identity in order to comply with China's regulation regarding AI (Laskai and Webster 2019). Quoting a price including the packaging fee is the industry norm. In order to ensure that the quoted prices are not confounded by the value-added tax or shipping fee, the buyers ask suppliers to quote a price excluding these fees. The original inquiry messages in the field experiment are in Chinese and are carefully translated and presented in Figure EC.1 in the online appendix.

In the "human recommendation" condition, the buyer discloses that the supplier is recommended by a peer. In the inquiry message, the buyer signals a human recommendation prior to requesting the price quote: "Your company was recommended to us by a peer." We follow the common practice and the industry norm to not include the peers' name in the inquiry message.[6] In the "AI recommendation" condition, the buyer reveals that the supplier is recommended by AI's market search and data analysis: "Your company was recommended to us by an AI system's market information collection and data processing."

Within a week after the inquiry, we record and compare the initial price quotes.[7] We received 1,807 responses that included a price quote from the 3,944 suppliers that we sent messages to.

6. Results

In this section, we study the effect of automation and smartness on suppliers' price quoting strategy. We

Table 2. Summary Statistics

		Membership	Credibility	No. of transactions	No. of buyers	Repeat purchase rate	Refund rate	Listed price	No. of reviews	Review rating	Trading volume	Observations
Chatbot		4.62	3.26	503.8	170.0	28.63	5.88	140.9	25.89	2.46	205.9	1,320
		(3.28)	(0.90)	(1,759)	(482.2)	(18.19)	(10.01)	(202.3)	(155.5)	(2.47)	(1,940)	
Female		4.47	3.24	597.4	174.9	27.47	6.50	142.0	18.54	2.41	166.3	1,320
		(3.08)	(0.93)	(2,959)	(529.6)	(17.52)	(11.57)	(198.4)	(102.4)	(2.47)	(1,625)	
Male		4.44	3.20	536.6	171.6	27.58	6.50	140.2	33.96	2.48	140.1	1,320
		(3.12)	(0.92)	(2,144)	(495.6)	(16.96)	(14.28)	(197.6)	(391.1)	(2.47)	(1,590)	
	N	4.79	3.29	502.1	163.7	29.01	5.62	139.7	32.24	2.51	340.5	440
		(3.46)	(0.91)	(1,940)	(428.3)	(18.40)	(9.17)	(205.7)	(194.4)	(2.48)	(3,132)	
Chatbot	H	4.62	3.26	494.1	169.7	29.07	6.08	133.9	25.24	2.35	121.5	440
		(3.39)	(0.93)	(1,391)	(477.7)	(18.68)	(11.25)	(191.8)	(157.7)	(2.47)	(650.4)	
	A	4.45	3.23	515.3	176.4	27.80	5.93	149.1	20.20	2.51	155.8	440
		(2.98)	(0.85)	(1,896)	(535.6)	(17.48)	(9.51)	(209.1)	(99.68)	(2.46)	(1,020)	
	N	4.47	3.25	492.0	167.4	26.12	7.09	132.7	21.84	2.42	145.6	440
		(3.05)	(0.95)	(1,799)	(456.1)	(16.88)	(12.6)	(173.6)	(148.6)	(2.48)	(1,057)	
Female	H	4.50	3.23	683.3	174.2	28.40	5.95	153.3	20.96	2.41	121.2	440
		(3.20)	(0.97)	(3,516)	(514.6)	(18.55)	(10.13)	(215.2)	(81.47)	(2.47)	(743.8)	
	A	4.44	3.23	617.0	183.2	27.90	6.45	140.0	12.83	2.40	232.1	440
		(2.98)	(0.87)	(3,269)	(608.0)	(17.05)	(11.77)	(204.0)	(52.30)	(2.47)	(2,501)	
	N	4.40	3.18	523.1	165.2	27.97	6.57	141.1	30.97	2.58	106.2	440
		(2.82)	(0.94)	(1,743)	(439.1)	(16.50)	(13.11)	(193.9)	(181.7)	(2.48)	(824.3)	
Male	H	4.43	3.19	632.2	171.5	27.50	6.29	140.1	41.95	2.34	105.9	440
		(3.14)	(0.95)	(2,953)	(489.7)	(17.52)	(10.60)	(197.3)	(636.1)	(2.47)	(892.2)	
	A	4.51	3.24	454.3	178.2	27.28	6.64	139.5	28.97	2.53	208.2	440
		(3.02)	(0.87)	(1,429)	(552.6)	(16.88)	(18.13)	(202.0)	(147.7)	(2.47)	(1,443)	

Note. N, H, and A represent no recommendation, human recommendation, and AI recommendation, respectively.

Table 3. Randomization Check (p-Value)

				Chatbot			Female			Male		
	C vs. F	C vs. M	F vs. M	N vs. H	N vs. A	H vs. A	N vs. H	N vs. A	H vs. A	N vs. H	N vs. A	H vs. A
Membership	0.22	0.15	0.83	0.48	0.13	0.43	0.89	0.88	0.77	0.87	0.56	0.70
Credibility	0.51	0.09	0.30	0.66	0.34	0.62	0.86	0.82	0.97	0.89	0.34	0.42
No. of transactions	0.32	0.67	0.55	0.94	0.92	0.85	0.31	0.48	0.77	0.51	0.52	0.26
No. of buyers	0.80	0.93	0.87	0.84	0.70	0.85	0.84	0.67	0.81	0.84	0.70	0.85
Repeat purchase rate	0.10	0.13	0.87	0.96	0.32	0.30	0.06	0.12	0.68	0.68	0.54	0.85
Refund rate	0.14	0.20	1.00	0.51	0.62	0.83	0.14	0.44	0.50	0.73	0.94	0.72
Listed price	0.89	0.93	0.82	0.67	0.50	0.26	0.12	0.57	0.35	0.94	0.90	0.96
No. of reviews	0.15	0.49	0.17	0.56	0.25	0.57	0.91	0.23	0.08	0.73	0.86	0.68
Review rating	0.65	0.78	0.46	0.34	1.00	0.33	0.97	0.91	0.94	0.17	0.80	0.26
Trading volume	0.57	0.28	0.63	0.15	0.24	0.55	0.69	0.51	0.37	1.00	0.20	0.21

Notes. C, F, and M represent chatbot buyer, female buyer, and male buyer, respectively. N, H, and A represent no recommendation, human recommendation, and AI recommendation, respectively.

examine the effect of automation by comparing the price quotes between female (or male) buyers and chatbot buyers in Section 6.1, the effect of smartness by comparing the price quotes between the no recommendation and AI recommendation conditions in Section 6.2, and the joint effect of automation and smartness by comparing the price quotes between female (or male) buyers under the no recommendation condition and chatbot buyers under the AI recommendation condition in Section 6.3.

6.1. Effect of Automation

In a B2B setting, it is an industry norm and a common practice that suppliers privately quote a lower price than their publicly listed prices (Cui et al. 2020). In order to conduct a fair comparison of the amount of price discount offered by suppliers, we follow previous literature (Cui et al. 2020) to compare the price discount percentage relative to the listed price:

$$\mathit{Discount} = 100\% \times \left(\frac{\text{Listed Price} - \text{Supplier's Quoted Price}}{\text{Listed Price}}\right). \tag{1}$$

6.1.1. Automation Without Smartness.

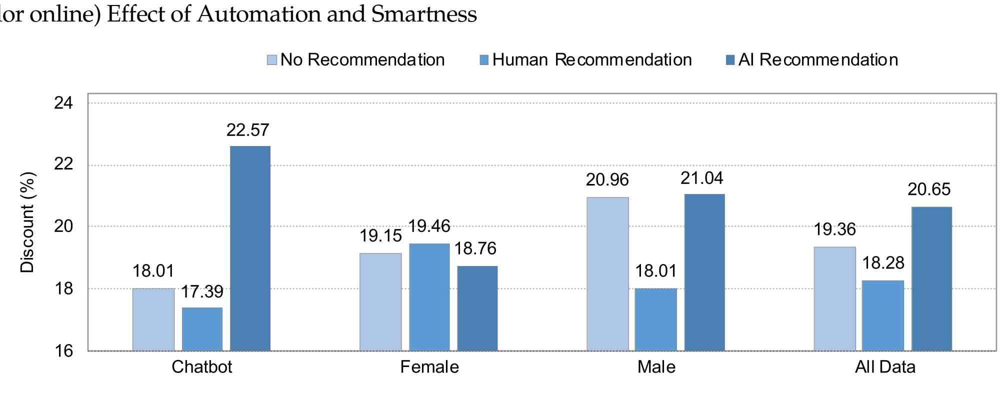
We first focus on the no recommendation condition and investigate the effect of automation on suppliers' price quoting strategy. Panel A of Table EC.3 in the online appendix presents the summary statistics of the suppliers' price discounts for chatbot, female, and male buyers. Figure 2 presents a visual illustration. In particular, chatbot, female, and male buyers receive an average price discount of 18.01%, 19.15%, and 20.96%, respectively—that is, both female and male buyers receive a lower price quote than chatbot buyers. Moreover, the difference of the price discount between male and chatbot buyers is statistically significant ($p = 0.07$).

In addition, we formally examine the price difference between chatbot buyers and human buyers:

$$\mathit{Discount}_i = \alpha + \beta \mathit{Type}_i + \gamma \mathit{Controls}_i + \epsilon_i, \tag{2}$$

where Type_i is a categorical variable that represents whether a buyer is a chatbot, female, or male; $\mathit{Controls}_i$ is a vector of control variables regarding supplier characteristics, including membership status, number of transactions, listed price, repeat purchase rate, and number of reviews.

Figure 2. (Color online) Effect of Automation and Smartness



The estimation results are presented in the first column of Table 4, where the omitted buyers' type is the chatbot group. The coefficients of Female (Male) represent the additional price discounts offered to female (male) buyers relative to chatbot buyers. The coefficient of Male is weakly positively significant ($p < 0.1$), which implies that the supplier quotes a significantly lower wholesale price to human, particularly male, buyers than chatbot buyers, which weakly supports Hypothesis 1. We conduct several analyses in order to confirm the robustness of this coefficient: a combined regression with all the observations in Section 7.1 and an analysis with time fixed effects in Section 7.2. All these analyses support Hypothesis 1. In other words, the implementation of pure automation does not help buyers and can even backfire in a procurement setting. This is because a chatbot buyer, due to its autonomous and unsmart nature, signals a higher willingness to pay than human buyers, and human suppliers are less interested in building a professional relationship with a chatbot buyer.

6.1.2. Automation Under Smartness. Next, we discuss the effect of automation on suppliers' pricing strategy in the presence of smartness. Panel C of Table EC.3 in online appendix presents the summary statistics of the suppliers' price discounts for chatbot, female, and male buyers under the "AI recommendation" condition. In particular, chatbot, female, and male buyers, when equipped with smart recommendations, receive a price discount of 22.57%, 18.76%, and 21.04%, respectively. The difference between chatbot buyers (having automation and smartness) and human buyers (only smartness) is significant (p-value = 0.02). We also test this effect by using Equation (2) and report the results in column III of Table 4. We can see that chatbot buyers receive a significantly lower price quote than (particular female) buyers when smartness is adopted (p-value < 0.05), thereby supporting Hypothesis 3(a). In other words, automation is helpful in the presence of smartness. This finding echoes the conjecture of Boute and Van Mieghem (2021): in the presence of smart controls, it is conceivable that trust in the algorithm increases and risk is contained, which opens up the possibility of higher levels of autonomy.

6.1.3. Automation Under Human Recommendation. In addition, from column II of Table 4, we can observe that under the human recommendation condition, the coefficient of Female is weakly positively significant ($p < 0.1$), which implies that the supplier quotes a significantly lower wholesale price to human—particularly female—buyers than chatbot buyers. In other words, the implementation of automation still results in a higher price even when human recommendations are adopted. This highlights the importance of having smart controls when implementing automation in a procurement setting.

6.1.4. Gender. A natural extension that we can study is whether suppliers price discriminate based on buyers' gender. Table EC.3 in the online appendix and Figure 2 summarize the price discounts for female and male buyers under different recommendation conditions. In the no recommendation condition, we find that female and male buyers receive an average price discount of 19.15% and 20.96%, respectively; there is no statistically significant difference between male and female buyers ($p = 0.26$). This result also holds under the human recommendation condition and the AI recommendation condition. We also formally test the price difference based on buyers' gender:

$$Discount_i = \alpha + \beta Gender_i + \gamma Controls_i + \epsilon_i, \qquad (3)$$

where $Gender_i$ is a binary variable that equals one when the buyer is male or equals zero when the buyer is female. The estimations are presented in Table 5, where the omitted variable is Female; the coefficient

Table 4. Effect of Automation on Price Quote

	Dependent variable: *Discount*			
	No recommendation (I)	Human recommendation (II)	AI recommendation (III)I	All data (IV)
Male	0.028*	0.009	−0.015	0.009
	(0.016)	(0.014)	(0.016)	(0.009)
Female	0.010	0.026*	−0.037**	0.004
	(0.016)	(0.014)	(0.016)	(0.009)
Supplier Controls	Yes	Yes	Yes	Yes
Observations	595	665	547	1,807
R^2	0.047	0.054	0.031	0.033

Notes. This table tests the effect of automation on the price discount for four different samples. Results from columns I–III are based on the sample under the no recommendation condition, under the human recommendation condition, and under the AI recommendation condition, respectively. Results from column IV are based on the full sample.
*$p < 0.1$; **$p < 0.05$.

of Male represents the additional price discount offered to male buyers, compared with female buyers, which is not significant.

We show that there is no gender discrimination in the B2B procurement context. This result differs from the findings in the business-to-consumer (B2C) settings—that female consumers receive a higher price than male consumers because they are perceived to be less knowledgeable (Busse et al. 2017, Mejia and Parker 2021). Unlike B2C consumers whose purchasing decisions are often emotional and irrational, B2B buyers are professional procurement managers whose job is to negotiate with suppliers. Consequently, male and female procurement managers are perceived to have a similar willingness to pay (Goldberg 2018).

6.2. Effect of Smartness

6.2.1. AI Recommendation. We investigate how AI recommendation affects suppliers' price quoting strategy for chatbot, female, and male buyers, respectively. Table EC.4 in the online appendix summarizes the suppliers' price discounts for chatbot, female, and male buyers. Figure 2 presents an illustration. In particular, for chatbot buyers, the average price discount is 18.01% under the no recommendation condition and 22.57% under the AI recommendation condition, respectively. This implies that, compared with the no recommendation condition, AI recommendation significantly reduces the wholesale price quoted for chatbot buyers ($p = 0.01$). For female (male) buyers, the average price discount is 19.15% (20.96%) under the no recommendation condition and 18.76% (21.04%) under the AI recommendation condition, respectively. This implies that, compared with the no recommendation condition, AI recommendation cannot reduce the wholesale price quoted for female or male buyers.

We also formally examine the impact of recommendation conditions on price discounts:

$$Discount_i = \alpha + \beta Condition_i + \gamma Controls_i + \epsilon_i, \qquad (4)$$

where $Condition_i$ is a binary variable that represents the no recommendation condition or AI recommendation condition. The estimation results are presented in Table 6, where the omitted variable is the no recommendation condition.

The coefficient of AI recommendation represents the additional price discount that a buyer can obtain when signaling that the supplier is recommended by an AI algorithm compared with the no recommendation condition. The coefficient of AI recommendation is significant and positive ($p < 0.05$) for a chatbot buyer but not significant for female or male buyers. These results confirm that a smart recommendation is effective for lowering prices for chatbot buyers but not for human buyers, thereby supporting Hypothesis 2. Because of AI's ability to search and learn about market information, suppliers believe that chatbot buyers have a lower reservation price and a lower willingness to pay, and therefore reduce their wholesale price. However, human buyers are deemed to not fully follow algorithms' recommendations and would not be able to benefit from claiming the use of AI recommendations.

In summary, having a purely autonomous process leads to a higher wholesale price, putting buyers in a disadvantageous position, whereas having a smart control leads to a lower wholesale price. In other words, automation is not very valuable when implemented without smart controls, which suggests that building smartness is necessary before high levels of autonomy are to be considered.

6.2.2. Human Recommendation. Recall that we introduced a treatment with human recommendation in order to disentangle the pure impact of having any recommendation at all and the pure impact of having smart controls. Next, we study this human recommendation effect. If this effect is weak, then we can conclude that the effect of AI recommendation stems from having smart controls. Table EC.4 in the online appendix and Figure 2 indicate that the average price discount for chatbot buyers is 18.01% under the no recommendation condition and 17.39% under the human recommendation condition, respectively. We perform a t test and find that the difference is

Table 5. Effect of Gender on Price Quote

	Dependent variable: *Discount*			
	No recommendation (I)	Human recommendation (II)	AI recommendation (III)	All data (IV)
Male	0.020	−0.017	0.022	0.006
	(0.016)	(0.014)	(0.015)	(0.009)
Supplier controls	Yes	Yes	Yes	Yes
Observations	410	453	395	1,258
R^2	0.046	0.040	0.045	0.033

Notes. This table tests the effect of gender on the price discount for four different samples. Results from columns I–III are based on the sample under the no recommendation condition, under the human recommendation condition, and under the AI recommendation condition, respectively. Results from column IV are based on the full sample.

Table 6. Effect of Smartness on Price Quote

	Dependent variable: *Discount*			
	Chatbot (I)	Female (II)	Male (III)	All data (IV)
AI recommendation	0.042**	−0.003	0.000	0.012
	(0.017)	(0.015)	(0.015)	(0.009)
Supplier controls	Yes	Yes	Yes	Yes
Observations	337	421	384	1,142
R^2	0.040	0.032	0.058	0.033

Notes. This table tests the effect of smartness on price discounts for four different samples. Results from columns I–III are based on the sample of chatbot, female, and male buyers, respectively. Results from column IV are based on the full sample.
$^{**}p < 0.05$.

insignificant ($p = 0.68$). We find a similar result for human buyers that human recommendations cannot help human buyers lower the wholesale price received from suppliers. We conjecture that this is driven by two reasons. First, because of humans' limitations in information processing (Payne 1982, Payne et al. 1988), the supplier may believe that the peer is not capable of providing a valid recommendation. Second, suppliers often distrust buyers when they present soft social information like recommendations (Özer et al. 2014, Cui et al. 2020). Therefore, human recommendations, in general, are less effective in changing suppliers' belief regarding buyers' willingness to pay and their pricing strategy.

6.3. Joint Effect of Automation and Smartness

Thus far, we have demonstrated that automation brings a negative effect to buyers, whereas smartness brings a positive effect. Next, we study the joint value of automation and smartness. Table EC.5 in the online appendix summarizes the price discounts received with and without automation and smartness. This table reveals that autonomous chatbot buyers, when informing suppliers that they are selected by smart algorithms, receive a lower wholesale price quote than human (particularly female) buyers without any recommendation ($p = 0.05$). We also formally test this joint effect:

$$Discount_i = \alpha + \beta Joint_i + \gamma Controls_i + \epsilon_i, \tag{5}$$

where $Joint_i$ is a categorical variable that represents a chatbot buyer aided by AI recommendations, a female buyer without recommendations, or a male buyer without recommendations. The estimation results are presented in Table 7, where the omitted variable is when a buyer is equipped with both automation and smartness. Table 7 reveals that having both automation and smartness can effectively reduce the price for (particularly female) buyers ($p < 0.05$). This implies that we should improve the levels of autonomy and smartness simultaneously.

Table 7. Joint Effect of Automation and Smartness on Price Quote

	Dependent variable: *Discount*
Male	−0.014
	(0.018)
Female	−0.034**
	(0.017)
Supplier controls	Yes
Observations	562
R^2	0.034

Notes. This table tests the joint effect of automation and smartness on price discount. Results are based on the sample of chatbot buyers under AI recommendation pooled with human buyers without recommendation.
$^{**}p < 0.05$.

We summarize the results of buyers' AI strategies in our framework in Figure 3. First, when a buyer adopts pure automation but without smartness by moving from the Human Buyer zone to the Automated zone, the buyer suffers from automation by receiving a higher price. However, when the buyer adopts automation in the presence of smartness by moving from the Smart zone to the Automated+Smart zone, the buyer benefits from automation by receiving a lower price. Second, when a human buyer is equipped with a smart algorithm by moving from the Human Buyer zone to the Smart zone, smartness does not change the price. However, when a chatbot buyer incorporates a smart recommendation system by moving from the Automated zone to the Automated+Smart zone, smartness becomes helpful in reducing the price. Last, when the buyer adopts both automation and smartness by moving from the Human Buyer zone to the Automated+Smart zone, the buyer can also benefit from receiving a lower price quote.

7. Robustness Check

In this section, we conduct additional analysis to check the robustness of our key insights regarding the individual and joint effects of automation and smartness.

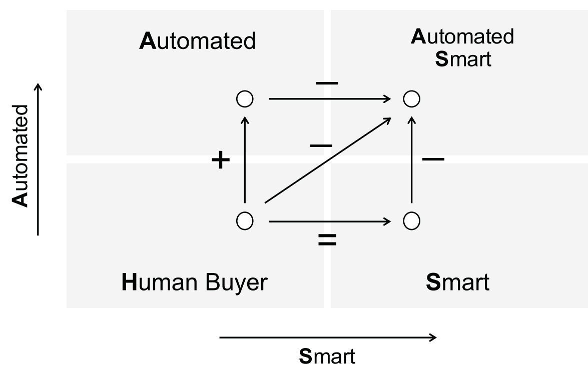
7.1. Combined Regression

In our main analysis, we studied the effect of automation and the effect of smartness in separate regressions. To show the robustness of our results, we now combine all observations with all nine experiment conditions into a single regression:

$$\begin{aligned} Discount_i = \alpha + \beta_0 Type_i + \beta_1 Recommendation_i \\ + \beta_2 Type_i \times Recommendation_i + \gamma Controls_i + \epsilon_i, \end{aligned} \tag{6}$$

where $Recommendation_i$ is a categorical variable that represents the no recommendation condition, human

Figure 3. Framework and Results of Automation and Smartness in Procurement



Note. +, −, and = represent higher, lower, and similar price quotes, respectively.

recommendation condition, or AI recommendation condition.

Table EC.6 in the online appendix reports the estimation results, where the omitted buyers' type is the chatbot buyer and the omitted recommendation condition is the no recommendation condition. This table shows three observations. First, the coefficient of Male is weakly positively significant ($p < 0.1$). That is, chatbot buyers receive a significantly higher price quote than human buyers without recommendations; this is consistent with our result on the effect of automation without smartness, thereby supporting Hypothesis 1. Second, the coefficient of AI Recommendation is positively significant ($p < 0.05$). That is, AI recommendations help chatbot buyers receive a lower price quote; this is consistent with our result on the effect of smartness on chatbot buyers, thereby supporting Hypothesis 2(a). Third, the coefficients of Male × Human Recommendation and Female × Human Recommendation are not significant, but the coefficients of Male × AI Recommendation and Female × AI Recommendation are weakly negatively significant ($p < 0.1$). That is, human recommendations cannot reduce price discrimination against chatbot buyers, but AI recommendations are effective in reducing such price discrimination; these results are consistent with our main result on the effect of automation under smartness, thereby supporting Hypothesis 3(a).

7.2. Time Fixed Effects

We test our key results by including the time fixed effects at two levels: the inquiries' request date and the inquiries' quote date. Because different suppliers may take different amounts of time to respond to a price inquiry, the quote dates for the same batch of inquiries might differ. To ensure rigor and robustness, we test for both time fixed effects.

The estimation results with time fixed effects are shown in Tables EC.7 and EC.8 in the online appendix. As shown in column I of Panel A in Tables EC.7 and EC.8, the coefficients of Male are weakly positively significant ($p < 0.1$), which implies that suppliers quote a lower wholesale price to human—particularly male—buyers than chatbot buyers in the absence of smartness. However, column III of Panel A in Tables EC.7 and EC.8 shows that the coefficients of Female are negatively significant ($p < 0.05$), which implies that chatbot buyers receive a significantly lower price quote than (particularly female) buyers when smartness is adopted. This is consistent with our main results regarding the effect of automation, thereby supporting Hypotheses 1 and 3(a).

As shown in Panel B of Tables EC.7 and EC.8, the coefficients of AI recommendation are positively significant ($p < 0.05$) for a chatbot buyer but not significant for female or male buyers. This is consistent with our main results regarding the effect of smartness, thereby supporting Hypotheses 2(a) and 2(b).

As shown in Panel C of Tables EC.7 and EC.8, having both automation and smartness can effectively reduce the price for (particularly female) buyers ($p < 0.05$). This is consistent with our main results regarding the joint effect of automation and smartness, thereby supporting Hypothesis 3.

7.3. Simulated AI Recommendation

In our design, the signal that the supplier is recommended by AI is randomly assigned to each supplier. In practice, it may be true that only some (high-quality) suppliers would receive such signals. In order to simulate such a scenario, we follow our collaborative company's guide to score 10 supplier/product characteristics (as shown in Section 5) according to how much they determine buyers' perceptions of suppliers' quality. We then apply these scores to compute the perceived quality of each supplier. We define suppliers above the average score as high-quality suppliers and the rest as low-quality suppliers. We then simulate an AI recommendation condition where buyers equipped with AI recommendation only contact the high-quality suppliers. In this way, we can simulate the situation where only high-quality suppliers are selected by AI algorithms and approached by buyers.

We next identify the effect of smartness in practice by comparing suppliers' wholesale prices across the no recommendation condition and the simulated AI recommendation condition. The average supplier quality score is 0.25 under the no recommendation condition, which is lower than 0.31 under the simulated AI recommendation condition, confirming that only high-quality suppliers are included in the sample.

Table EC.9 in the online appendix summarizes the suppliers' price discounts for chatbot, female, and male buyers under the simulated AI recommendation condition and the no recommendation condition. In particular, for chatbot buyers, the average price discount is 18.01% without recommendations and 23.91% with the simulated AI recommendation. This means that the simulated AI recommendation significantly reduces the wholesale price quoted for chatbot buyers ($p = 0.01$). However, consistent with our main result, the simulated AI recommendation cannot reduce the wholesale price quoted for human buyers; for female (male) buyers, the average price discount is 19.15% (20.96%) without AI recommendation and 18.76% (21.34%) with simulated AI recommendation, respectively.

We also formally examine the impact of the simulated AI recommendation on price by

$$Discount_i = \alpha + \beta AIRecommendation_i + \gamma Controls_i + \epsilon_i, \tag{7}$$

where $AIRecommendation_i$ is a binary variable that represents the no recommendation condition or the simulated AI recommendation condition. The estimation results are presented in Table EC.10 in the online appendix, where the coefficient of simulated AI recommendation is significant ($p < 0.05$) and positive for chatbot buyers but not significant for human buyers. These results again confirm that a smart recommendation is effective in lowering prices for chatbot buyers but not for human buyers.

7.4. Heterogeneous Treatment Effect

We next test whether any supplier or product characteristics (i.e., the number of transactions, listed price, review rating, and trading volume) could change the effect of automation and smartness.

For the effect of automation, we use the following estimation:

$$Discount_i = \alpha + \beta_1 Type_i + \beta_2 Moderator_i + \beta_3 Moderator_i \times Type_i + \gamma Controls_i + \epsilon_i, \tag{8}$$

where β_2 represents how a supplier or product characteristic moderates the effect of automation on the wholesale price quotes. $Moderator_i$ represents the number of transactions for the supplier, product's listed price, review rating, or trading volume. $Controls_i$ includes all other control variables except for the tested moderator. Table EC.11 in the online appendix presents the estimation results.

For the effect of smartness, we use the following estimation. Table EC.12 in the online appendix presents the estimation results.

$$Discount_i = \alpha + \beta_1 Condition_i + \beta_2 Moderator_i + \beta_3 Moderator_i \times Condition_i + \gamma Controls_i + \epsilon_i. \tag{9}$$

For the joint effect of automation and smartness, we use the following estimation. Table EC.13 in the online appendix presents the estimation results.

$$Discount_i = \alpha + \beta_1 Joint_i + \beta_2 Moderator_i + \beta_3 Moderator_i \times Joint_i + \gamma Controls_i + \epsilon_i. \tag{10}$$

Overall, none of the studied characteristics (except for the listed price) has an impact on the individual and joint effects of automation and smartness. A higher listed price weakens the effectiveness of smartness for chatbot buyers, probably because suppliers are more prudent when selling expensive products and are less likely to regard AI-driven price quotations as a serious negotiation.

8. Conclusion

AI is transforming the very nature of procurement—how to operate and how to interact with supply chain partners. According to the Roland Berger's survey on Fortune Global 500 companies, 67% of chief procurement managers rank AI among their top three priorities for the next 10 years (Marlinghaus 2018). Thus, we explore how a buyer's AI strategy would affect the wholesale price received from suppliers. By designing and conducting a randomized field experiment, we find that having a purely autonomous request-for-quotation process results in a higher price quote—that is, suppliers price discriminate a not-so-smart chatbot buyer. Furthermore, we find that introducing a smart control—signaling that the supplier is recommended by a smart system—can reduce the price quoted for chatbot buyers. Last, we show that automation and smartness can jointly reduce the wholesale price quoted by suppliers, thereby highlighting the potential of a smart automation in procurement.

8.1. Managerial Implications

Our work can provide implications for the management of B2B platforms and buyers aiming to embrace AI in procurement.

For procurement companies, our study provides strategic guidance for them moving toward in automating their standard and routine processes, such as price quoting and new supplier selection. In fact, excessive and duplicated processes can comprise up to 40%–60% of a procurement company's capacity (Papa et al. 2019). AI is capable of unlocking employees' workload for more strategic pursuits, thereby transforming the transaction-oriented procurement toward the strategy-oriented procurement, which is known as Procurement 4.0 (Loo and Santhiram 2018, Marlinghaus 2018). Our results indicate that in addition to the advantages of AI in releasing workload, AI also creates value by reducing the wholesale price.

Our findings further shed light on how to implement AI strategies for procurement companies. First, in the absence of AI smartness, automation alone can backfire. This implies that a company should first initiate and strengthen its smart control algorithms, such as improving the data quality, analytics capability, and prediction accuracy of its recommendation systems, before considering a high level of autonomy. Second, when implementing AI smartness, in order to ensure the effectiveness of smartness, companies should help their employees get along with AI—that is, reduce their biases and enhance their trust in algorithms. Third, our results suggest that, to obtain the most value from AI, a company should eventually adopt automation and smartness together in procurement. To conclude, our work unlocks the optimal steps for buyers to develop AI in procurement: first build smartness, then sharpen the effectiveness of smartness, and finally build automation.

For online trading platforms, our work provides the following managerial implications. Platforms such as Alibaba have initiated the automatic request-for-quotation systems as a premium service provided for buyers (Alibaba 2020b). Our study suggests that such automatic systems should be facilitated with a smart supplier identification system in order to reduce the wholesale price charged to downstream buyers and reducing the inefficiencies of supply chains arising from the double marginalization issue. In addition, our result highlights that the value of such a smart supplier identification system can be much more significant than human recommendation systems that often facilitate peer recommendations between buyers.

AI has become the universal engine of execution, driving the explosive growth of new business models, but there is limited empirical research to understand and quantify how AI works and when it is the most powerful (Terwiesch 2019, Terwiesch et al. 2020). Our study is among the first to research how AI creates and delivers value in a critical business process, namely, procurement. We hope that our paper will serve as a stepping stone for future AI-related business research.

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Endnotes

[1] We discuss our interviews in detail in Section 5.1.

[2] The sample size is determined by the statistics power calculation. By running a pilot experiment with 40 chatbot buyers, 40 female buyers, and 40 male buyers under the no recommendation, human recommendation, and AI recommendation conditions, respectively, we compare the price discounts across treatment arms and obtain their effect size. Based on a two-sided t test with a power level of 0.8 and a significance level of 0.05, we require 99 observations with a 0.40 effect size between chatbot and female buyers under the no recommendation condition, 38 observations with a 0.65 effect size between chatbot and male buyers under the no recommendation condition, 393 observations with a 0.20 effect size between the no recommendation and human recommendation conditions, and 164 observations with a 0.31 effect size between the no recommendation and AI recommendation conditions. We determined the sample size per treatment arm to be 440 (>393) to further ensure the validity of the experiment.

[3] In order to explore new markets, the trading company specifies these 14 product categories from which our research team independently selects the supplier and product sample. We validate with the company that there is no previous supplier in the sample.

[4] The chatbot buyer has a standard robotic profile picture. We edit the photos of human buyers using Photoshop to ensure their photos have a similar attractiveness.

[5] Our experiment (which was from December 18, 2019 to January 20, 2020) was conducted before the outbreak of COVID-19 (which caused the first lockdown measure to take place on January 23, 2020) and before the Chinese New Year (which was from January 24, 2020, to January 30, 2020). As a result, our experiment was not affected by the pandemic or the holiday.

[6] In our human recommendation message design, a buyer does not provide the name of the peer who recommended the supplier, and it has been validated that such a design format conforms to norms regarding both confidentiality and industry practice (Cui et al. 2020).

[7] Following the literature (Ayres and Siegelman 1995, Busse et al. 2017, Cui et al. 2020), our study focuses on the initial price quote because (1) the initial price quote reflects the supplier's perception of the buyer's willingness to pay; (2) suppliers could easily lose customers to competitors if they do not offer an attractive initial price in an online trading platform; and (3) the initial price quote, unlike a second price quote or price concession, is not confounded by any bargaining or negotiation techniques.

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