AI and Procurement

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In a world advancing toward Artificial Intelligence (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. In this research, we study how buyers' usage of AI affects suppliers' price quoting strategies. Specifically, we study the impact of automation—i.e., the buyer uses a chatbot to automatically inquire about prices instead of asking in person—and the impact of smartness—i.e., the buyer signals the usage of a smart AI algorithm in selecting the supplier. 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. 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. 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.

Key words: artificial intelligence, procurement, wholesale pricing, automation, smartness

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Forty-five percent of chief procurement officers are using, piloting, or planning to use AI.

—Deloitte global survey, 2018 (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, 2020). 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 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.*
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> —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 US—utilizes 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 utilize 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; Sun et al., 2020; Tan and Staats, 2020). Due to 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

AI Automation and Recommendation. Prior research indicates that automation creates value in inventory replenishment (Van Donselaar et al., 2010) and financial services (Acimovic et al., 2020; Köhler et al., 2011; Luo et al., 2019). 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., 2020); 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 (2020). 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 Boute and Van Mieghem's insights 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.

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, i.e., 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.

Further, 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

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

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—i.e., 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 usage.

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; Sun et al., 2020; Tan and Staats, 2020). 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., 2020); 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' 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 8 in the 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 out 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' usage 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.*

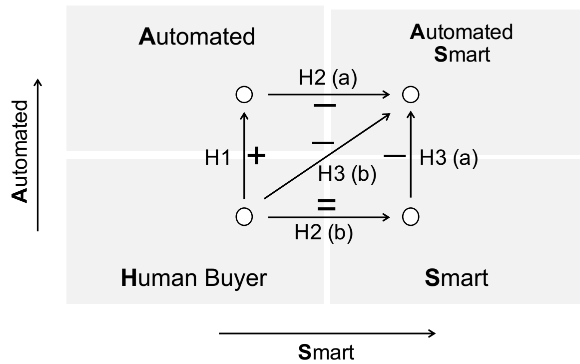
3.3. Automation and Smartness

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. And according to Hypothesis 2(b), human buyers may not fully follow the AI's recommendations due to their tendency to deviate from AI-instructed decisions. Therefore, suppliers will react to chatbot buyers' and ignore human buyers' usage 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 above 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.*

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.

We summarize the effect of automation and smartness on suppliers' price decisions in Figure 1. We follow Boute and Van Mieghem's (2020) framework 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 "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. Figure 4 in the appendix illustrates an example of a supplier's profile and product pages. 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, as depicted in Figure 4. 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 employ 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 6 in the 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.

Table 1: Field Experiment Design

Design	Automation × Recommendation Condition								
	No Recommendation			Human Recommendation			AI Recommendation		
	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.

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 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.

Note that all of our studied products are commodity products. Relative to non-commodities which 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

[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.

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 9 in the appendix. On the other hand, when procuring non-commodity products, chatbots might be less knowledgeable in product specifics due to their uniqueness. Therefore, the estimated effect of automation for non-commodities 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. Further, 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

[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.

Table 2: Summary Statistics

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

Notes. "No. of Trans." indicates the numbers of transactions. "Obs." represents the number of observations. N, H, and A represent no recommendation, human recommendation, and AI recommendation, respectively.

Table 3: Randomization Check (p-value)

	C vs F	C vs M	F vs M	Chatbot			Female			Male		
				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 Trans.	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. "No. of Trans." indicates the numbers of transactions. 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.

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 5 in the 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 examine the effect of automation in Section 6.1, the effect of smartness in Section 6.2, and the joint effect of automation and smartness 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:

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

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 10 in the 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-value = 0.07).

[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).

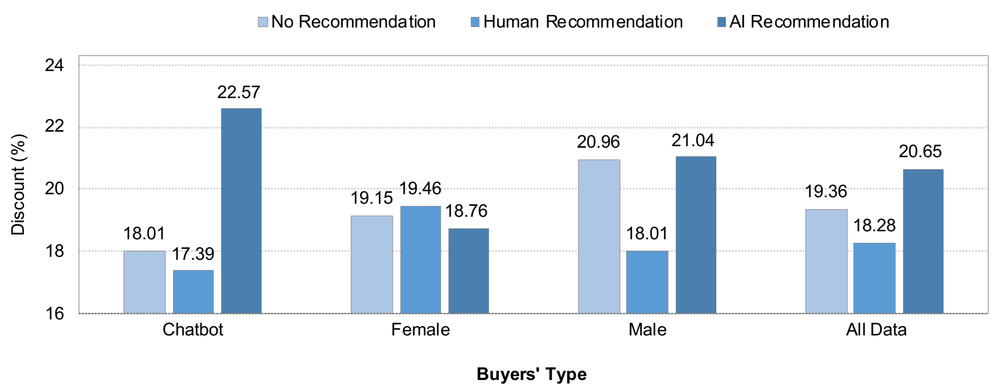
[7] Following the literature (Ayres and Siegelman, 1995; Busse et al., 2017; Cui et al., 2020), our study focuses on the initial price quote because (1) the initial price quote reflects the supplier's perception of the buyer's willingness to pay; (2) suppliers could easily lose customers to competitors 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.

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

$$Discount_i = \alpha + \beta Type_i + \gamma Controls_i + \epsilon_i, \tag{2}$$

where $Type_i$ is a categorical variable that represents whether a buyer is a chatbot, female, or male; $Controls_i$ 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: 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-value < 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. Note that 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.

Automation under Smartness. Next, we discuss the effect of automation on suppliers' pricing strategy in the presence of smartness. Panel C of Table 10 in the 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 (2020): 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.

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-value < 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.

Table 4: Effect of Automation on Price Quote

	Dependent Variable: Discount			
	No Recommendation I	Human Recommendation II	AI Recommendation III	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. $^{*}p < 0.1$; $^{**}p < 0.05$.

Gender. A natural extension that we can study is whether suppliers price discriminate based on buyers' gender. Table 10 in the 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-value $= 0.26$). 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,

$$Discount_i = \alpha + \beta Gender_i + \gamma Controls_i + \epsilon_i, \tag{3}$$

where $Gender_i$ is a binary variable that equals 1 when the buyer is male or equals 0 when the buyer is female. The estimations are presented in Table 5, where the omitted variable is Female; the coefficient of Male represents the additional price discount offered to male buyers, compared to female buyers, which is not significant.

Table 5: Effect of Gender on Price Quote

	Dependent Variable: Discount			
	No Recommendation	Human Recommendation	AI Recommendation	All Data
	I	II	III	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.

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, 2019). 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

AI recommendation. We investigate how AI recommendation affects suppliers' price quoting strategy for chatbot, female, and male buyers, respectively. Table 11 in the 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 to the "no recommendation" condition, AI recommendation significantly reduces the wholesale price quoted for chatbot buyers (p-value $= 0.01$). 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 to 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,

$$Discount_i = \alpha + \beta Condition_i + \gamma Controls_i + \epsilon_i, \tag{4}$$

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.

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. $^{**}p < 0.05$.

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 to the "no recommendation" condition. The coefficient of AI Recommendation is significant and positive (p-value < 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.

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 11 in the 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 insignificant (p-value $= 0.68$). 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, due to 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 while smartness brings a positive effect. Next, we study the joint value of automation and smartness. Table 12 in the 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-value $= 0.05$). 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-value < 0.05). This implies that we should improve the levels of autonomy and smartness simultaneously.

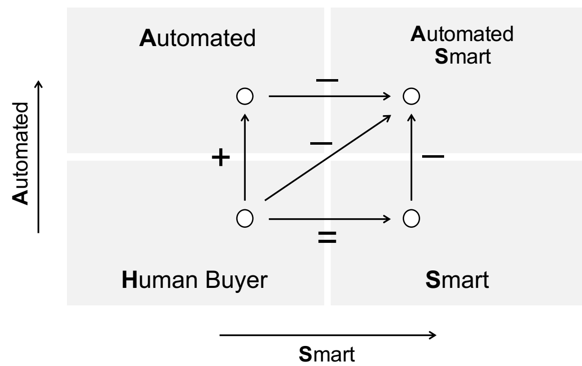
Table 7: Joint Effect of Automation and Smartness on Price Quote

	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,

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



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

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 separately. We now combine all observations 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 recommendation" condition, or "AI recommendation" condition.

Table 13 in the 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-value < 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-value < 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 negatively significant (p-value < 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 14 and 15 in the appendix. As shown in column I of Panel A in Tables 14 and 15, the coefficients of Male are positively significant (p-value < 0.1), which implies that suppliers quote a significantly lower wholesale price to human—particularly male—buyers than chatbot buyers in the absence of smartness. However, column III of Panel A in Tables 14 and 15 shows that the coefficients of Female are negatively significant (p-value < 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 Hypothesis 1 and Hypothesis 3(a).

As shown in Panel B of Tables 14 and 15, the coefficients of AI recommendation are positively significant (p-value < 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 Hypothesis 2(a) and Hypothesis 2(b).

As shown in Panel C of Tables 14 and 15, having both automation and smartness can effectively reduce the price for (particularly female) buyers (p-value < 0.05). This is consistent with our main results regarding the joint effect of automation and smartness, thereby supporting Hypothesis 3(b).

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 16 in the 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-value $=$ 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 17 in the appendix, where the coefficient of Simulated AI Recommendation is significant (p-value < 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 18 in the appendix presents the estimation results.

For the effect of smartness, we use the estimation below. Table 19 in the appendix presents the estimation results.

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

For the joint effect of automation and smartness, we use the estimation below. Table 20 in the 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. Further, 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.

Our study provides guidance for companies moving toward automating their standard and routine processes, such as price requests 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 (Marlinghaus, 2018; Loo and Santhiram, 2018). Our results indicate the great potential of these AI-related initiatives in procurement.

Our findings further shed light on how to implement AI strategies in procurement. 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 prediction accuracy of its recommendation systems, before considering a high level of autonomy. 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. Our work also provides managerial implications for online trading platforms aiming to embrace AI. 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 as well as reducing the inefficiencies of supply chains arising from the double marginalization issue.

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 et al., 2020; Terwiesch, 2019). 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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Appendix

Table 8: Supplier Quotes in Interviews on AI Recommendations

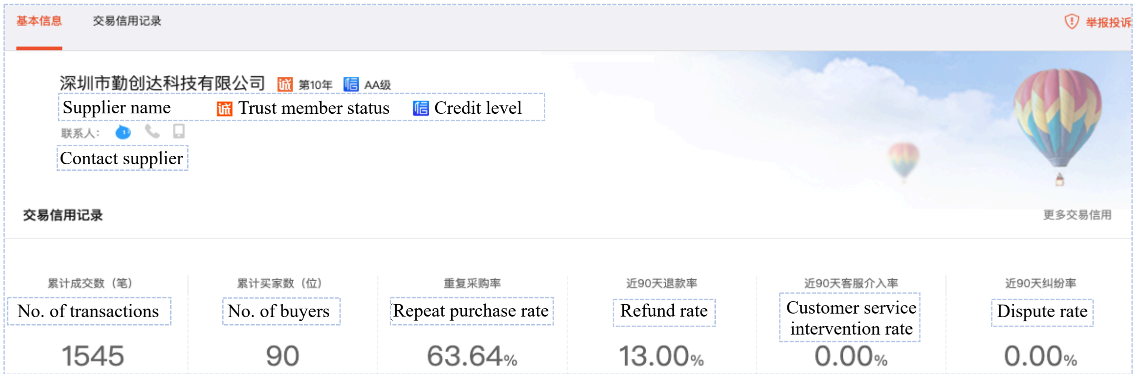
"*The AI recommendation system is known to be an effective tool for buyers to know about the market information. But for human buyers who have already had their own professional understanding and expertise in the market, I think that the AI recommendation will have little influence on them. For chatbots who are programmed bots without any knowledge, I believe in the influence that the AI recommendation system has on them.*"
"*If I receive an inquiry message with such an AI recommendation information from an autonomous chatbot, I will believe that the AI recommendation system is able to help the chatbot learn more market knowledge. But if I receive such a message from a human buyer, I don't believe that the AI recommendation system can dictate human decisions because they have their own judgment on the market.*"
"*I perceive that this AI recommendation will help the chatbot buyers lower their price, but fail to do so for the human buyers. Humans tend to follow their own beliefs to make decisions and therefore not heavily influenced by the system suggestions.*"
"*A chatbot will probably follow an AI recommendation, but a human is unlikely to strictly adhere to an AI recommendation. Thus, when I receive such an inquiry message from a chatbot, I tend to trust it; however, when I receive such an inquiry message from a human, I tend to ignore it.*"
"*I think that a chatbot is equipped with professional market knowledge when the chatbot sends an inquiry message with an AI recommendation information. But I think that a human buyer will rely on their own knowledge on the market rather than the knowledge collected by the AI system.*"
"*I believe in AI's capacity of collecting and learning market information. I believe that a chatbot will follow AI recommendation. But I don't believe that a human will strictly follow AI recommendation.*"
"*A human buyer often has rich training and work experience in procurement, which is more effective than the information collected by the AI recommendation system for better evaluating the market. That is, I perceive that an AI recommendation is only effective for a chatbot buyer.*"
"*Human buyers' knowledge, experience, and education background are more effective to help them obtain price advantages in negotiation than the information collected and learned by AI recommendation system. I only believe in the influence of AI recommendation on chatbot buyers rather than on human buyers.*"
"*I think that AI recommendation will help both the chatbot and human buyers learn more knowledge. Chatbots are used to automate repeated inquiring tasks. Human buyers have limited cognitive capacity on collecting and processing information, but AI can free up some of the human processing capacity. I believe that AI recommendation can help both of them learn more market knowledge.*"

Table 9: Supplier Quotes in Interviews on Chatbots' Knowledge in Product Specifics

"*The traditional chatbots simply repeat tasks without smart controls. They are not able to address complex requirements of B2B suppliers, who expect in-depth communications with buyers. For example, when a buyer sends a price inquiry for an automobile data recorder, the supplier may expect in-depth communications with the buyer regarding product specifics of their products, such as the mirror resolution (1080P or 720P), the screen type (12-inch IPS full touch screen or 10-inch non-touch screen), and the functionality (waterproof, night vision, or parking monitor).*"
"*Chatbots are effective to automate repeated inquiries and preprogrammed responses but they lack knowledge for different products from different suppliers. That is, the preprogrammed chatbot is not able to be equipped with professional knowledge, such as product materials, size, functionality, quality and after-sales services, in the same way as professional procurement managers. I expect that in the future, the B2B setting will need knowledgeable bots instead of chatbots.*"
"*The professional procurement managers often have professional education backgrounds, rich training and work experience in procurement, which chatbots do not possess. This experience is able to help them learn the best price in the market, which gives them a competitive edge in the inquiry and negotiation process with suppliers.*"

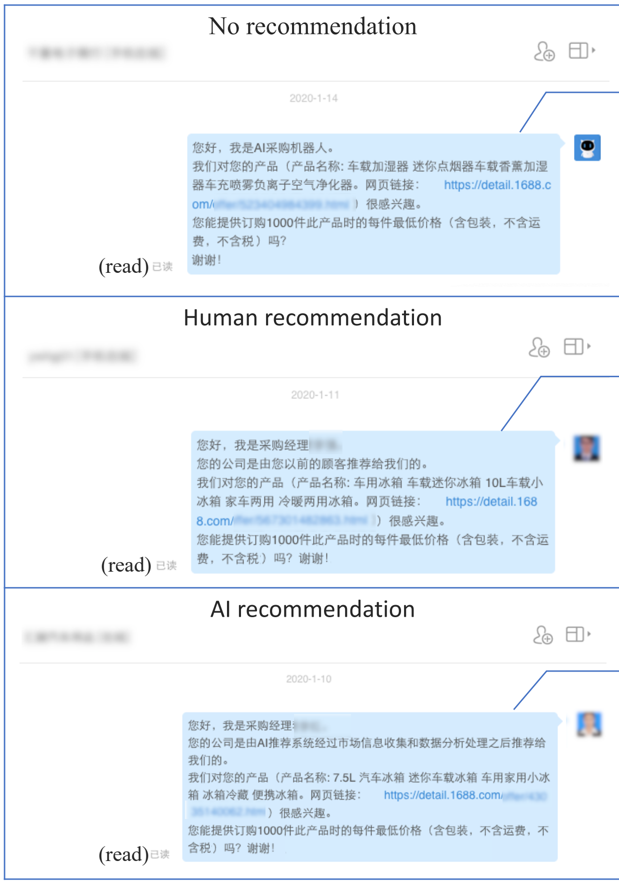
Figure 4: Supplier Profile Page and Product Page Examples

Panel A: Supplier Profile Page



Panel B: Supplier Product Page

Figure 5: Inquiry Messages in the Experiment



Hello, I am an AI procurement chatbot.
We are interested in your product: [vehicle air purifier]. Could you please quote us your best price per piece for an order of 1,000 units? (Note: Please quote a price including the packaging fee, but excluding the value-added tax and shipping fee.)
Thanks.

Hello, I am a procurement manager.
Your company was recommended to us by a peer.
We are interested in your product: [10-liter vehicle refrigerator]. Could you please quote us your best price per piece for an order of 1,000 units? (Note: Please quote a price including the packaging fee, but excluding the value-added tax and shipping fee.)
Thanks.

Hello, I am a procurement manager.
Your company was recommended to us by an AI system's market information collection and data processing.
We are interested in your product: [7.5-liter vehicle refrigerator]. Could you please quote us your best price per piece for an order of 1,000 units? (Note: Please quote a price including the packaging fee, but excluding the value-added tax and shipping fee.)
Thanks.

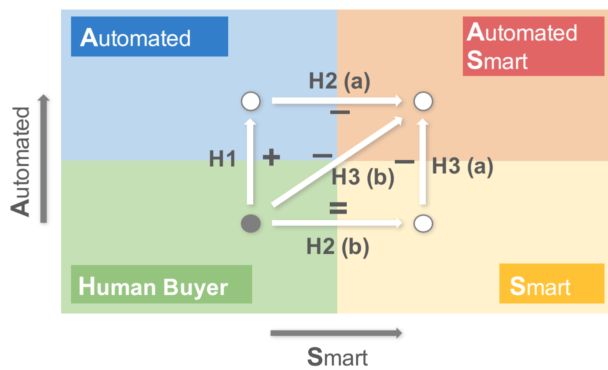
Notes. This figure depicts three inquiry message examples in our experiment: a message sent by a chatbot buyer under the "no recommendation" condition, a message sent by a male buyer under the "human recommendation" condition, and a message sent by a female buyer under the "AI recommendation" condition.

Figure 6: Experiment Design and AI Framework

Panel A: Experiment Design

	No Recommendation	Human Recommendation	AI Recommendation
Chatbot	Automated	Automated + Human Recommendation	Automated + Smart
Female	Human Buyer	Human Recommendation	Smart
Male	Human Buyer	Human Recommendation	Smart

Panel B: AI Framework



Panel C: Matching Experiment Design and Framework

Hypotheses in AI Framework		Comparisons in AI Framework		Comparisons in Designed Treatments	
H1	Effect of automation without smartness	Human Buyer	Automated	Female (or Male) under no recommendation	Chatbot under no recommendation
H2(a)	Effect of smartness for chatbot buyer	Automated	Automated + Smart	Chatbot under no recommendation	Chatbot under AI recommendation
H2(b)	Effect of smartness for human buyer	Human Buyer	Smart	Female (or Male) under no recommendation	Female (or Male) under AI recommendation
H3(a)	Effect of automation under smartness	Smart	Automated + Smart	Female (or Male) under AI recommendation	Chatbot under AI recommendation
H3(b)	Effect of automation and smartness	Human buyer	Automated + Smart	Female (or Male) under no recommendation	Chatbot under AI recommendation

Notes. This figure outlines how our experiment design matches our AI framework. We introduce a treatment with human recommendation in order to disentangle the effect of having recommendations and the effect of having smart recommendations.

Table 10: Summary Statistics of Automation

	Chatbot (C)	Female (F)	Male (M)	Chatbot (C)	Female (F)	Male (M)
	Panel A: No Recommendation			Panel B: Human Recommendation		
Number	185	224	186	212	217	236
Mean (%)	18.01	19.15	20.96	17.39	19.46	18.01
Std. (%)	15.06	16.51	15.81	14.42	15.87	13.76
	C vs F	C vs M	F vs M	C vs F	C vs M	F vs M
Mean Difference (%)	-1.14	-2.95	-1.81	-2.07	-0.62	1.45
P-value of T-test	0.47	0.07	0.26	0.16	0.64	0.30
	Panel C: AI Recommendation			Panel D: All Data		
Number	152	197	198	549	638	620
Mean (%)	22.57	18.76	21.04	19.03	19.13	19.86
Std. (%)	15.81	15.25	14.64	15.17	15.89	14.73
	C vs F	C vs M	F vs M	C vs F	C vs M	F vs M
Mean Difference (%)	3.81	1.53	-2.28	-0.10	-0.83	-0.73
P-value of T-test	0.02	0.35	0.13	0.91	0.34	0.40

Notes. This table reports the price discounts received by buyers under three different buyer types. “Number” refers to the number of inquiries replied with price quotes.

Table 11: Summary Statistics of Smartness

	No Reco. (N)	Human Reco. (H)	AI Reco. (A)	No Reco. (N)	Human Reco. (H)	AI Reco. (A)
	Panel A: Chatbot			Panel B: Female		
Number	185	212	152	224	217	197
Mean (%)	18.01	17.39	22.57	19.15	19.46	18.76
Std. (%)	15.06	14.42	15.81	16.51	15.87	15.25
	N vs H	N vs A	H vs A	N vs H	N vs A	H vs A
Mean Difference (%)	0.62	-4.56	-5.18	0.39	0.30	0.70
P-value of T-test	0.68	0.01	0.00	0.81	0.85	0.65
	Panel C: Male			Panel D: All Data		
Number	186	236	198	595	665	547
Mean (%)	20.96	18.01	21.04	19.36	18.28	20.65
Std. (%)	15.81	13.76	14.64	15.87	14.69	15.24
	N vs H	N vs A	H vs A	N vs H	N vs A	H vs A
Mean Difference (%)	2.95	-0.08	-3.03	1.08	-1.29	-2.37
P-value of T-test	0.05	0.96	0.03	0.21	0.16	0.01

Notes. This table reports the price discounts received by buyers under three different recommendation conditions. “Number” refers to the number of inquiries replied with price quotes.

Table 12: Summary Statistics of Both Automation and Smartness

	Automation + Smartness	Human Buyer without Recommendation	
	Chatbot (C) I	Female (F) II	Male (M) III
Number	152	224	186
Mean (%)	22.57	19.15	20.96
Std. (%)	15.81	16.51	15.81
	C vs F	C vs M	
Mean Difference (%)	-3.43	-1.61	
P-value of T-test	0.05	0.35	

Notes. This table reports the price discounts received by buyers with and without AI technology. Results from column I are based on the sample of chatbot buyers with AI recommendation. Results from columns II and III are based on the sample of female buyers and male buyers without recommendation, respectively.

Table 13: Combined Regression

	Dependent Variable: Discount
Male	0.028*
	(0.016)
Female	0.010
	(0.015)
Human Recommendation	-0.013
	(0.015)
Male × Human Recommendation	-0.018
	(0.021)
Female × Human Recommendation	0.017
	(0.021)
AI Recommendation	0.041**
	(0.016)
Male × AI Recommendation	-0.041*
	(0.022)
Female × AI Recommendation	-0.045**
	(0.022)
Supplier Controls	Yes
Observations	1,807
R^2	0.036

Note: This table tests the combined regression. $^{*}p<0.1$; $^{**}p<0.05$.

Table 14: Request Time Fixed Effects

	Dependent Variable: Discount			
	Panel A: Effect of Automation			
	No Recommendation	Human Recommendation	AI Recommendation	All Data
	I	II	III	IV
Male	0.029*	0.005	-0.015	0.010
	(0.017)	(0.014)	(0.016)	(0.009)
Female	0.009	0.020	-0.038**	0.003
	(0.016)	(0.014)	(0.016)	(0.009)
Supplier Controls	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	595	665	547	1,807
R^2	0.094	0.098	0.078	0.049
	Panel B: Effect of Smartness			
	Chatbot	Female	Male	All Data
	I	II	III	IV
AI Recommendation	0.042**	-0.001	0.000	0.012
	(0.018)	(0.016)	(0.016)	(0.009)
Supplier Controls	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	337	421	384	1,142
R^2	0.112	0.077	0.125	0.057
	Panel C: Joint Effect of Automation and Smartness			
Male	-0.012			
	(0.018)			
Female	-0.032*			
	(0.017)			
Supplier Controls	Yes			
Time Fixed Effects	Yes			
Observations	562			
R^2	0.067			

Notes. This table tests the effect of automation, the effect of smartness, and the joint effect of automation and smartness on the price discount with request time fixed effects. $^{*}p<0.1$; $^{**}p<0.05$.

Table 15: Quote Time Fixed Effects

	Dependent Variable: Discount			
	Panel A: Effect of Automation			
	No Recommendation I	Human Recommendation II	AI Recommendation III	All Data IV
Male	0.028*	0.005	-0.014	0.009
	(0.017)	(0.014)	(0.017)	(0.009)
Female	0.008	0.021	-0.037**	0.002
	(0.016)	(0.014)	(0.017)	(0.009)
Supplier Controls	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	595	665	547	1,807
R^2	0.100	0.097	0.064	0.045
	Panel B: Effect of Smartness			
	Chatbot I	Female II	Male III	All Data IV
AI Recommendation	0.040**	0.001	0.001	0.012
	(0.018)	(0.016)	(0.016)	(0.009)
Supplier Controls	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	337	421	384	1,142
R^2	0.102	0.080	0.122	0.053
	Panel C: Joint Effect of Automation and Smartness			
Male	-0.015			
	(0.018)			
Female	-0.034**			
	(0.017)			
Supplier Controls	Yes			
Time Fixed Effects	Yes			
Observations	562			
R^2	0.069			

Notes. This table tests the effect of automation, the effect of smartness, and the joint effect of automation and smartness on the price discount with quote time fixed effects. $^{*}p < 0.1$; $^{**}p < 0.05$.

Table 16: Summary Statistics of Simulated AI Recommendation

	Chatbot		Female		Male	
	No I	AI II	No III	AI IV	No V	AI VI
Number	185	72	224	101	186	97
Mean (%)	18.01	23.91	19.15	18.76	20.96	21.34
Std. (%)	15.06	18.38	16.51	15.90	15.81	14.65
		No vs AI		No vs AI		No vs AI
Mean Difference (%)		-5.90		0.39		-0.38
P-value of T-test		0.01		0.84		0.85

Notes. This table reports the price discounts with and without simulated AI recommendation. "No" and "AI" indicate the conditions with and without simulated AI recommendation, respectively. Results from column I–VI are based on the sample for chatbot buyers, female buyers, and male buyers without and with simulated AI recommendation, respectively.

Table 17: Effect of Simulated AI Recommendation on Price Quote

	Dependent Variable: Discount			
	Chatbot I	Female II	Male III	All Data IV
Simulated AI Recommendation	0.053**	0.002	0.006	0.019
	(0.024)	(0.020)	(0.019)	(0.012)
Supplier Controls	Yes	Yes	Yes	Yes
Observations	257	325	283	865
R^2	0.044	0.038	0.059	0.034

Notes. This table tests the effect of simulated smartness on price discounts. 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. $^{**}p < 0.05$.

Table 18: Moderating Effect for Automation

	Dependent Variable: Discount				
	Panel A: Without Smartness				
	No Moderator	No. of Trans	Listed Price	Review Rating	Trading Volume
Male	0.028*	0.026	0.038*	0.038	0.028*
	(0.016)	(0.017)	(0.020)	(0.026)	(0.017)
Female	0.010	0.013	0.023	0.010	0.010
	(0.016)	(0.017)	(0.019)	(0.024)	(0.016)
Moderator		-0.000	0.000**	-0.000	-0.000
		(0.000)	(0.000)	(0.005)	(0.000)
Male × Moderator		0.000	-0.000	-0.003	0.000
		(0.000)	(0.000)	(0.007)	(0.000)
Female × Moderator		-0.000	0.000	0.000	-0.000
		(0.000)	(0.000)	(0.006)	(0.000)
Supplier Controls	Yes	Yes	Yes	Yes	Yes
Observations	595	Yes	Yes	595	595
R^2	0.047	0.049	0.050	0.048	0.050
	Panel B: Under Smartness				
	No Moderator	No. of Trans	Listed Price	Review Rating	Trading Volume
Male	-0.015	-0.027	-0.031	-0.004	-0.013
	(0.016)	(0.018)	(0.020)	(0.026)	(0.017)
Female	-0.037**	-0.043**	-0.046**	-0.021	-0.037**
	(0.016)	(0.017)	(0.020)	(0.026)	(0.017)
Moderator		-0.000	-0.000	0.006	-0.000
		(0.000)	(0.000)	(0.005)	(0.000)
Male × Moderator		0.000	0.000	-0.005	-0.000
		(0.000)	(0.000)	(0.007)	(0.000)
Female × Moderator		0.000	0.000	-0.006	0.000
		(0.000)	(0.000)	(0.007)	(0.000)
Supplier Controls	Yes	Yes	Yes	Yes	Yes
Observations	547	547	547	547	547
R^2	0.033	0.036	0.035	0.034	0.033

Notes. This table reports the estimated coefficients and standard errors (in parentheses) for moderators regarding the effect of automation. $^{*}p < 0.1$; $^{**}p < 0.05$.

Table 19: Moderating Effect for Smartness

	Dependent Variable: Discount				
	Panel A: Chatbot Buyers				
	No Moderator	No. of Trans	Listed Price	Review Rating	Trading Volume
AI Recommendation	0.042**	0.048***	0.069***	0.024	0.041**
	(0.017)	(0.018)	(0.021)	(0.028)	(0.018)
Moderator		-0.000	0.000***	0.002	-0.000
		(0.000)	(0.000)	(0.005)	(0.000)
AI Recommendation × Moderator		-0.000	-0.000**	0.005	0.000
		(0.000)	(0.000)	(0.007)	(0.000)
Supplier Controls	Yes	Yes	Yes	Yes	Yes
Observations	337	337	337	337	337
R^2	0.040	0.044	0.056	0.046	0.043
	Panel B: Female Buyers				
	No Moderator	No. of Trans	Listed Price	Review Rating	Trading Volume
AI Recommendation	-0.003	-0.006	-0.001	-0.003	-0.004
	(0.015)	(0.019)	(0.019)	(0.023)	(0.016)
Moderator		-0.000	0.000	0.000	-0.000
		(0.000)	(0.000)	(0.004)	(0.000)
AI Recommendation × Moderator		0.000	-0.000	0.000	0.000
		(0.000)	(0.000)	(0.006)	(0.000)
Supplier Controls	Yes	Yes	Yes	Yes	Yes
Observations	421	421	421	421	421
R^2	0.032	0.033	0.032	0.032	0.034
	Panel C: Male Buyers				
	No Moderator	No. of Trans	Listed Price	Review Rating	Trading Volume
AI Recommendation	0.000	-0.004	-0.001	-0.009	0.001
	(0.015)	(0.016)	(0.018)	(0.024)	(0.016)
Moderator		0.000	0.000*	-0.003	-0.000
		(0.000)	(0.000)	(0.005)	(0.000)
AI Recommendation × Moderator		0.000	0.000	0.003	-0.000
		(0.000)	(0.000)	(0.006)	(0.000)
Supplier Controls	Yes	Yes	Yes	Yes	Yes
Observations	384	384	384	384	384
R^2	0.058	0.060	0.058	0.059	0.061

Notes. This table reports the estimated coefficients and standard errors (in parentheses) for moderators regarding the effect of smartness. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 20: Moderating Effect for Automation and Smartness

	Dependent Variable: Discount				
	No Moderator	No. of Trans	Listed Price	Review Rating	Trading Volume
Male	-0.014	-0.023	-0.030	0.009	-0.014
	(0.018)	(0.018)	(0.022)	(0.029)	(0.018)
Female	-0.034**	-0.038**	-0.047**	-0.019	-0.034**
	(0.017)	(0.018)	(0.021)	(0.026)	(0.017)
Moderator		-0.000	-0.000	0.006	-0.000
		(0.000)	(0.000)	(0.005)	(0.000)
Male × Moderator		0.000	0.000	-0.008	-0.000
		(0.000)	(0.000)	(0.007)	(0.000)
Female × Moderator		0.000	0.000	-0.005	-0.000
		(0.000)	(0.000)	(0.007)	(0.000)
Supplier Controls	Yes	Yes	Yes	Yes	Yes
Observations	562	562	562	562	562
R^2	0.034	0.023	0.037	0.036	0.036

Notes. This table reports the estimated coefficients and standard errors (in parentheses) for moderators regarding the joint effect of automation and smartness. $^{**}p < 0.05$.