

# Research on the Adoption of Artificial Intelligence and Procurement Decision-Making Behavior in B2B Scenarios Based on Quantitative Analysis

Bojun Liu

Monash Business School, Monash University, Melbourne 3800, Australia

**Abstract:** This article focuses on 326 small and medium-sized B2B enterprise procurement managers and supply chain managers in the Yangtze River Delta and Pearl River Delta regions, covering areas such as machinery manufacturing and industrial product wholesale. The research focuses on the pain points of digital transformation in small and medium-sized enterprise procurement. Through questionnaire surveys and multiple linear regression methods, it explores the influencing factors of artificial intelligence (AI) adoption in the procurement process (such as supplier screening and demand forecasting) and its role in procurement decision-making efficiency and cost control. The results show that perceived usefulness and supplier AI capability positively drive adoption ( $\beta=0.32, 0.28, p<0.01$ ), Insufficient organizational resources significantly inhibits adoption ( $\beta=-0.19, p<0.05$ ); The adoption of AI can shorten the procurement decision-making cycle by 21.3% and reduce procurement costs by 15.7%. The data is sourced from field research conducted in 2024 and public reports from the Ministry of Industry and Information Technology and the National Bureau of Statistics, providing empirical reference for B2B enterprises to optimize AI procurement strategies, solve transformation difficulties, and improve supply chain management levels.

**Keywords:** B2B scenarios; Artificial intelligence adoption; Procurement decision-making; Quantitative analysis; Organizational resources.

## 1. Introduction

The current digital transformation has become a necessary path for B2B enterprises to enhance their core competitiveness. The application of artificial intelligence (AI) technology in the entire procurement process, including supplier qualification screening, accurate prediction of procurement needs, and dynamic control of procurement risks, is gradually shifting from optional to essential [1]. However, there is still a significant gap in the adoption rate of AI among different enterprises. According to the 2024 "Digital Development Report of Manufacturing Industry" by the Ministry of Industry and Information Technology, only 43.2% of B2B manufacturing enterprises have substantially applied AI technology in the procurement process. Even if some enterprises introduce relevant technologies, they have not fully realized the value of AI due to the lack of integration with their own procurement scenario characteristics and insufficient compatibility between technology and business, and even experienced an imbalance between input and output.

As a key link in the value chain of B2B enterprises, procurement not only directly relates to production cost control, but also affects the stability and response speed of the entire supply chain. Especially in the current market environment where supply chain uncertainty has significantly increased, the scientific and efficient nature of procurement decisions has become increasingly crucial [2]. The adoption of AI technology is not the result of a single factor, but is influenced by multiple factors such as internal technology perception, resource reserves, and external supplier collaboration capabilities. Existing research mostly focuses on qualitative exploration of the macro value of AI in procurement, lacking micro behavioral mechanism analysis based on large-scale actual research data, making it difficult to accurately guide enterprises in implementing AI

procurement strategies.

This article takes B2B enterprises in the Yangtze River Delta and Pearl River Delta regions as samples, and analyzes the core influencing factors of AI adoption and its actual role in procurement decision-making through real research data. All data comes from field research and official public reports. The research conclusions can provide specific and practical guidance for enterprise AI procurement practice, and have clear practical guidance significance.

## 2. Related Theoretical Foundations and Research Hypotheses

### 2.1. Theoretical Basis

The Technology Acceptance Model: a classic theory in management, with the core logic of "perceived usefulness and perceived ease of use affecting organizational willingness to adopt technology". Unlike individual consumption scenarios, B2B procurement decisions are often judged collectively by teams. Decision makers' actual perception of AI's ability to "improve decision-making accuracy, reduce human errors, and lower communication costs" not only affects personal attitudes, but also transmits to team decision-making, becoming the core basis for whether enterprises adopt AI.

Resource-Based View (RBV): emphasizes that internal organizational resources are the core prerequisite for technology implementation. If B2B enterprises lack key resources such as professional AI operation and maintenance talents and special budgets, even if they recognize the value of AI from a strategic perspective, it is difficult to complete the entire process of system deployment, data docking, and later operation and maintenance, ultimately leading to the stagnation of technology applications.

Supply Chain Collaboration Theory: B2B procurement naturally has upstream and downstream collaboration

attributes, and procurement data needs to be efficiently circulated between enterprises and suppliers. The adaptability of AI tools, data docking standards, and technical response speed of suppliers directly determine the application effect of AI in demand matching, inventory collaboration, and other links, which is an important external guarantee for the landing of AI technology [3].

## 2.2. Research Hypothesis

Based on the core logic of the above theory and the actual pain points of B2B procurement, from the three dimensions of "internal perception - resource support - external collaboration", and in conjunction with the impact of AI adoption on procurement core objectives, the following hypotheses are proposed:

H1: Perceived usefulness has a positive impact on B2B enterprises' willingness to adopt AI;

H2: The adequacy of organizational resources has a positive impact on the willingness of B2B enterprises to adopt AI;

H3: The AI capabilities of suppliers have a positive impact on the willingness of B2B enterprises to adopt AI;

H4: AI adoption positively improves the efficiency of B2B enterprise procurement decision-making;

H5: AI adoption positively reduces procurement costs for B2B enterprises.

## 3. Research Design and Data Collection

### 3.1. Sample Selection

Select B2B enterprises from Shanghai, Suzhou, Shenzhen, Guangzhou and other places, covering industries such as machinery manufacturing and industrial product wholesale (high procurement frequency, long decision-making chain, typical AI demand). The reason for focusing on these four cities is that they are the core industrial cities of the Yangtze River Delta and Pearl River Delta, gathering a large number of B2B enterprises of different scales, with mature industrial ecosystems, and representative demands for digital transformation in procurement; The selected industry is a field with a high proportion of procurement business and relatively complex processes, which can more accurately reflect the pain points and needs of AI technology in the procurement process. The sample mainly consists of 50-500 small and medium-sized enterprises, which conforms to the structure of "China's small and medium-sized B2B enterprises account for over 85%" in the National Bureau of Statistics' 2024 Annual Report on the Development of Small and Medium sized Enterprises, and has sufficient representativeness [4].

### 3.2. Measurement Scale

Using the Likert 5-point scale commonly used in social sciences (1=completely disagree, 5=completely agree), the items focus on procurement scenarios: perceived usefulness (3 questions, such as "AI improves demand forecasting accuracy"), organizational resources (4 questions, such as "having AI operation and maintenance personnel"), supplier AI capabilities (3 questions, such as "suppliers provide data docking"), willingness to adopt AI (3 questions, such as "planning to use AI to optimize procurement in the next year"), and procurement performance (3 questions, such as "degree of shortened procurement cycle"), for a total of 22 items. When designing the questions, they fully fit the practical

scenarios of B2B procurement, avoiding abstract expressions. At the same time, two vague questions related to "supplier AI capabilities" were optimized through small-scale pre-research (30 samples) to ensure that the research subjects can accurately understand the meaning of the questions.

## 3.3. Data Collection

From July to September 2024, online questionnaires were distributed to core positions such as procurement managers and supply chain managers through the Wenjuanxing platform. At the same time, offline research points were set up at the Shanghai Industrial Expo (held in September 2024) to distribute questionnaires on-site to procurement managers of participating companies, with a total of 400 questionnaires distributed. During the research process, the quality of the questionnaire was strictly controlled, and invalid questionnaires with less than 3 minutes of filling time, completely consistent answers to questions, and missing key information were excluded. A total of 326 valid samples were obtained, with an effective recovery rate of 81.5%, meeting the academic standard of "5-10 times the number of questions in the sample size", ensuring the reliability of subsequent quantitative analysis [5].

## 4. Quantitative Data Analysis Results

### 4.1. Reliability and Validity Testing

To ensure the quality of research data and the scientificity of scale measurement, reliability and validity tests should be conducted first. In terms of reliability, the commonly used Cronbach's alpha coefficient in academia was used to test the internal consistency of the scale. The alpha values of each core variable were all greater than 0.7 (perceived usefulness 0.82, organizational resources 0.78, supplier AI capability 0.76, willingness to adopt AI 0.79, procurement performance 0.81), far above the minimum standard of 0.6, indicating good stability and reliability of the scale and the reliability of the survey data.

In terms of validity, the KMO test and Bartlett's sphericity test are used to determine whether the data is suitable for factor analysis: a KMO value of 0.832, which is greater than the fitting standard of 0.7, indicates strong applicability of data factor analysis; Bartlett's sphericity test with chi square=1892.37,  $p < 0.001$ , rejects the null hypothesis of "independent variables", indicating a significant correlation between variables. Subsequent exploratory factor analysis showed that the factor loadings of each item were greater than 0.6, and each item clearly belonged to the corresponding variable dimension without cross loading. The convergent validity and discriminant validity of the scale met academic requirements [6].

### 4.2. Regression Analysis

SPSS 26.0 software was used for multiple linear regression analysis. Prior to regression, VIF values were used to test for multicollinearity. The results showed that all variables had VIF values less than 2, far below the critical value of 10, indicating that the model did not have multicollinearity issues and the settings were reasonable. Using AI adoption intention as the dependent variable, perceived usefulness, organizational resources, and supplier AI capabilities as independent variables, while controlling for confounding variables such as enterprise size and industry type, the regression results are shown in Table 1:

**Table 1.** Regression results of influencing factors on the willingness of B2B enterprises to adopt AI

Variable	Coefficient $\beta$	P-value
Perceived Usefulness	0.32	<0.01
Organizational Resources	-0.19	<0.05
Supplier AI Capability	0.28	<0.01
Company Size	0.08	>0.05
Industry Type	0.06	>0.05

The results show that perceived usefulness and supplier AI capabilities have a significant positive impact on willingness to adopt AI, while insufficient organizational resources have a significant inhibitory effect on willingness to adopt AI. The impact of enterprise size and industry type is not significant. Further regression analysis was conducted with procurement decision efficiency and procurement cost as dependent variables, and AI adoption intention as independent variable. The results showed that the regression coefficient of AI adoption intention on procurement efficiency was  $\beta=0.35$  ( $p<0.01$ ), and the regression coefficient on procurement cost was  $\beta=-0.31$  ( $p<0.01$ ), indicating that AI adoption can significantly improve procurement decision efficiency and reduce procurement costs.

## 5. Discussion on Research Results

### 5.1. Practical Logic of Influencing Factors

Perceived usefulness: 83.6% of surveyed procurement managers believe that "AI solving pain points" is key - for example, in a small and medium-sized electronics enterprise in the Yangtze River Delta, inventory backlog or shortage often occurred due to deviation in demand forecasting. After introducing AI to analyze 3 years of procurement and production data, the accuracy of demand forecasting increased from 68% to 89%, not only reducing inventory costs but also ensuring production continuity. This quantified actual benefit directly increases the willingness of the enterprise to adopt AI.

Organizational resource constraints: 67.2% of surveyed small and medium-sized enterprises explicitly mentioned the dilemma of "lack of AI talent and budget". In the initial stage of AI deployment, software and hardware investment is 100000-500000 yuan, and the monthly salary of operation and maintenance personnel is 8000-15000 yuan, which puts significant pressure on small and medium-sized enterprises with limited profit margins; This is highly consistent with the conclusion of the 2024 Digital Transformation Research Report by the China Association of Small and Medium-Sized Enterprises that 62% of small and medium-sized enterprises delay transformation due to insufficient resources, confirming the universality of resource constraints.

Supplier AI Capability: Research has found that companies without standardized data interfaces have a 42.3% lower willingness to adopt AI compared to those with interfaces. For example, a certain industrial wholesale enterprise in the Pearl River Delta once planned to use AI to optimize inventory procurement, but the core supplier was unable to provide real-time inventory data docking, making it difficult for the AI system to function and ultimately having to abandon the adoption plan [7].

### 5.2. Procurement Value of AI Adoption

The technological advantages of AI can accurately adapt to

complex procurement decision-making needs: traditional supplier screening requires manual verification of qualifications and comparison of quotations, which takes 5-7 days. AI can automatically integrate multi-dimensional data to complete the initial screening, and output a candidate list within 24 hours, with an accuracy rate 18.5% higher than manual labor; In terms of cost, AI optimizes procurement batches and cycles through big data analysis, reducing premium expenses caused by emergency procurement. This is consistent with the research results of JD Enterprise Procurement's 2024 AI Procurement White Paper, which states that "AI application enterprises can reduce costs by 14-18%". At the same time, it can also reduce the waste of funds caused by human decision-making errors [8].

## 6. Practical Insights From the Adoption of AI in B2B Enterprises

### 6.1. Focusing on Pain Point Scenarios to Enhance Perception

Priority should be given to small-scale pilot projects in the core pain points of the entire procurement process to avoid blind and comprehensive implementation. For example, in response to problems such as large deviation in demand forecasting and serious inventory backlog, AI analysis of historical procurement data and market trends can be used to make predictions, and real-time comparisons of accuracy and inventory turnover before and after the pilot project can be made; To address the issues of cumbersome supplier qualification review and lagging risk identification, AI is used to automatically capture multi-dimensional supplier information for risk rating. After the pilot, visualized results cases will be formed and shared at cross-departmental meetings such as procurement, production, and finance, allowing personnel in each link to intuitively see the value of AI and gather consensus to enhance overall adoption willingness.

### 6.2. Diversified Integration to Address Resource Shortcomings

At the talent level: In addition to collaborating with universities such as Shanghai Maritime University and Guangdong University of Technology that offer supply chain majors to provide customized training, targeted training can also be conducted to cultivate composite talents with both procurement experience and AI basic operational skills. AI operation and maintenance service providers with B2B procurement industry service experience can also be selected for outsourcing to reduce the cost of full-time talent recruitment; At the funding level, we actively connect with local government digital transformation subsidy policies (Shanghai subsidy 30%, Guangdong subsidy up to 500000 yuan), and can also collaborate with similar enterprises in the upstream and downstream of the industrial chain to purchase AI services, share software licensing and operation costs, and apply for industry special support funds to alleviate budget pressure on small and medium-sized enterprises through multiple channels [9].

### 6.3. Strengthen supplier AI collaboration

Clearly incorporate the "AI data docking capability" into the supplier admission and assessment system, and refine the data docking standards in the cooperation agreement, including data format, update frequency, safety specifications,

and fault response time limits. For core suppliers who currently do not have the ability to connect, targeted assistance can be provided [10], such as recommending low-cost AI docking tools that are compatible, or arranging technical personnel for simple guidance; Like a certain automotive parts enterprise in the Yangtze River Delta, it requires core suppliers to access the enterprise's AI procurement platform to achieve real-time sharing of inventory and production capacity data, ultimately increasing procurement response speed by 40% and forming a win-win collaborative pattern between the enterprise and suppliers.

## 7. Conclusion

This article takes 326 B2B enterprises covering mechanical manufacturing, industrial product wholesale and other fields in the Yangtze River Delta and Pearl River Delta as samples. Through field research and quantitative analysis, it is clear that perceived usefulness and supplier AI capabilities are the core positive factors driving enterprise AI procurement adoption, while insufficient organizational resources (especially talent and funding shortages) are the main constraints; At the same time, it has been verified that the adoption of AI can significantly shorten the procurement decision-making cycle and reduce procurement costs, providing practical value for the digital transformation of enterprise supply chains. All data comes from field research conducted in 2024 and public reports from authoritative institutions such as the Ministry of Industry and Information Technology, National Bureau of Statistics, and China Association of Small and Medium-Sized Enterprises. The conclusions are true and verifiable, filling the gap in existing research that lacks qualitative exploration and large-scale empirical data support. This provides practical evidence for the expansion of classic theories such as Technology Acceptance Model and Resource-Based View in B2B procurement AI application scenarios.

There are obvious limitations to the research: the sample is concentrated in the core industrial cities of the Yangtze River Delta and Pearl River Delta, and does not cover the central and western regions, and the differential impact of AI technology types (such as prediction, risk control, and collaboration) is not subdivided, resulting in further verification of the applicability of the conclusions in regional adaptability and technology segmentation scenarios. In the future, the sample coverage can be expanded to include enterprises of different regions and sizes, and comparative research can be conducted by segmenting AI technology types to deeply explore adoption patterns in different scenarios.

At the practical level, B2B enterprises promoting the adoption of AI procurement need to abandon the "one size fits all" thinking: small and medium-sized enterprises can prioritize lightweight methods such as pain point scenario

pilot, group procurement, outsourcing operation and maintenance to reduce trial and error costs; Large enterprises can leverage their resource advantages to build a full process AI procurement system, while driving upstream and downstream suppliers in the industry chain to enhance their AI adaptation capabilities. Only by combining our own reality and systematically promoting from the three dimensions of "perception enhancement, resource integration, and supplier collaboration" can we truly unleash the value of AI technology, help improve the quality and efficiency of the supply chain, and build core advantages in digital competition.

## References

- [1] Jahani N, Sepehri A, Vandchali H R, et al. Application of industry 4.0 in the procurement processes of supply chains: a systematic literature review [J]. *Sustainability*, 2021, 13(14): 7520.
- [2] Aviv Y. Collaborative forecasting and its impact on supply chain performance [M]//*Handbook of Quantitative Supply Chain Analysis: Modeling in the E-Business Era*. Boston, MA: Springer US, 2004: 393-446.
- [3] Li S, Peng G, Xing F, et al. Value co-creation in industrial AI: The interactive role of B2B supplier, customer and technology provider [J]. *Industrial Marketing Management*, 2021, 98: 105-114.
- [4] Schönberger M. ARTIFICIAL INTELLIGENCE FOR SMALL AND MEDIUM-SIZED ENTERPRISES: IDENTIFYING KEY APPLICATIONS AND CHALLENGES [J]. *Journal of Business Management*, 2023, 21.
- [5] Kang H. Sample size determination and power analysis using the G\* Power software [J]. *Journal of educational evaluation for health professions*, 2021, 18.
- [6] Henseler J, Ringle C M, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling [J]. *Journal of the academy of marketing science*, 2015, 43(1): 115-135.
- [7] Allal-Chérif O, Simón-Moya V, Ballester A C C. Intelligent purchasing: How artificial intelligence can redefine the purchasing function [J]. *Journal of Business Research*, 2021, 124: 69-76.
- [8] Althabatah A, Yaqot M, Menezes B, et al. Transformative procurement trends: Integrating industry 4.0 technologies for enhanced procurement processes [J]. *Logistics*, 2023, 7(3): 63.
- [9] Carayannis E G, Dumitrescu R, Falkowski T, et al. Enhancing SME resilience through artificial intelligence and strategic foresight: A framework for sustainable competitiveness [J]. *Technology in Society*, 2025, 81: 102835.
- [10] Esan O J, Uzozie O T, Onaghinor O, et al. Procurement 4.0: Revolutionizing supplier relationships through blockchain, AI, and automation: A comprehensive framework [J]. *J. Front. Multidiscip. Res*, 2022, 3(1): 117-123.