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Procurement Process Digitalization in China's Construction Supply Chains: Enabling Data-Driven Decision Making and Strategic Change

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ABSTRACT

With the dual challenges of the global economy and the need for sustainability, digital procurement has become an essential means of increasing supply chain resilience and agility. For China's construction supply chain, which is characterized by complex subcontracting, high-value materials, and long-cycle projects, these factors make the impact of digital transformation particularly significant. This study proposes and empirically tests an integrated model that combines Technology-Organization-Environment (TOE) framework, Diffusion of Innovations theory (DOI), dynamic capabilities (DC), and Information Processing Theory (IPT) perspectives to explore the impact of Procurement Process Digitization (PPD) on Data-Driven Decision-Making (DM) and Strategic Change (SC). The study analyzes empirical data from 383 Chinese construction supply chain firms. Data were collected using a structured survey questionnaire, which demonstrated a Cronbach's alpha reliability ranging from 0.783 to 0.912. The sample consisted of middle and senior managers with over five years of work experience, selected through convenience sampling. Descriptive statistics and Partial Least Squares Structural Equation Modeling (PLS-SEM) were employed for data analysis. The results show that Relative Advantage (RA), Compatibility (CB), Top Management Support (TMS), Organizational Readiness (OR), Information Sharing Culture (ISC), and Partner Readiness (PR) all significantly and positively influence the deeper implementation of PPD, while complexity does not significantly impede the advancement of digital sourcing. PPD plays a key role in facilitating DM and consequently drives SC. In addition to providing new perspectives for technology adoption research in large project industries, this study also provides practical insights into digital transformation, sustainability, and supply chain management. Further mediation effect analysis shows that PPD plays an important bridge role between DM and SC and that RA, CB, PR, TMS, OR, and ISC drive SC through the dual mediation effects of PPD and DM. Finally, this study is further validated in terms of the reliability and validity of the results through robustness tests such as the endogeneity test and unobserved heterogeneity assessment.

Keywords: *data-driven decision-making, information processing, strategic change, supply chain resilience, technology adoption*

1. INTRODUCTION

In the last two decades, frequent adjustments in international trade policies (Jakob *et al.*, 2022; Bezditnyi, 2024), disruptions to raw material supply chains caused by geopolitical conflicts (e.g., steel shortages due to regional tensions) and public health crises (e.g., the COVID-19 lockdown), which have hindered on-site construction,have made the global economic environment more complex (Azim *et al.*, 2024; Bakulina, 2024; Moreno *et al.*, 2023). At the same time, organizations not only have to cope with these uncertainties, but also have to meet increasingly stringent sustainability and green compliance requirements (Zhou *et al.*, 2022; Zhanbayev, Madenova, & Sagintayeva, 2023). In this context, digital technologies such as big data analytics, artificial intelligence, and cloud computing have had a profound impact on supply chain management across industries (Luo, 2022). Digital transformation has gone beyond mere information technology upgrades to become a core strategic task for organizations to continuously improve competitiveness and cope with uncertainty (Brynjolfsson & McAfee, 2014).

Among many industries, the construction sector's multiple levels of subcontracting, procurement of high-value materials, long construction cycles, and stringent environmental constraints (Matos *et al.*, 2024) make digital solutions indispensable. This study focuses on construction supply chain firms, which are at the center of subcontracting and material procurement. Longer project cycles make construction supply chains more vulnerable to raw material price fluctuations and policy changes, increasing procurement and construction uncertainty. At the same time, stricter emission standards and green building requirements challenge traditional paper-based and siloed processes (Ma & Zhu, 2024; Wei *et al.*, 2024). As a result, Procurement Process Digitization (PPD) has become a key strategy to promote cost control, transparency, and collaboration (Welsh & Martinez, 2023; Gurgun *et al.*, 2024).

However, research on digital procurement and data-driven decision-making (DM) in the construction sector is still limited, and most of the current literature is mainly orientated toward the manufacturing, retail, or public sectors (Adebayo *et al.*, 2024; Simões *et al.*, 2023). For the construction industry, which is complex and project-based, it is unclear how advanced digital procurement can lead to specific strategic outcomes such as sustainable competitive advantage or agile organizational transformation (Welsh & Martinez, 2023). After decades of rapid growth, China's construction supply chain is facing the challenges of rising labor costs, tighter environmental regulations, and increased international competition (Zhang *et al.*, 2023; Gurgun *et al.*, 2024). To overcome resource and efficiency bottlenecks, digital transformation is seen as an important way out (Matos *et al.*, 2024). Therefore, understanding how PPD implementation can catalyse transformative strategic impacts is not only of great theoretical value but also of significant practical implications.

This study thus proposes an integrated model based on the Technology-Organization-Environment (TOE) framework, the Diffusion of Innovations Theory (DOI), and the Dynamic Capabilities (DC) and Information Processing Theory (IPT) perspectives (see Figure 1). The research questions are as follows:

RQ1: Which technological, organizational, and environmental factors will significantly influence the adoption depth of PPD in construction supply chain firms?

RQ2: How does a deeper application of PPD influence DM within construction supply chain organizations?

RQ3: How does DM affect SC in construction supply chain organizations, particularly concerning speed, magnitude, and content?"

This study innovatively integrates the TOE framework, DOI theory, DC, and IPT theory in order to systematically explain how digital procurement affects DM and SC in a complex, project-based environment. By focusing on the post- adoption phase of digital procurement, this study responds to research claims about the maturity and sustained adoption of digital technologies (Omorodion & Osifo, 2020; Asif *et al.*, 2024) and further expands theoretical explorations in the areas of e-procurement, supply chain digitization, and diffusion of innovations. In addition, the insignificant effect of complexity (CX) offers fresh insights into DOI applicability in similar enterprise environments.

This study provides actionable guidance for stakeholders in construction supply chain to deepen their adoption of digital procurement. The study highlights the importance of key internal factors (i.e., Top Management Support[TMS], Organizational Readiness[OR], and Information-Sharing Culture[ISC]) as well as key external factors (Partner Readiness[PR]). In particular, the linkage between PPD and DM proved to be a "catalyst" mechanism that transforms business tools into strategic enablers. The empirical results also provide an important basis for government and industry organizations to develop better e-procurement standards, build stronger digital infrastructure, and accelerate the digital and green transformation of the entire construction value chain.

Moreover, to ensure that the empirical results of this study are robust and reliable, we incorporated a series of robustness tests into the study design to explicitly address potential endogeneity and unobserved heterogeneity. This approach ensured that the conclusions drawn from the subsequent methods and results stood up to scrutiny, thereby shedding more light on the PPD-DM-SC relationship.

2. LITERATURE REVIEW

In order to gain a deeper understanding of how digital procurement and data-driven decision-making can influence an organization's strategic transformation, this paper first reviews the current state of digital procurement in the construction supply chain. Subsequently, by elaborating on the three-stage model of DOI theory, the TOE framework, and the integrated perspectives of DC and IPT in the post-adoption phase, it highlights how their integration can provide a more holistic view of understanding PPD adoption outcomes. Finally, a systematic overview of the research hypotheses is provided.

2.1 Digital Procurement in the Construction Supply Chain

Supply chain management in the construction industry is very complex, characterized by multi-level subcontracting and project-based operating models. As key players, the activities of Chinese construction supply chain firms have significantly shaped their practices and related behaviors. In construction, the traditional procurement process leans heavily on paper- based processes and is burdened by information silos that delay the construction project cycle and reduce the collaborative efficiency of the construction supply chain (Gurgun *et al.*, 2024; Ibem and Laryea, 2014).

In this context, the emergence of "e-procurement", or digital procurement, is an interesting opportunity to optimize processes related to bidding, contract management, material traceability, and financial settlement. Additionally, the experience of established sectors such as manufacturing and the public sector indicates that e-procurement can be supportive of cost savings and improved transparency (*Ibem & Laryea,* 2015).

However, the construction sector has been slow to implement and embed digital procurement due to the highly fragmented nature of actors, lengthy project cycles, and frequent changes in project quality and actual project implementation (Yevu *et al.*, 2021; Laryea & Ibem, 2014). While some firms have started to integrate some of the more basic digital procurement tools such as e-tendering, email, and document digitization, full digitalization of end-to-end processes, along with real-time data monitoring and analysis systems, is an aspiration yet to be fully realized (Ibem & Laryea, 2015; Perera *et al.*, 2021). To gain a clearer understanding of the digital procurement landscape, it is necessary to distinguish between two closely related yet distinct concepts: Digital Procurement System (DPS) and Procurement Process Digitization (PPD). DPS refers to an integrated system platform deployed at the organizational level, or composed of multiple collaborative procurement IT modules. Its typical components include e-tendering, contract lifecycle management, supplier relationship management, e-invoicing, and expenditure analysis (Ibem & Laryea, 2014; Matos, Cruz, & Branco, 2024).

In contrast, PPD focuses more on the extent of digital coverage and the depth of implementation in various sub-processes of procurement—such as demand planning, tendering, contract execution, payment, and performance evaluation. It represents a "usage-level" manifestation of digitization, measuring the maturity of digital technology application throughout the procurement process from requisition to settlement. While DPS provides the necessary technical infrastructure, PPD reflects the level of digital transformation achieved by an organization in its workflows (Welsh & Martinez, 2023; Matos *et al.*, 2024).

Furthermore, with the rapid development of technologies such as the Internet of Things (IoT), cloud computing, and particularly Building Information Modeling (BIM) in the construction industry, the functional boundaries of DPS continue to expand. Meanwhile, the depth and breadth of digitization in PPD are also constantly increasing, gradually demonstrating differentiated implementation characteristics (Matos *et al.*, 2024; Gurgun *et al.*, 2024). As a result,a pertinent area of research to examine how construction firms can leverage their digital procurement processes initiatives to achieve higher- level strategic benefits and promote further PPD development.

In discussing such issues, PPD is increasingly seen as a definitive mechanism for developing DC and information processing capabilities that could influence an organization's strategic agility and sustainability (Harju *et al.*, 2023; Darvizeh & Eldridge, 2022). Considering that prior studies have focused on mature industries or different country contexts, there has yet to be an in-depth empirical study on the complex regulatory environment and rapid growth potential of Chinese construction firms in the supply chain sector of construction (Papadopoulos *et al.*, 2022; Cheng *et al.*, 2024). Therefore, the paper seeks to further attend to this situation through an empirical investigation-based approach.

2.2 Diffusion of Innovation Three-Stage Model and the Integrated TOE+DOI Framework

2.2.1 Diffusion of Innovations (DOI) and the Three-Stage Adoption Model

Rogers (1995) noted that organizations go through a continuum of knowledge acquisition, persuasion, decision-making, implementation, and validation when adopting innovations. Subsequent research has simplified this process into three key stages—pre-adoption, adoption decision and post-adoption—to better reflect organizational practices (Hameed *et al.*, 2012; Wu & Chuang, 2010). However, most existing research focuses on the pre-adoption and adoption decision phases, with relatively little attention paid to the further deepening and diffusion of the technology after formal adoption (Hameed & Arachchilage, 2016). In the construction industry, although studies have explored the adoption of e-procurement, there is still a lack of systematic research on how to continuously optimize and realize wider strategic benefits through procurement process digitization (PPD) after e-procurement has been implemented (Wu & Chuang, 2010).

2.2.2 TOE Framework and DOI Theory

When exploring how organizations adopt and integrate digital technologies, researchers often combine the TOE framework (Tornatzky and Fleischer, 1990) with the DOI theory (Rogers, 1995; Oliveira & Martins, 2011; Hiran & Henten, 2020). The TOE framework emphasizes the influence of external pressures, internal resource allocation, and technological factors on adoption decisions (Sayginer & Ercan, 2020). Whereas DOI theory focuses on the perception of innovation attributes such as relative advantage and complexity (Dash & Anusandhan, 2018). The convergence of these two perspectives helps to shed light on why different construction firms exhibit varying degrees of adoption of digital procurement (Elghdban *et al.*, 2020; Cheung *et al.*, 2023).

Research has shown that organizations require strong Relative Advantage (RA) and high Compatibility (CB) as part of the technology, while also lowering both the real and perceived CX to achieve higher levels of PPD (Elghdban *et al.*, 2020). Important contributors of the organization including but not limited to TMS and OR have been identified as most crucial safeguards to lead the digitization processes (Shaharul *et al.*, 2024; Li, 2020). Also, PR has been previously recognized as an most external influential factor in this process (Hatoum & Nassereddine, 2024). Although prior studies have indicated that the adoption of new technology in the construction industry is often driven by multiple complex factors such as cultural contexts, institutional frameworks, and supply chain collaboration (Wang *et al.*, 2022), targeted empirical inquiries on the post-adoption phase remain underexplored. As such, this paper proposes to adopt the TOE and DOI integrated framework as the guiding analytical model to understand the relationship between predictor variables and the extent of PPD adoption.

2.3 Dynamic Capabilities and Information Processing Theory (IPT): The Behind-the-Scenes Mechanism

The introduction of new technologies does not, by itself, confer a competitive advantage or significantly enhance strategic performance (Teece, 2007; Hallikas *et al.*, 2021). After organizations have adopted new technology, researchers have focused on how digital procurement enables data-based decisions to shift towards strategy. This paper focuses on the change process, which is conceptualized using DC and IPT (Galbraith, 2014; Tiwari *et al.*, 2024).

2.3.1 Dynamic Capabilities (DC)

As long as firms are able to see the market change quickly enough to act on a new opportunity, they can sustain a competitive advantage in highly uncertain environments (Teece *et al.*, 1997). Digital procurement enables organizations to better manage supply chain and project data while improving their ability to detect changes and adjust their resources to meet demand (Herold *et al.*, 2023; Dubey *et al.*, 2024). Organizational agility is enhanced by digital procurement; firms can react faster and more accurately to external pressures, such as increases in raw material prices and green legislation changes.

2.3.2 Information Processing Theory (IPT)

According to Galbraith (1973, 2014), organizations need to improve their information processing capabilities (IPC) at both structural and systemic levels in order to cope with external uncertainty and meet internal decision-making needs (Yan *et al.*, 2023). In construction projects, where information is exchanged frequently between departments and contractors, digital procurement has become an efficient solution. PPD improves the efficiency of information flow and enhances the transparency of decision-making by integrating the procurement application, bidding, invoice management, and billing to build a unified digital platform. This integration not only breaks down information silos and enhances supply chain collaboration, but also enables real-time data processing, intelligent predictive analytics, and optimization of procurement strategies with the help of big data technology (Aben *et al.*, 2021; Alnuaimi *et al.*, 2024).

Fundamentally, advancing the PPD enhances procurement data collection and analysis, improves the organization's IPC, and facilitates DM (Gökalp *et al.*, 2021; Alnuaimi *et al.*, 2024). Through continuous perception, adaptation, and capability reconfiguration, firms are able to achieve more effective SC in market expansion, supply chain reorganization, and green projects (Bilkštytė-Skanė &

Akstinaite, 2024; Simões *et al.*, 2023). Therefore, this paper integrates TOE + DOI with DC and IPT into a unified framework (TOE + DOI → PPD → DM → SC) to explain the strategic implications of digital procurement more comprehensively.

2.4 Hypotheses and Conceptual Model

Considering the literature and theoretical underpinnings, the following conceptual model (see Figure 1) is proposed. The model first examines the impact of key TOE and DOI factors on the depth of PPD use and then tests the relationship between PPD and DM and between DM and SC.

2.4.1 TOE and DOI Factors Impact on PPD

2.4.1.1 Relative Advantage (RA)

RA is defined as the perceived advantages a new technology offers compared to traditional methods in terms of efficiency, quality, and/or costs (Rogers, 1995). A considerable number of studies have shown that RA is a principal driver of technology adoption and has entered the empirical analysis in a variety of fields, including e-commerce (Ifinedo, 2011; Mndzebele, 2013), online banking (Tan & Teo, 2000), and other IT applications (Zolait & Sulaiman, 2008). Studies conducted specifically in the construction industry also showed substantial advantages of digital procurement, including improved transparency, more efficient procurement processes, and better resource allocation (Mabad *et al.*, 2021). Furthermore, not only does digital procurement save time by significantly reducing procurement cycles, it also facilitates compliance and adds transparency to the operation. Therefore, when companies are well aware of these advantages, they are more likely to invest more in the post-adoption phase to further advance the PPD (Van Slyke *et al.*, 2008; Yevu *et al.*, 2021).

H1: RA will have a positive impact on the depth of adoption of PPD.

2.4.1.2 Compatibility (CB)

CB refers to the extent to which a new technology is aligned with an organization's existing culture and systems (Rogers, 1995). Integration of PPD with other systems (e.g., ERP, BIM, or financial systems) can be meaningfully improved alongside the much lower resistance by employees to use it (Sun *et al.*, 2009; Welsh & Batalla Martinez, 2023). Studies have also examined compatibility as a factor in technology adoption: the adoption of enterprise information management systems (Oliveira & Martins, 2011), the integration of technology in small- and micro-enterprises (Mairura *et al.*, 2016), and digital transformation (Karahanna *et al.*, 2006). Therefore, CB increases the likelihood that an enterprise will optimize or increase the use of PPD functionality or modules during the post-adoption phase (Karahanna *et al.*, 2006; Cheng, 2015).

H2: It is hypothesized that CB has a positive effect on the depth of adoption of PPD.

2.4.1.3 Complexity (CX)

Beyond the usual assumptions regarding complexity, Rogers (1995) noted that CX generally involves cognitive and operational challenges that new technologies would bring. In theory, however, excessive CX of new technologies inhibits their broad-based acceptance (Ifinedo, 2011; Oliveira & Martins, 2011), an observation supported by a plethora of empirical studies in different areas (Gallivan, 2001; England *et al.*, 2000). However, claim that a large enterprise or a state-owned enterprise has more appropriate resources and training facilities to offset the adverse impact of CX(Salah & Mohamed, 2021); some such enterprises are somehow efficient in minimizing operational challenges by their strict controls and focused training (Russell and Hoag, 2004). As alluded to, this assumption forms the basis for testing DOI theory in this study.

H3: Complexity has a negative influence on PPD adoption intention.

2.4.1.4 Top Management Support (TMS)

TMS means expressing commitment in the form of allocating resources to PPD and ensuring that strategic priorities are implemented. Previous studies have shown that TMS is a champion of system integration and implementation and has a direct impact on the uptake of digitization in the procurement process (Elbanna, 2013; Masudin *et al.* ,2021). With regard to the construction field, TMS is an important part of the digital transformation process due to the rigid hierarchy and reliance on project budgets, which are especially pertinent in terms of resource allocation and cultural behavior (Luo *et al.*,2023).

H4: TMS has a positive effect on the depth of PPD adoption.

2.4.1.5 Organizational Readiness (OR)

OR implies preparedness in respect of information technology infrastructure, capital, employee skill sets, and a corporate culture that stands as a change facilitator (Machado *et al.*, 2020). Another research underscores that corporate culture and leadership support basically mount up to be key driving forces for the adoption digital procurement. Especially relative to the construction sector, readiness assessment of firms for digital technologies is the backbone of the smooth integration of PPD (Chen *et al.*, 2022). Without these vital aspects, it is impossible to further develop PPD in the post-adoption phase.

H5: OR is likely to have a positive influence on the depth of PPD adoption.

2.4.1.6 Information Sharing Culture (ISC)

From its name, ISC deal with any norms and practices attached aboard promoting open communication and cross-departmental sharing. Concerning the construction industry, information sharing is extremely fundamental because the project's team invariably necessitates collaboration across various departments and even requires cooperation across organizations, hence such cultures must be embedded, to ensure effective data flow within and between organizations (Kwofie *et al.*, 2020). Studies have shown that nurturing this culture improves collaboration efficiency and optimization in the construction supply chain and practically solve pretty much information silos using ICT technologies like BIM, the IoT, or cloud collaboration platforms (Zhao & Ding, 2010).

H6: ISC had a positive effect on the depth of PPD adoption.

2.4.1.7 Partners Preparation (PR)

PR allocated towards the digital competence and technological readiness which ought to be demonstrated by important supply chain partners (i.e., suppliers, subcontractors, and logistics providers), and this is a prerequisite in an e-procurement setting. The readiness of the partners is perceived as central to boosting PPD adoption. Research on the construction industry indicates that unfavorable technological readiness on the part of partners would deny smooth adoption and effective implementation of e-procurement (Zuo *et al.*, 2013; Abdul Azeez *et al.*, 2015; Luo *et al.*, 2023).

H7: PR has a positive impact on the depth of PPD adoption.

2.4.2 PPD and DM

The increased PPD enables organizations to automatically access data that spans various projects and departments in real- time. Therefore, management has access to visualization and analytics of big data to analyze the primary elements impacting supply chain risk, supplier performance issues, and fluctuations in material costs (Adebayo *et al.*,2024). Data of this type can be highly influential in informing decision-making through data-driven DM, especially if framed with the appropriate analytical capabilities and a conducive organizational culture (Simões *et al.*, 2023; Jelodar *et al.*, 2021). When viewing PPD improvement from the perspective of IPT, improving PPD enhances an organization's Information Processing Capability - in conjunction with the DC cycle - to recognize and capture opportunities (Teece, 2007).

H8: PPD is posited to have a noteworthy significant positive influence on DM.

2.4.3 DM and SC

SC refers to major shifts in an organization's business framework, distribution of resources, operational processes, or culture to stay competitive amid external uncertainty or capitalize on new opportunities (Rajagopalan & Spreitzer, 1997). When DM can more accurately capture market fluctuations and regulatory requirements, senior executives tend to have more confidence and flexibility to drive wider SC (Brynjolfsson & McAfee, 2014; Sustersic & Vouldis, 2014; Bilkštytė-Skanė & Akstinaite, 2024; Dubey *et al*. 2020; Zhu & Zhang, 2024). In the construction industry, where cost control and green building compliance are critical, DM provides important data support for project material procurement strategies and organizational restructuring.

H9: DM is hypothesized to have a significant positive effecton SC.

In summary, the conceptual model of this study contains a total of nine research hypotheses (H1–H9), demonstrating the complete logical path from TOE and DOI to PPD to DM and SC (see Figure 1).

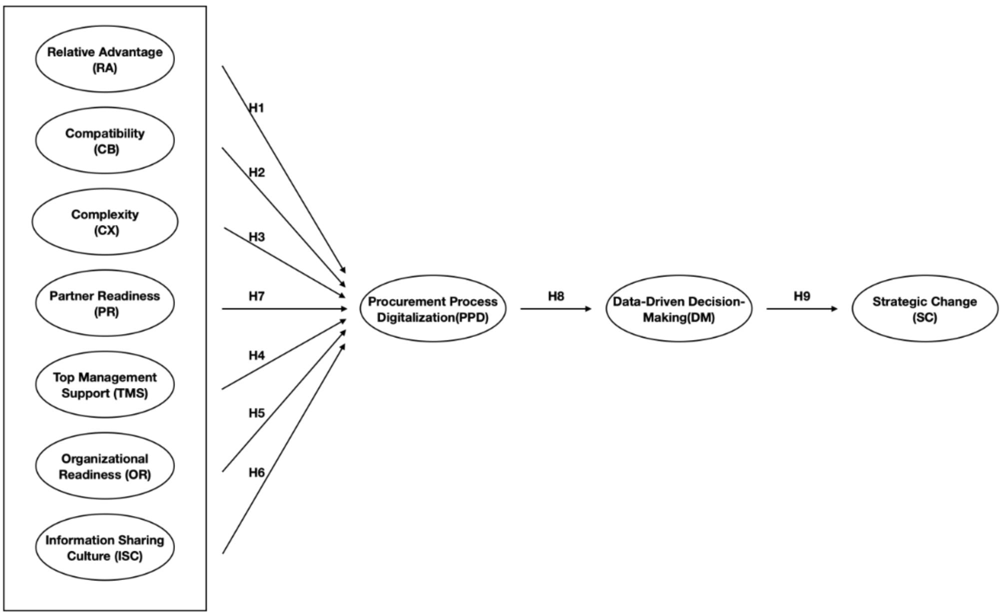

Figure 1 Conceptual framework.

3. METHODOLOGY

3.1 Research Sample and Data Source

This study focuses on the post-adoption stage of digital procurement.It involves Chinese construction supply chain enterprises that currently or previously used any type of e-procurement tool, including e-tendering and cloud-based procurement systems. A total of 1,056 enterprises were randomly selected from the directory of the China Construction Industry Association and subjected to an online questionnaire survey.

- **Pilot test:** Nine procuring executives and IT managers from eight separate enterprises were interviewed prior to the questionnaire distribution in order to check both the translation and the questions of the survey were clear. The supplementation of the feedback proved useful in improving the wording comprehensibility.
- **Screening Criteria:** A screening question was included at the very beginning of the questionnaire, in order to guarantee the data relevance and reliability. In case an e-procurement tool had not been used, the respondent got filtered out.
- **Survey Responses:** Of 395 responses collected, 383 were considered valid, yielding a valid response rate is approximately 36.26%. The sample size is also large enough for PLS-SEM requirements according to Hair *et al*. 2014.

Tables 1 and 2 present the basic characteristics of the surveyed firms and respondents. Overall, these firms frequently take on multiple roles in the supply chain: 17.9% acted as general contractors, 21.3% as construction material suppliers (e.g., steel or cement), 20.2% as distributors and wholesalers, 17.9% as logistics service providers, and another 22.6% fall into other categories, including digital procurement platforms for construction materials.

As the Chinese government encourages construction enterprises to participate in infrastructure projects through an "investment-construction-operation" model, many firms have pursued vertical diversification along the industrial chain (Zhang, 2023). Consequently, the questionnaire allowed respondents to select multiple supply-chain roles. The 383 surveyed firms selected a total of 870 roles, yielding an average of 2.27 roles per firm (870/383). This phenomenon of assuming multiple roles underscores the complex and tightly interconnected nature of China's construction supply chain.

The diversity of China's construction industry is evident in the size of enterprises, ranging from less than 100 to more than 10,000, and in the annual procurement volume, which ranges from tens of millions to billions of renminbi (RMB). About 85% of the respondents have more than five years of experience, and most serve as middle and senior managers. This ensures the authority and reliability of the information provided.

Table 3 shows the digital infrastructure of the surveyed companies; the survey shows that more than half of the companies had basic information technology (IT) systems, such as enterprise resource planning (ERP) and supply chain management (SCM) systems, in place before adopting PPD, which provided strong support for subsequent digital upgrades.

Table 1 Types of roles in the supply chain of interviewed firms.

Types	Percent of Cases	Responses	
		N	Percent
What is your organization's main role in the Chinese construction supply chain?			
Building construction companies	40.7%	156	17.9%
Building material suppliers (e.g. steel mills, cement plants, concrete providers)	48.3%	185	21.3%
Distributors/wholesalers	46.0%	176	20.2%
Logistics and distribution service providers	40.7%	156	17.9%
Construction material procurement platforms	51.4%	197	22.6%
or related intermediary service organizations			
Total	227.2%	870	100.0%

Note. N (frequency) = number of times each role was selected.
Percent (of total role selections) = (selections for a role / 870 [total selections]); column sums to 100%.
Percent of Cases (of total firms) = (firms selecting the role / 383 [total firms]). Because firms could select multiple roles, these percentages sum to 227.2%, indicating an average of 2.27 roles per firm (227.2% ÷ 100%).
a. Dichotomy group tabulated at value 1.

Table 2 Firm and respondent characteristics.

Variable	Category	N	Percentage
Firm Size (No. of Employees)	Fewer than 100	80	20.9%
	100-500人	184	48.0%
	500-1000人	79	20.6%
	More than 1,000	40	10.4%
Annual Procurement	Under 50 million	131	34.2%
(or Revenue), RMB	50 million–100 million	116	30.3%
	100 million–500 million	55	14.4%
	500 million–1 billion	22	5.7%
	Over 1 billion	59	15.4%
Position Level	Senior Management (Director, VP, GM, etc.)	133	34.7%
	Middle Management (Department, Project Manager)	190	49.6%
	Front-Line Supervisor	42	11.0%
	Other	18	4.7%
Department/Function	Procurement/Supply Chain	141	36.8%
	Strategic Management	132	34.5%
	IT/Information Systems	98	25.6%
	Finance/Cost Control	12	3.1%
Work Experience	Under 3 years	13	3.4%
	3–5 years	44	11.5%
	5–10 years	130	33.9%
	Over 10 years	196	51.2%

3.2 Research Measures and Scales

All measurement scales used in this study were adapted from scales in the published literature (Appendix A). The different aspects of the measurement items were based on a five-point Likert scale, with 1 = strongly disagree (never used) and 5 = strongly agree (in-depth use). Respondents' anonymity was appropriately ensured in the development and distribution of the questionnaire. A post hoc evaluation was conducted using the Harman one-way test and model fit indexs (Podsakoff *et al*., 2003).

Table 3 Firms' digital foundations.

Systems	Percent of Cases	Responses	
		N	Percent
Prior to implementing digital procurement, has your firm used the following systems?			
ERP System	52.5%	201	22.1%
SCM System	70.0%	268	29.5%
Electronic Bidding Platform	62.9%	241	26.5%
EDI (Electronic Data Interchange)	51.2%	196	21.6%
Others	0.8%	3	0.3%
Total	237.4%	909	100.0%

3.3 *Data Analysis Methods*

Given the complexity of the proposed model, the involvement of multiple latent variables, and a moderate sample size (N = 383), partial least squares structural equation modeling (PLS-SEM) was used for hypothesis testing in this study (Hair *et al*., 2017). Relative to traditional covariate structural equation modeling (CB-SEM), PLS-SEM has less stringent data distribution requirements, is more suitable for prediction-oriented or exploratory studies (Astrachan *et al*., 2014; Dash & Paul, 2021), and can still provide robust estimation results even when the sample sizes are not very large (Jannoo *et al*., 2014). This study was analyzed using SmartPLS 4.0 software in several major stages including measurement model assessment, structural model assessment, and robustness testing.

Given the complexity of the proposed model, the involvement of multiple latent variables, and the relatively moderate sample size (N = 383), we interpreted our results with caution.

4. DATA ANALYSIS AND RESULTS

4.1 *Descriptive Statistics*

After invalid questionnaires were excluded, 383 valid responses were obtained. Table 1 presents the key characteristics of the surveyed enterprises and respondents. Most companies (64.5%) reported an annual procurement volume of less than 100 million RMB. In comparison, 15.4% exceeded 1 billion RMB, ensuring that the sample encompasses a range of enterprise sizes and procurement complexities. Respondents were predominantly middle managers (49.6%) and senior managers (34.7%). Most of the individuals involved came from the procurement, supply chain, strategy, or IT departments, which ensures the professionalism and accuracy of responses. As indicated in Table 2, approximately 52.5% of the companies had implemented an ERP system before launching PPD, 70% had SCM systems, and 62.9% had utilized an e- tendering platform. These findings indicate a high level of informatization in the sector, providing a good basis for further deepening of digital procurement.

4.2 *Reliability and Validity Testing*

The PLS-SEM assessment measurement model was used in this study. *Cronbach's α* values for all latent variables ranged from 0.783 to 0.880, and composite reliability (CR) ranged from 0.858 to 0.912, which were above the conventional threshold of 0.50 (Fornell & Larcker, 1981). Convergent validity was assessed through average variance extraction (AVE), with AVE values for the 13 constructs ranging from 0.604 to 0.768, all of which exceeded the recommended critical value of 0.50 (Hair *et al*., 2017), as shown in Table 4. Discriminant validity was further validated by the heterogeneity- monomorphism ratio (HTMT), which ranged from 0.146 (PR-SCM) to 0.818 (SCC-SCS) for the first-order constructs, and the highest HTMT value of 0.742 for the second-order constructs SC and PPD, which were below the critical value of 0.85, suggesting that discriminant validity was acceptable (Henseler *et al.* 2015), as shown in Table 5. In addition, the Harman one-way test showed that the variance contribution of the first principal component was 30.93%, which is much lower than the critical value of 50% (Podsakoff *et al*., 2003), implying that the effect of common method bias on the measurements is small and almost negligible.

Table 4 Reliability and convergent validity of constructs.

	Cronbach's alpha	CR	AVE
CB	0.872	0.912	0.722
CX	0.783	0.874	0.697
DM	0.872	0.904	0.612
ISC	0.850	0.909	0.768
OR	0.849	0.909	0.768
PPD	0.834	0.884	0.604
PR	0.833	0.899	0.749
RA	0.880	0.912	0.677
SC	0.875	0.858	0.671
SCC	0.804	0.885	0.719
SCM	0.842	0.905	0.760
SCS	0.849	0.908	0.768
TMS	0.818	0.891	0.731

4.3 *Structural Model Estimation and Hypothesis Testing*

In this paper, Table 6 shows the main path coefficients and their significance levels, while Figure 2 presents the model paths and the corresponding R^2 values. To fully assess the structural model, we tested for multicollinearity, path coefficients, coefficient of determination (R^2), and effect size (f^2), as shown in Table 7, as well as predictive relevance (Q^2), as shown in Table 8.

The results show that both internal VIF values (1.432-2.868) and external VIF values (1.000-1.425) are well below the critical value of 5, indicating that there is no multicollinearity problem. In terms of R^2, the R^2 value of PPD is 0.513 (adjusted 0.504), SC is 0.386, and DM is 0.327, and all the values are significantly higher than the benchmark value of 0.10, indicating that the model has strong explanatory power.

The results of the effect size analysis showed that PPD had a significant effect on DM (f^2 = 0.486) and DM had a significant effect on SC (f^2 = 0.629). Among the antecedent variables of PPD, ISC produced a relatively large effect (f^2 =

0.110); RA had a moderate effect ($f^2 = 0.073$); and the remaining variables had small effects, with CX having the weakest effect ($f^2 = 0.001$). In addition, DM ($Q^2 = 0.184$), PPD ($Q^2 = 0.489$) and SC ($Q^2 = 0.305$) were all greater than zero, while both RMSE and MAE indices verified the strong predictive power of the model. These results indicate that the model performs well in interpretation and prediction.

Table 5 Discriminant validity of HTMT.

FIRST ORDER

	CB	CX	DM	ISC	OR	PPD	PR	RA	SCC	SCM	SCS	TMS
CB												
CX	0.379											
DM	0.339	0.276										
ISC	0.421	0.393	0.391									
OR	0.311	0.415	0.333	0.303								
PPD	0.511	0.454	0.671	0.635	0.487							
PR	0.215	0.191	0.244	0.279	0.227	0.418						
RA	0.364	0.485	0.265	0.424	0.407	0.595	0.268					
SCC	0.524	0.571	0.641	0.603	0.482	0.706	0.373	0.567				
SCM	0.165	0.211	0.482	0.291	0.226	0.354	0.146	0.159	0.552			
SCS	0.549	0.606	0.654	0.629	0.553	0.807	0.44	0.652	0.818	0.442		
TMS	0.286	0.387	0.348	0.356	0.355	0.513	0.239	0.365	0.532	0.317	0.602	

SECOND ORDER

	CB	CX	DM	ISC	OR	PPD	PR	RA	SC	TMS
CB										
CX	0.379									
DM	0.339	0.276								
ISC	0.421	0.393	0.391							
OR	0.311	0.415	0.333	0.303						
PPD	0.511	0.454	0.671	0.635	0.487					
PR	0.215	0.191	0.244	0.279	0.227	0.418				
RA	0.364	0.485	0.265	0.424	0.407	0.595	0.268			
SC	0.491	0.551	0.707	0.605	0.501	0.742	0.381	0.547		
TMS	0.286	0.387	0.348	0.356	0.355	0.513	0.239	0.365	0.577	

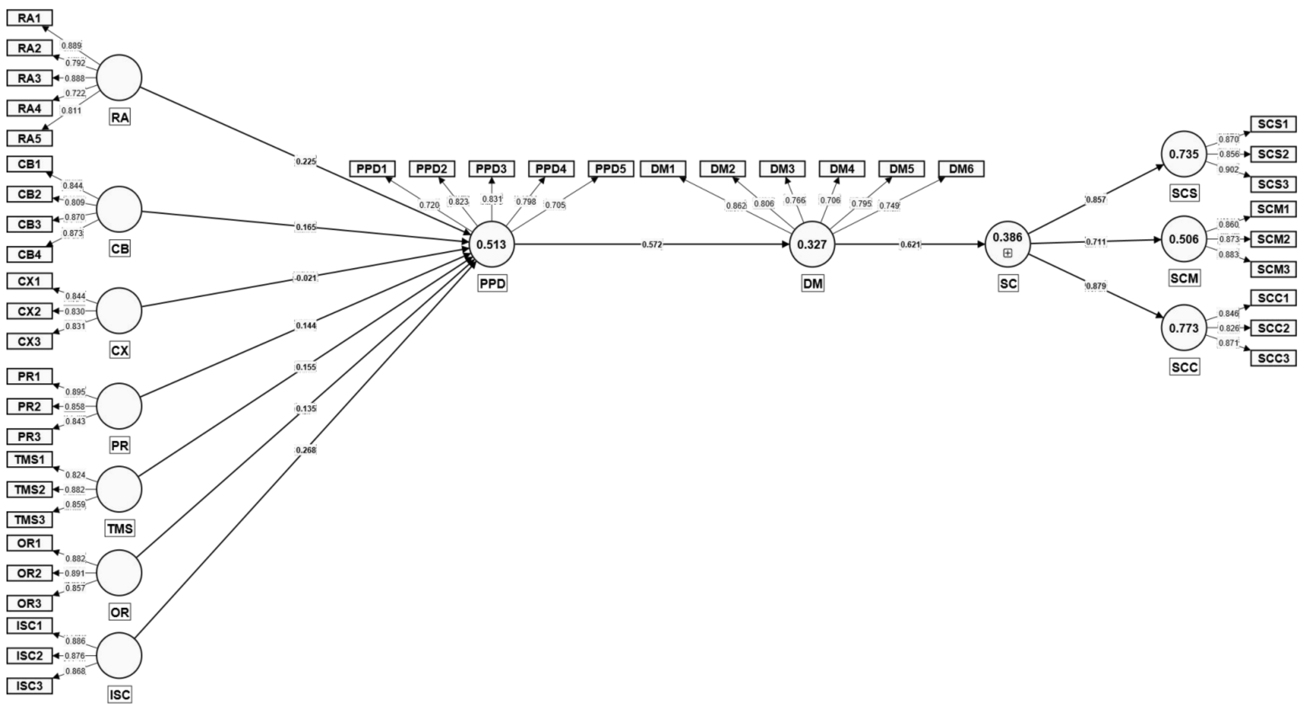

Figure 2 Final model output.

The results of the path coefficient analysis showed that RA, CB, PR, TMS, OR, and ISC all had a significant effect on PPD, with ISC having the strongest effect (β = .268). In contrast, CX had a non-significant effect on PPD (β = -.021, t = .487, p = .627, 95% CI [-.109, .064]), and therefore the H3 hypothesis was not supported. In addition, PPD was found to have a significant positive effect on DM (β = .572), while DM further had a significant effect on SC (β = .621). All results were statistically significant at the P < 0.05 level.

Table 6 Path coefficients and hypotheses evaluation.

Hypothesis	PATH	β	SD	T	P	95%CI		Result
						2.50%	97.50%	
H1	RA →PPD	0.225***	0.043	5.290	0.000	0.139	0.309	support
H2	CB → PPD	0.165***	0.041	3.994	0.000	0.081	0.244	support
H3	CX → PPD	-0.021	0.044	0.487	0.627	-0.109	0.064	reject
H4	PR → PPD	0.144***	0.037	3.876	0.000	0.071	0.215	support
H5	TMS → PPD	0.155**	0.044	3.483	0.001	0.071	0.248	support
H6	OR → PPD	0.135**	0.044	3.050	0.002	0.046	0.219	support
H7	ISC → PPD	0.268***	0.049	5.444	0.000	0.174	0.364	support
H8	PPD → DM	0.572***	0.041	14.041	0.000	0.481	0.644	support
H9	DM → SC	0.621***	0.035	17.946	0.000	0.545	0.682	support

Note:*p-value<0.05,**p-value<0.01,***p value<0.001;β=PathCoefficients ;SD=Standard Deviation;

Impact of TOE-DOI on PPD:The results of the study show that hypotheses H1-H7 are supported,i.e.RA, CB, TMS, OR, ISC, and PR all have a significant positive impact on the depth of PPD adoption.In contrast, CX did not show the expected negative impact. This may be due to the fact that large construction firms in China usually have sufficient resources, and the government also strongly promotes the digital transformation of firms, thus alleviating the hindrance of complexity to some extent (Luo *etal*.,2023).

PPD vs. DM and DM vs. SC: For H8 (PPD → DM), the analyses show β = .572 (p < 0.001), indicating that PPD significantly enhances DM capabilities. For H9 (DM → SC), the results show β = .621 (p < 0.001), suggesting that DM strongly drives the speed and depth of SC.These findings suggest that when construction firms achieve a high degree of digitization and data integration in their procurement processes, their management capabilities are significantly enhanced, enabling them to respond more quickly and comprehensively to market fluctuations and policy adjustments. This evidence further supports the positive role of dynamic capabilities theory and information processing theory in driving digital transformation (Galbraith, 2014; Teece, 2007).

Table 7 Summary of R^2, adjusted $R^2$and F^2.

	R-square	R-square adjusted	F^2
DM	0.327	0.325	
PPD	0.513	0.504	
SC	0.386	0.385	
CB →PPD			0.044
CX →PPD			0.001
DM→SC			0.629
ISC→PPD			0.110
OR →PPD			0.029
PPD→DM			0.486
PR →PPD			0.038
RA →PPD			0.073
TMS→PPD			0.039

Table 8 Results of Q^2 values.

	Q²predict	RMSE	MAE
DM	0.184	0.909	0.767
PPD	0.489	0.720	0.564
SC	0.305	0.838	0.700

4.4 Mediation Effect Analysis

To further clarify the process by which each of the antecedent variables influenced SC through PPD and DM, this study applied 5,000 bootstrap samples to assess the mediation effect as suggested by Hayes (2018) and Zhao *etal*. (2010), where mediation effect was determined to be significant if the 95% confidence interval did not include zero.

As can be seen from Table 9, the mediation effects analysis revealed multiple significant paths. In the dual mediation model through the PPD→DM pathway, RA, CB, PR, TMS, OR, ISC all demonstrated significant effects, whereas the pathway of CX showed no significance. In the triple mediation of PPD→DM→SC, all variables besides CX also indicated significant effects, while the direct PPD→DM→SC pathway was also very significant, indicating that PPD had significant indirect effects on the final outcome through DM and SC.

The overall findings provide a strong rationale for supporting our theoretical model: the mediators of PPD and DM play a central mediating role connecting the organizational variables (RA, CB, PR, TMS, OR, ISC) together with SC outcomes. Conversely, CX did not significantly predict PPD; therefore, organizational complexity may be acted upon by different modes of action through different mechanisms or contexts.

Table 9 Mediation effect.

PATH	Coefficients	SD	T	P	95% CI	
					LCI	UCL
OR→PPD→DM	0.077	0.026	2.979	0.003	0.026	0.129
CB→PPD→DM→SC	0.059	0.016	3.655	0.000	0.029	0.092
PR→PPD→DM	0.082	0.023	3.597	0.000	0.039	0.128
RA→PPD→DM	0.129	0.025	5.108	0.000	0.078	0.178
OR→PPD→DM→SC	0.048	0.017	2.882	0.004	0.016	0.081
TMS→PPD→DM	0.089	0.027	3.256	0.001	0.037	0.143
TMS→PPD→DM→SC	0.055	0.018	3.075	0.002	0.022	0.092
PR→PPD→DM→SC	0.051	0.015	3.343	0.001	0.023	0.084
CX→PPD→DM→SC	-0.008	0.016	0.485	0.627	-0.040	0.021
ISC→PPD→DM→SC	0.095	0.021	4.455	0.000	0.056	0.140
PPD→DM→SC	0.355	0.039	9.016	0.000	0.278	0.433
RA→PPD→DM→SC	0.080	0.017	4.694	0.000	0.047	0.115
CB→PPD→DM	0.094	0.025	3.820	0.000	0.047	0.144
CX→PPD→DM	-0.012	0.025	0.488	0.626	-0.063	0.034
ISC→PPD→DM	0.153	0.031	4.919	0.000	0.095	0.215

4.5 Robustness Checks

To evaluate the robustness of PLS-SEM findings, we conducted two important analyses: an endogeneity test and an evaluation of unobserved heterogeneity.

4.5.1 Testing for Endogeneity

To evaluate the robustness of our model structure, we used the Gaussian copula approach proposed by Park and Gupta (2012) to test for endogeneity issues. This approach is well-suited to evaluate endogeneity concerns in non-normally distributed constructs in PLS-SEM models. We conducted eight Gaussian covariance tests on the main relationships in the model, including the four important exogenous predictors of PPD (RA, ISC, CB, and TMS), the key mediating relationships (PPD → DM, DM → SC), and the portfolio test.

The tests indicated that endogeneity was present for predicting PPD from ISC (^{c}ISC = .227, *p* = .001) and TMS (^{c}TMS = -.152, *p* = .018), respectively, as shown in Table 10. Likewise, in the combined test, both copula terms for ISC (^{c}ISC = .243, *p* <.001) and TMS (^{c}TMS = -.159, *p* = .013) were significant. In summary, we did not find significant copula terms for RA, CB, PPD, or DM, which indicated there were no endogeneity issues detected in these relationships. While there was some endogeneity present, important to note was that for those affected variables, the path coefficients remained significant and consistent in direction, indicating that endogeneity did not pose a major threat to our main conclusions. Based on the recommendations by Hult *etal.* (2018), researchers should proceed with caution when interpreting results when endogeneity is present and acknowledge limitations. It is also suggested that researchers may develop instrumental variables to alleviate above mentioned concerns. That said, we concluded that our main path relationships remained robust; particularly, the key mediating paths of PPD → DM → SC indicated no significant endogeneity threats.

4.5.2 Checking for Heterogeneity

The presence of unobserved heterogeneity was examined through Finite Mixture modeling (FIMIX-PLS), which can identify significant differences in structural model relationships between unobserved data groups (Becker *etal.*, 2013). The FIMIX- PLS algorithm was executed 10 times for segments 1-5 using multiple information criteria: Akaike Information Criterion (AIC), modified AIC with factor 3 (AIC3), modified AIC with factor 4 (AIC4), Bayesian Information Criterion (BIC), Consistent AIC (CAIC), Hannan-Quinn Criterion (HQ), minimum description length with factor 5 (MDL5), and normed Entropy Statistics (EN) to determine the appropriate segmentation solution (Matthews *etal.*, 2016; Sarstedt *etal.*, 2011).

Different optimal solutions are indicated by several information criteria, as detailed in Table11. While AIC, AIC3, AIC4, and HQ values decline as the number of segments increases, suggesting a possible five-segment solution, BIC indicates a four-segment solution (4,342.57), and CAIC indicates a three-segment solution (4,402.31). The MDL5 criterion is more penalized for complexity, and indicated a one-segment solution (5,095.01) as the most appropriate. Entropy statistic values for all solutions ranged from .695 to .741, and considered all above the .50 threshold, indicating good segmentation quality. A comprehensive evaluation of these information criteria, combined with theoretical considerations and sample size requirements, suggests that a one-segment solution is most robust for our model. Although different information criteria point to different numbers of segments (AIC, AIC3, AIC4, and HQ pointing to a five-segment solution, BIC pointing to a four-segment solution, CAIC pointing to a three-segment solution, and MDL5 pointing to a one-segment solution), this inconsistency itself suggests that there is no significant unobserved heterogeneity in the model.

Considering the inconsistency that exists between the various information criteria and the sample size requirements, the single segmentation scheme appears to be the most appropriate. This suggests that our structural model exhibits a high level of robustness across the entire sample without the need for further segmentation. We believe that this finding not only makes the interpretation more concise but also improves the generalizability of the findings.

Table 10 Endogeneity test using Gaussian copula approach.

Test	Construct	Coefficient	P-value
Endogeneity Tests for PPD - Key Exogenous Variables			
Gaussian copula model 1 (Endogenous variable: RA)	RA	0.296	0.001
	CB	0.165	0.000
	CX	-0.020	0.648
	PR	0.143	0.000
	TMS	0.153	0.001
	OR	0.135	0.002
	ISC	0.270	0.000
	^{c}RA	-0.066	0.344
Gaussian copula model 2 (Endogenous variable: ISC)	RA	0.222	0.000
	CB	0.160	0.000
	CX	0.000	0.995
	PR	0.146	0.000
	TMS	0.158	0.000
	OR	0.122	0.005
	ISC	0.033	0.721
	^{c}ISC	0.227	0.001
Gaussian copula model 3 (Endogenous variable: CB)	RA	0.227	0.000
	CB	0.120	0.159
	CX	-0.021	0.627
	PR	0.145	0.000
	TMS	0.155	0.001
	OR	0.131	0.004
	ISC	0.268	0.000
	^{c}CB	0.038	0.508
Gaussian copula model 4 (Endogenous variable: TMS)	RA	0.226	0.000
	CB	0.166	0.000
	CX	-0.032	0.465
	PR	0.144	0.000
	TMS	0.315	0.000
	OR	0.135	0.002
	ISC	0.266	0.000
	^{c}TMS	-0.152	0.018
Key Mediating Path Tests			
Gaussian copula model 5 (Endogenous variable: PPD)	PPD	0.730	0.000
	^{c}PPD	-0.154	0.119
Gaussian copula model 6 (Endogenous variable: DM)	DM	0.533	0.000
	^{c}DM	0.073	0.186
Combined Tests			
Gaussian copula model 7 (Endogenous variables: RA, ISC, CB, TMS)	RA	0.338	0.000
	CB	0.123	0.145
	CX	-0.008	0.863
	PR	0.145	0.000
	TMS	0.324	0.000
	OR	0.118	0.007
	ISC	0.017	0.857
	^{c}RA	-0.107	0.131
	^{c}ISC	0.243	0.000
	^{c}CB	0.032	0.587
	^{c}TMS	-0.159	0.013
Gaussian copula model 8 (Endogenous variables: PPD, DM)	PPD	0.730	0.000
	DM	0.533	0.000
	^{c}PPD	-0.154	0.119
	^{c}DM	0.073	0.186

Table 11 Information criteria by segment by FIMIX-PLS.

	Criterion								Relative Segment Size				
	AIC	AIC3	AIC4	BIC	CAIC	HQ	MDL5	EN	g1	g2	g3	g4	g5
S1	4595.68	4613.68	4631.68	4666.75	4684.75	4623.87	5095.01	n/a	1				
S2	4284.69	4321.69	4358.69	4430.77	4467.77	4342.64	5311.08	0.732	0.640	0.36			
S3	4125.22	4181.22	4237.22	4346.31	4402.31	4212.92	5678.67	0.695	0.359	0.346	0.295		
S4	4046.47	4121.47	4196.47	4342.57	4417.57	4163.93	6126.98	0.73	0.325	0.296	0.273	0.106	
S5	4000.38	4094.38	4188.38	4371.49	4465.49	4147.59	6607.95	0.741	0.290	0.264	0.194	0.146	0.105

Legend: AIC - Akaike's Information Criterion, AIC3 - Modified AIC with Factor 3, AIC4 - Modified AIC with Factor 4, BIC - Bayesian Information Criteria, CAIC - Consistent AIC, HQ - Hannan Quinn Criterion, MDL5 - minimum description length with factor 5,EN - Entropy Statistic (Normed).

5. DISCUSSION

5.1 Theoretical Contributions

This section combs through and summarizes the theoretical contributions of this study, which are mainly reflected in the deepening of digital procurement research through cross-theoretical integration, the strengthening of the validity of core findings by the integrated application of robustness tests in methodology, the theoretical extension of the post-adoption stage, and the re-understanding of the complexity effect.

At the level of cross-theoretical integration, this study combines TOE, DOI, DC Theory, and IPT to holistically explore the deepening mechanisms of PPD in the post-adoption phase. In contrast to previous studies that only consider digital procurement as a purely operational innovation, this study expands the scope of prior research on e-procurement by pointing out that PPD can have a significant impact on organizational SC through DM (Alabdali & Salam, 2022; Hameed & Arachchilage, 2016).

In terms of robustness tests at the methodological level, this study further ensures the validity and reliability of the theoretical model by testing for endogeneity and unobserved heterogeneity. In particular, the potential endogeneity of relationships such as ISC (which may refer to industry supply chain-related factors) and TMS in predicting PPD was explored using a Gaussian Copula approach. However, the results showed that these endogeneity issues did not overturn the significance of the main path coefficients. In addition, the results of the FIMIX-PLS analysis show that there is no significant unobserved heterogeneity in the sample of this study, i.e., the structure of the proposed model is consistent across subgroups. Thus, this series of robustness assessments provides reliable and stable support for the PPD → DM → SC framework constructed in this study.

Based on the above robust empirical foundation, this study further expands the theoretical horizon of digital procurement research, especially focusing on the research in the post-adoption stage. Although studies have paid extensive attention to the early adoption of e-procurement and digital procurement (Zhu *etal*., 2006), there is still a relative lack of discussion on its subsequent in-depth application, continuous optimization, and strategic value creation. Based on an empirical analysis of several construction firms, this study finds that PPD can contribute to DM and positively influence SC in the post-adoption stage. Therefore, this study fills the gap in research on the post-adoption stage of e-procurement and provides a new perspective for the improvement of related theories.

On the basis of the above research, this study also re-examines the mechanism of complexity in technology adoption. Although the traditional DOI theories often view CX as a major barrier to technology adoption (Rogers, 1995; Ifinedo, 2011), the results of this study show that the effect of CX on PPD is not significant. This may indicate that in medium and large construction firms in China, sufficient resource reserves and supportive government policies have largely weakened the resistance posed by complexity (Luo *etal*., 2023). This finding provides a new entry point for revisiting the DOI hypothesis in a different context.

5.2 Practical Implications

This section puts forward actionable practical suggestions for the implementation of digital procurement by integrating organizational management practices with government and industry policies.

From the perspective of organizational management, TMS plays a key role in fully advancing PPD. To truly realize the strategic value of digital procurement, it needs to be viewed as part of an organization's core business strategy, rather than a general IT upgrade. At the same time, it is not enough to focus on optimizing internal capabilities; external synergies are also crucial. Establishing a tight culture of information sharing and collaboration with supply chain partners can help to more fully utilize and deeply apply digital procurement, accelerating the goal of intelligent and collaborative procurement. Enterprises can also encourage suppliers and subcontractors to use digital systems by setting up incentives or relevant clauses in procurement contracts to create a truly collaborative digital procurement ecosystem. This will not only make the procurement process more transparent and efficient but also promote a collaborative atmosphere within the enterprise and the supply chain. It enhances the enterprise's ability to respond nimbly to market and policy changes and improves resource integration and competitive advantage.

From the perspective of government and industry policies, governments and industry associations have the ability to drive digital transformation of the supply chain by setting uniform e-procurement standards, offering tax incentives or project subsidies. In the face of increasingly stringent green building codes and carbon reduction requirements, digital procurement platforms can quickly provide material-related information to help companies fulfill their compliance and resource optimization responsibilities.

5.3 Further Discussion on the Insignificant Influence of CX

This section, combining the DOI with research findings, conducts an in-depth discussion on the reasons why complexity has an insignificant effect in the digitization of procurement processes and puts forward the research implications arising therefrom.

According to DOI theory, CX is often viewed as an inhibitor to technology adoption. Nonetheless, this study found that the effect of CX on PPD is not considerable, this phenomenon may result from the combined effect of multiple factors. On the one hand, most respondents constituted mid and large-sized enterprises that possess sufficient IT expenditure to manage technical complexity appropriately. In addition, as a result of national digitalization policies and the development of a specific industry, a significant number of third-party platforms and professional service organizations have arisen to facilitate the provision of technical services, which may mitigate the complexity of implementation. Furthermore, most companies in the study have already formed a digital infrastructure, with some expertise, which can neutralize aspects of complexity.

As a result, when it comes to the adoption process of digital procurement, size and technical background may have some moderating effect. Evidently, for smaller firms, complexity may still prove to be a large barrier, which warrants further exploration in future studies.

6. CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

6.1 Conclusions

This study analyzed the post-adoption stage of digital procurement by integrating a comprehensive model of TOE, DOI, DC and IPT. The study empirically tested the model using data from 383 Chinese construction supply chain firms and examined the impact of PPD on DM and SC. The findings suggest that RA, CB, TMS, OR, ISC, and PR are strong enablers of deeper PPD adoption; while CX does not have the expected adverse effects; and strong PPD adoption significantly improves DM capability, which in turn drives accelerated and deeper SC.

This means that the construction industry can respond more profoundly and flexibly to market dynamics and green regulatory pressures; the experience in examining organizational practices in relation to these working conditions is novel to the academic literature base related to digital sourcing in large project-based industries, and provides a practical approach to stimulating digital transformation and sustainable competitiveness in business management and public policy. Finally, it is worth noting that these findings are further justified by our robustness tests, and despite some endogeneity of ISC and TMS found in terms of PPD, the overall path direction and significance remain reliable and there is no significant unobserved heterogeneity, so that we can consider the contributions of this study to be sound and generalizable.

6.2 Limitations

Cross-sectional design: Relying on a one-time questionnaire alone makes it difficult to capture the changes and long- term impacts of digital procurement at different stages, leading to limitations in inferring causal relationships. The paper points out that the benefits of digital sourcing become apparent over time, and therefore a longitudinal or multi-stage research design is needed to more accurately track and validate the dynamic impact of digital procurement on firm performance and other key indicators.

Self-Reported Data and Common Methodology Deviations: In a self-reported model, even with anonymization and statistical tests, effects such as cognitive bias and subjective embellishment may still occur, which are among the common research limitations that are difficult to fully address. In the future, if secondary data or case studies can be combined, it will help to overcome the limitations of self-reporting and to validate and refine the findings from more dimensions.

6.3 Future Research Directions

Longitudinal studies: More complete process evidence can be obtained through multiple data collections, continuous observation of the various stages of digital procurement implementation, and the dynamic interaction between technological deepening and strategic change. This longitudinal perspective helps researchers distinguish between short-term and long- term impacts, and avoids biased conclusions based on a single cross-section of time.
Cross-country comparisons: Comparing China's construction industry with other countries or regions can provide a better understanding of the differences in the impact of multiple factors, such as culture, regulatory policies, and market environments, on digital procurement. As the construction industry has significant differences in norms, technology levels, market structures, and government support in different regions, such comparative studies can provide more targeted evidence on the pervasiveness and limitations of digital procurement and digital management.

Green Performance and Environmental, Social, and Corporate Governance (ESG) Perspective: Incorporating carbon emissions, energy efficiency, and sustainability performance indicators into the research model is an effective way to expand on the question of whether digital procurement brings additional green value. With the growing importance of green buildings and sustainability, the assessment of the impact of digital procurement and digital management on energy efficiency and emissions reduction, as well as on broader ESG goals, deserves to be explored in depth.

Mediating and moderating mechanisms: Further exploring the mediating roles that organizational learning, supplier management strategies, and other factors may play between PPD and DM, as well as between DM and strategic change (SC), can shed more light on the paths of internal and external resource integration in firms. Meanwhile, the inclusion of moderating factors such as firm size and management style can help to understand the variability that different types of firms may exhibit in digital transformation and strategic alignment.

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APPENDIX A: MEASUREMENT ITEMS AND THEIR SOURCES

Item	Measured Variable	Source
Technological Factors		
H1: Relative advantage (1—strongly disagree and 5—strongly agree)		
RA1	Digital procurement technologies allow the company to manage procurement operations in an efficient way.	
RA2	The use of digital procurement tools improves the quality of procurement processes.	Ifinedo,2011
RA3	Using digital procurement solutions allows the company to perform specific procurement tasks more quickly.	Ghobakhloo et al.,2011; Moore and Benbasat,1991
RA4	The use of digital procurement technologies offers new opportunities for the procurement function.	Oliveira et al.,2014
RA5	Using digital procurement solutions helps increase the overall productivity of procurement activities.	Ifinedo,2011
H2:Complexity (1—strongly disagree and 5—strongly agree)		
CX1	The skills required to implement and use the digitization of the procurement process are too complex for our company	Ifinedo,2011
CX2	The skills required to use the digitization of the procurement process are too complex for our employees	Thiesse et al.,2011
CX3	Digitally integrating procurement processes into our current working practices will be a challenge	Moore and Benbasat,1991
H3:Compatibility (1—strongly disagree and 5—strongly agree)		
CB1	The use of digital procurement technologies aligns with the work style of the company.	Ifinedo,2011
CB2	The use of digital procurement tools is fully compatible with current procurement operations.	Thiesse et al.,2011
CB3	Using digital procurement technologies is compatible with the company's corporate culture and value system.	Zhu et al.,2006; Oliveira et al.,2014
CB4	The use of digital procurement technologies is compatible with existing hardware and software in the company	Oliveira et al.,2014
Organizational factors		
H4:Top management support(1—strongly disagree and 5—strongly agree)		
TMS1	The company's management supports the implementation of digital procurement technologies.	Shah et al.,2011
TMS2	The company's top management provides strong leadership and actively engages in the digital transformation of procurement processes.	Chwelos et al.,2001; Zhu et al.,2010; Oliveira et al.,2014
TMS3	The company's management is willing to take financial and organizational risks involved in the adoption of digital procurement solutions.	Oliveira et al.,2014
H5:Organizational Readiness(1—strongly disagree and 5—strongly agree)		
OR1	Our firm understands how digital procurement technologies can be used to support procurement technologies.	Acovou et al.,1995
OR2	Our firm has a good understanding of how digital and e-business technologies can enhance procurement processes.	Kuan and Chau,2001
OR3	We have the necessary technical, managerial, and other skills to implement digital procurement technologies.	Merthens et al.,2001
OR4	Our business values and norms would not prevent us from adopting digital procurement technologies in our operations.	
H6:Information Sharing Culture(1—strongly disagree and 5—strongly agree)		
ISC1	Information sharing is encouraged within my organization.	Malhotra et al.,2006
ISC2	My organization has a culture of sharing information.	Teo et al.,2009
ISC3	My organization values information sharing.	
ISC4	Information sharing is practiced by employees.	
ISC5	We usually share information among different organizational departments	
Environmental factor		
H7:Partner Readiness(1—strongly disagree and 5—strongly agree)		
PR1	The extent to which downstream customers have digital systems ready to support digital procurement processes.	
PR2	The extent to which upstream partners have digital systems ready to support digital procurement activities.	Zhu et al.,2006

APPENDIX A: MEASUREMENT ITEMS AND THEIR SOURCES (CONT'D)

Item	Measured Variable	Source
PR3	The extent to which digital systems owned by trading partners are interoperable with our systems	
For the resulting construction		
Digitization of procurement process (1 - not used and 5- used routinely)		
PPD 1	Request for quotation (buyer requests quotation from seller).	Van Weele,2014
PPD 2	Offer (seller delivers offer to buyer).	
PPD 3	Product catalog (transmission of product information).	
PPD 4	Tender (buyer organizes tender for several sellers).	
PPD 5	Order (the buyer delivers the order to the seller of the product or service).	
PPD 6	Order tracking.	
PPD 7	Order change (seller or buyer can propose a change to the order).	Harju et al.,2023
PPD 8	Invoicing (seller delivers invoice to buyer; product,service).	
H8:Data-driven decision (1—strongly disagree and 5—strongly agree)		
DM1	In assessing the current situation	Simon,2013
DM2	When identifying problems	
DM3	Exploring alternative courses of action	
DM4	In the assessment of alternative courses of action	
DM5	When choosing between alternative courses of action	Szuksits and Móricz,2024
DM6	When planning the implementation of decisions	
DM7	In communicating decisions	
DM8	To monitor the implementation of decisions	
H9:Strategic change(Speed of strategic change-S;Magnitude of strategic change-M;Content of strategic change-C)		
Speed of strategic change		
SC-S1	We design strategic plans very quickly	Kim and McIntosh,1996
SC-S2	We implement strategic plans very quickly	Kraatz and Zajac,2001
SC-S3	Our top managers agree with each other very quickly on design and implementation of new strategies	Yi et al.,2017
SC-S4	Our employees accept firms' new strategies or strategic adjustments very quickly	
Magnitude of strategic change		
SC-M1	We diversifying our product and/or service continuously	Golden and Zajac,2001
SC-M2	We continue to work on the market promotion of new product/service	Barker and Duhaime,1997
SC-M3	We continue to expand our scope of business	Yi and Wei,2017
Content of strategic change		
SC-C1	Product focus	
SC-C2	Organizational structure	Waldman et al.,2004
SC-C3	Financial structure	Aslan et al.,2011
SC-C4	Internal organizational processes/programs	

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