The Transformation of China Construction Supply Chain Management by using Intelligent Automation (IA): An Empirical Framework Based on Resource Dependence Theory

Huang Samian, School of Housing, Building and Planning, Universiti Sains Malaysia, 11700 Gelugor, Palua Pinang, Malaysia.
Email: huangsamian@student.usm.my

*Khoo Terh Jing, School of Housing, Building and Planning, Universiti Sains Malaysia, 11700 Gelugor, Palua Pinang, Malaysia.
Email: terhjing@usm.my

Arman Bin Abdual Razak, School of Housing, Building and Planning, Universiti Sains Malaysia, 11700 Gelugor, Palua Pinang, Malaysia.
Email: arm_raz@usm.my

Corresponding author: Khoo Terh Jing, Email: terhjing@usm.my

ABSTRACT

China's construction sector is experiencing an accelerated digital transformation propelled by Intelligent Automation (IA) technologies, including Artificial Intelligence (AI), Robotic Process Automation (RPA), and Collaboration and Integration (CI). Conventional supply chains are increasingly inadequate for addressing growing demands for complexity management, sustainability, and real-time responsiveness. This study examines the transformative role of IA in developing smart supply chains by promoting transparency, flexibility, and comprehensive traceability. A mono-method approach was adopted, beginning with a Systematic Literature Review (SLR) to conceptualise the key variables and establish a framework grounded in Resource Dependence Theory (RDT). Subsequently, quantitative data were gathered via a structured questionnaire administered to 218 construction professionals in China. Employing Exploratory Factor Analysis (EFA) and Multiple Linear Regression (MLR), the analysis identified three IA dimensions—AI capability, RPA implementation, and CI extent—that exert a significant impact on supply chain performance. Results indicate that RPA and digital collaboration serve as the primary drivers of enhanced transparency and adaptability, whereas AI's effect is still emerging. These findings provide empirical support for IA as a mechanism to improve strategic flexibility and mitigate reliance on legacy systems. The study presents a validated IA-SCM performance framework, offering actionable insights for industry practitioners and policymakers seeking to establish resilient and intelligent supply networks.

Keywords: Intelligent Automation, Construction Smart Supply Chain, Systematic Literature Review, Regression Analysis, and Supply Chain Optimization

INTRODUCTION

The construction sector, a fundamental pillar of China's economic growth, is experiencing a substantial digital transformation (Aziz et al., 2024). At the core of this evolution lies the modernisation of construction supply chain management (CSCM), a field historically challenged by fragmentation, uneven information flows, and slow responsiveness to dynamic project requirements (Vignesh & Prabakaran, 2024). In this context, Intelligent Automation (IA)—an integrated set of technologies comprising AI, RPA, and platforms supporting CI—has emerged as a critical enabler (Attajer & Mecheri, 2024). Implementing IA offers the potential to improve operational efficiency, enhance transparency, and increase adaptability, thereby reshaping the movement of materials, data, and financial resources within construction projects (Maatar et al., 2022). This study empirically examines the transformative role of these IA technologies in creating a smart supply chain within China's rapidly advancing construction sector.

Despite increasing attention to digital technologies in construction, empirical evidence on the mechanisms and relative effectiveness of individual IA components remains limited (Bhattacharya & Chatterjee, 2021; Parshuramkar et al., 2024). Much of the existing literature remains fragmented, either analysing technological capabilities in isolation or presenting conceptual frameworks lacking robust empirical support (Adeusi & Onah Louis, 2024; Haloul et al., 2024). For example, theoretical studies highlight the potential of Building Information Modeling (BIM) for supply chain integration (Liu et al., 2022), while Shamsuddoha et al. (2025)explores AI's predictive analytics for logistics.

However, comprehensive studies that concurrently assess the distinct contributions of AI, RPA, and CI to essential supply chain performance metrics are scarce. Furthermore, much prior research originates from technologically mature environments (Cataldo et al., 2022), leaving limited insight into the adoption and value creation of these technologies under China's specific institutional, regulatory, and scale-related conditions (Benjamin et al., 2024; Dalsaniya & Kishan, 2022; Ji, 2024). This absence of a nuanced, component-level analysis leaves practitioners and theorists uncertain about how best to prioritise technological investments for optimal impact.

This study addresses these gaps by constructing and empirically testing a framework that disaggregates the influence of core IA technologies on smart CSCM. Moving beyond theoretical discourse, it provides quantifiable evidence on how AI, RPA, and CI individually and collectively enhance capabilities such as Supply Chain Transparency and Traceability (STT) and Infrastructure Demands Adaptability (IDA). By situating the investigation in China, the research delivers context-specific intelligence, rendering the findings highly relevant to construction managers, supply chain professionals, policymakers, and technology providers operating in one of the largest construction markets globally. The study outlines a clear, evidence-based strategy for technology adoption, assisting stakeholders in navigating the complexities of digital transformation within an industry historically slow to innovate.

The contributions of this research are threefold. First, it offers rigorous empirical validation, confirming that RPA and CI presently serve as the primary drivers of transparency and adaptability in China's construction supply chain, while AI's effect, though positive, remains emerging. This provides a critical reality check against prevalent AI hype. Second, the study advances theory by applying RDT to the construction technology domain, illustrating how IA alleviates environmental uncertainties and reshapes inter-organisational dependencies. Finally, from a practical perspective, the research presents a validated conceptual framework and actionable insights, guiding stakeholders towards prioritised investments in technologies that yield immediate and tangible benefits for establishing smarter, more resilient supply chains.

LITERATURE REVIEW

Operational Definition

Intelligent Automation (IA), characterised as the substantial enhancement of process automation through the integration of AI with RPA, enables organisations to automate processes that are flexible, intelligent, selective, and capable of learning, by utilising techniques such as Machine

Learning (ML), Natural Language Processing (NLP), and cognitive automation (Dalsaniya & Kishan, 2022). This framework incorporates AI, which consists of intelligent systems capable of learning and emulating human reasoning, facilitating task automation and the analysis of complex operations (Mandala & Dolu Surabhi, 2024), alongside RPA, a technology essential for reducing labour and time expenditures, improving precision, and supporting logistics management. RPA frameworks enhance development efficiency, shorten project preparation periods, and optimise the performance of logistics operations (AlRushood et al., 2023; Zhang & Huang, 2022).

The combination of these technologies gives rise to the Smart Supply Chain (SC), which emphasises areas such as transportation, warehousing, and demand forecasting. SC identifies the most efficient routes by considering factors including traffic conditions, weather, and delivery schedules, thereby reducing fuel consumption, accelerating deliveries, and lowering costs. Additionally, SC improves production planning and customer service by integrating diverse information sources, consumer behaviour patterns, and social media data to generate accurate demand predictions, supporting more informed decision-making (Adesoga et al., 2024).

Systematic Literature Review

To conduct a rigorous and comprehensive SLR, peer-reviewed articles published between 2015 and 2025 were retrieved from the scholarly databases Web of Science (WOS) and Scopus. Boolean operators (AND, OR, NOT) were employed in combination to refine and filter the search results. The search strategy included keyword combinations such as (“Intelligent Automation” OR “IA” OR “Smart Automation”) AND (“Artificial Intelligence” OR “AI”) AND (“Robotic Process Automation” OR “RPA”) AND (“Construction Industry” OR “Construction Sector” OR “Construction Projects”) AND (“Intelligent Supply Chain” OR “Smart Supply Chain” OR “Digital Supply Chain”) AND (“Sustainability” OR “Sustainable Development” OR “Sustainable Growth”) NOT “Manufacturing”. Table 1 presents the specific keywords and terms applied in this study.

Table 1: Keywords and Related Terms

Boolean Operators	Keywords	Related Terms
OR, AND, NOT	Intelligent Automation (IA)	Smart Automation, AI-powered Automation, Intelligent Process Automation (IPA), Automation with Artificial Intelligence, AI-driven Workflow Automation
	Construction Industry	Construction Sector, Building Industry, Construction Projects, Construction Management, Construction Operations, Construction Planning, Construction Technology, Smart Construction, Digital Construction, Sustainable Construction
	Construction Supply Chain (CSC)	Construction Supply Chain Management (CSCM), Smart Construction Supply Chain, Sustainable Construction Supply Chain (SCSC), Supply Chain Integration in Construction, Digital Supply Chain in Construction, End-to-End Construction Supply Chain
	Smart Supply Chain	Intelligent Supply Chain, Digital Supply Chain, Automated Supply Chain, Real-Time Supply Chain, End-to-End Visibility in Supply Chain

Inclusion and Exclusion Criteria

The inclusion and exclusion criteria for this study were carefully defined to ensure that only relevant and high-quality articles were considered for the review. As illustrated in the PRISMA diagram (Figure 1), a total of 157 records were initially retrieved from academic databases, comprising 72 from Scopus and 85 from Web of Science (WOS). An initial screening based on the relevance of titles and abstracts led to the removal of 77 out-of-context records and 12 duplicates, leaving 68 records for further evaluation. Subsequent filtering involved the exclusion of 10 articles due to their titles and abstracts, along with 8 additional studies whose objectives did not align with the focus of this review. The remaining 58 papers underwent a full-text review, with inclusion restricted to those demonstrating substantial methodological rigor and direct relevance to the research questions. Ultimately, 50 studies were retained for the final review.

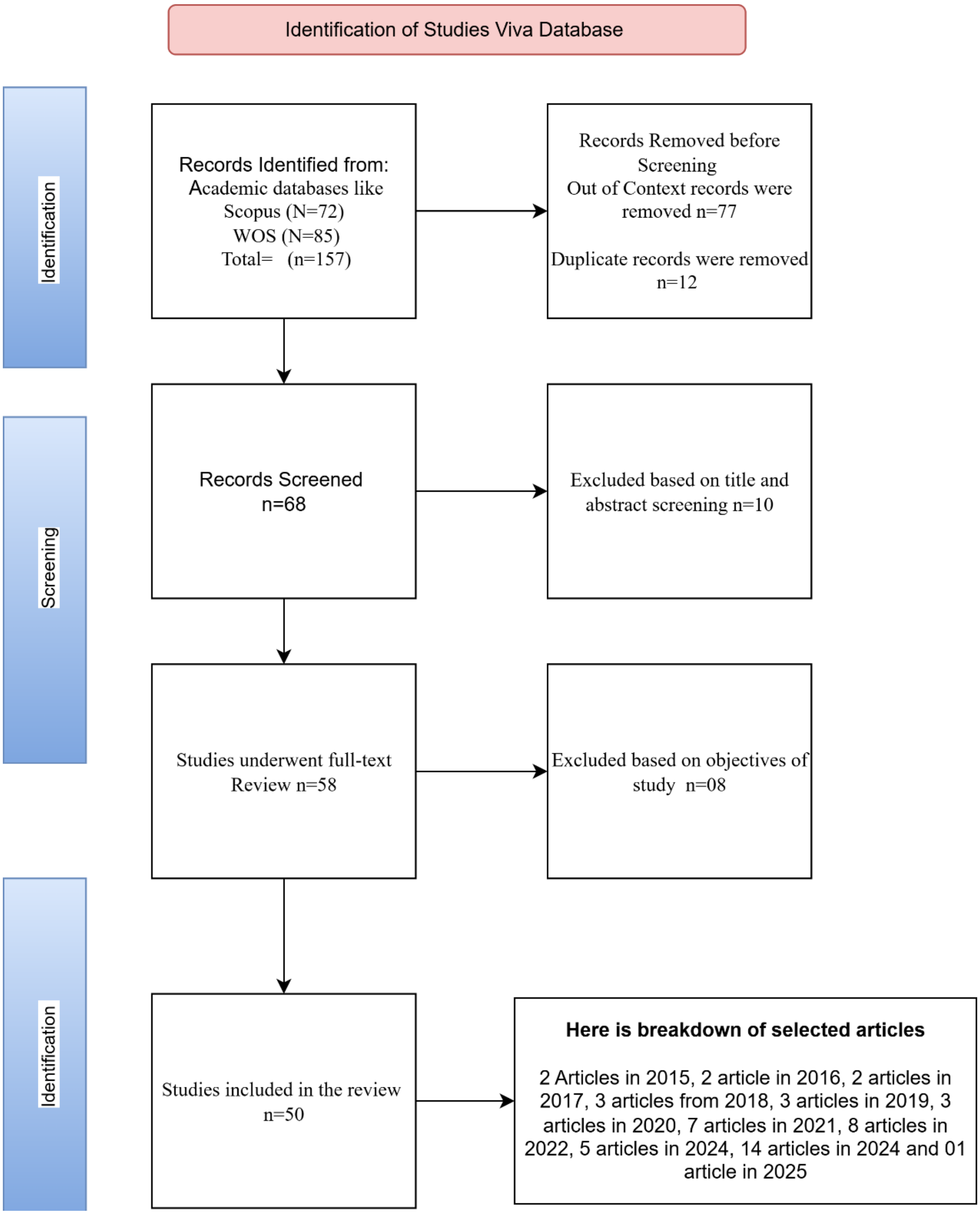

Figure 1: PRISMA Process

The selected studies were analysed according to their year of publication, revealing a broad temporal distribution. Two articles were published in 2015, followed by two in 2016, with the highest number of relevant publications occurring in 2024 (14 articles), followed by 8 in 2022 and 7 in 2021. The review encompassed research from 2015 through to 2025, ensuring a comprehensive coverage of the field. This meticulous selection process guaranteed that the review incorporated high-quality studies aligned with the research objectives while maintaining academic rigour. Figure 1 provides a clear representation of the inclusion and exclusion criteria.

Figure 2 presents the co-citation and cluster analysis performed using CiteSpace. This SLR highlights key research domains, emerging technological trends, and evolving practices in the application of AI and automation within the construction smart supply chain. Evidence from these studies indicates that IA adoption substantially improves transparency, risk resilience, sustainability, and overall efficiency across the construction value chain. Among the enabling technologies, IA stands out as the primary driver of transformation within the construction smart supply chain. IA, comprising AI, ML, RPA, and decision-support systems, integrates these technologies to deliver transformative impacts on the construction sector, enhancing workflow efficiency, mitigating risks, and promoting environmental sustainability. Nevertheless, the literature also underscores significant implementation challenges, particularly concerning interoperability, data governance, and workforce adaptation.

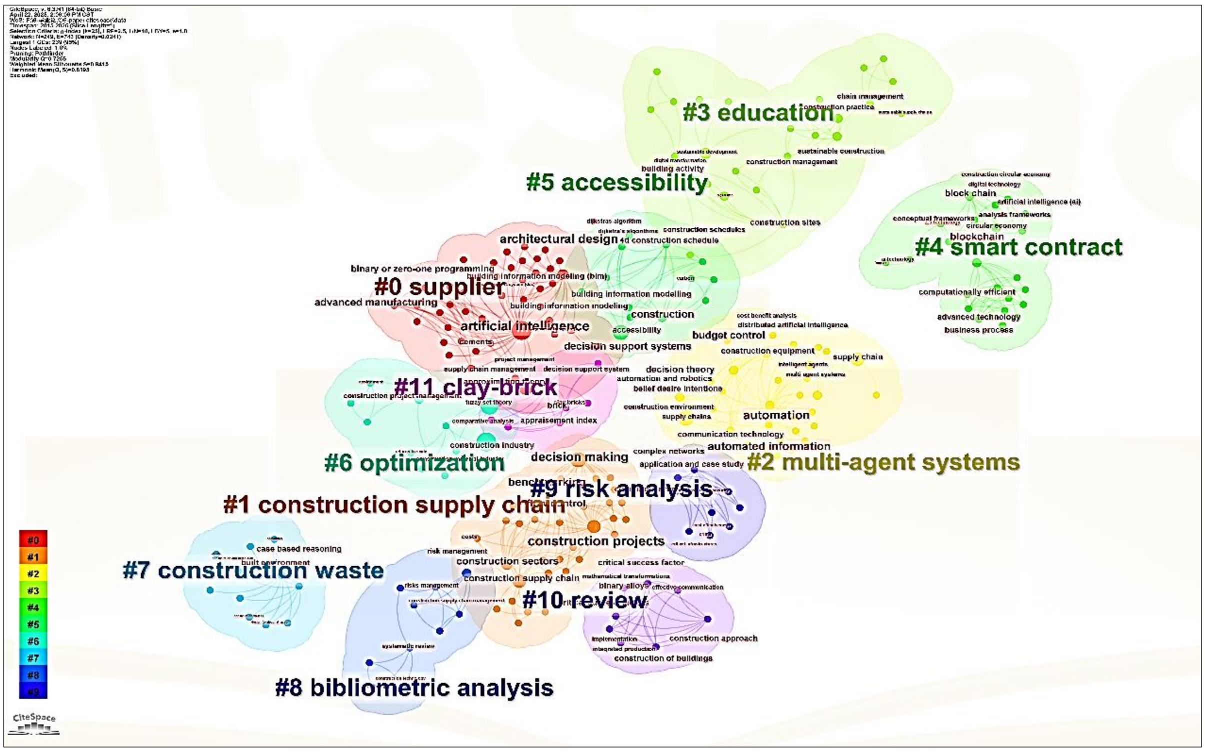

Figure 2: Co-Citation and Cluster Analysis

Intelligent Automation Technology

The independent variables in this study are derived directly from the thematic clusters identified in the SLR, with each cluster representing a distinct category of IA technology. AI Capability (Cluster #3 – Artificial Intelligence Framework) is a core component of IA, encompassing predictive analytics, neural networks, and intelligent decision-support systems that are increasingly applied to optimise CSC (Yusoff, 2021). These technologies facilitate data-driven planning and real-time responsiveness, thereby enhancing operational efficiency within complex and dynamic supply chains.

RPA Level (Cluster #2 – Construction Site Logistics) refers to the deployment of automation technologies to streamline labour-intensive and repetitive tasks. Applications include the sorting of materials by robots and personnel, as well as the monitoring of staff and equipment on-site (Shamsuzzoha & Pelkonen, 2025). RPA diminishes dependency on human intervention, resulting in faster, more standardised, and cost-efficient supply chain processes (Nielsen et al., 2023). CI (Cluster #7 – Urban Area) captures how SC actors utilise technology to implement SC processes that enable real-time data exchange and end-to-end visibility across geographically dispersed firms, devices, products, and personnel. It also facilitates the integration of technological intelligence at the SC level, supported by trusted collaboration and secure, reliable communications (Pessot et al., 2022). This variable reflects the growing importance of integrated communication infrastructures in managing the complexities of smart urban construction environments.

Table 2 presents a structured overview of the three principal independent variables identified through the SLR, outlining their conceptual definitions and corresponding sources in the academic literature. The table illustrates that AI Capability, which supports optimisation, is derived from research centred on AI technologies; RPA Level, associated with task automation, is informed by studies on construction site logistics; and CI Degree, reflecting collaborative and integrative systems, is based on literature concerning urban environments. Each variable is substantiated by relevant seminal references.

Table 2: Independent Variables from SLR

Source Cluster(s)	Variables	Introduction	Citation
Cluster #3 – Artificial Intelligence Framework	Artificial Intelligence (AI) Capability	It encompasses predictive analytics, neural network models, and intelligent decision-support systems utilised to enhance the optimisation of the construction supply chain.	(Yusoff et al., 2021)
Cluster #2 – Construction Site Logistics Cluster #6 – Construction Site	Robotic Process Automation (RPA) Level	It denotes the automation of routine activities, encompassing resource allocation, workforce monitoring, and robot-assisted operations within the construction supply chain.	(Nielsen et al., 2023; Shamsuzzoha & Pelkonen, 2025)
Cluster #7 – Urban Area	Collaborative and Integration (CI) Degree	It characterises cloud-enabled platforms and industry-wide networks that facilitate interoperability, seamless data exchange, and collaborative engagement among supply chain partners.	(Pessot et al., 2022)

Construction Smart Supply Chain

The dependent variables (DVs) represent the primary outcomes or areas of influence of IA technologies within the construction smart supply chain. Supply Chain Visibility (SCV), one such DV (Cluster #4 – Smart Contract Design; Cluster #3 – AI Framework) (Dharmapalan et al., 2021), is defined as the capability to achieve real-time tracking and visibility across the supply chain. The second dependent variable, Infrastructure Demands Adaptability (IDA) (Cluster – Urban Area), reflects the responsiveness and agility of SC systems in addressing the evolving requirements of urban construction projects (Philips et al., 2024). As urban environments become increasingly dynamic and infrastructure initiatives more complex, the ability of SC to adjust through digital integration and intelligent coordination is essential. Together, these variables serve as key indicators of the transformational effects of IA on CSC in China. By linking specific IA technologies to measurable SC outcomes, this study establishes a structured framework for assessing both the effectiveness and potential limitations of IA in developing construction smart supply chain mechanisms.

Table 3 provides an organised overview of the dependent variables identified from the SLR clusters, highlighting key dimensions of construction supply chain performance. The first variable, STT, underscores the significance of real-time monitoring, process tracking, and auditability across the supply chain, ensuring that operations remain transparent and fully traceable. This is supported by evidence from Cluster #4 and Cluster #3 (AI Framework) (Dharmapalan et al., 2021). The second variable, Infrastructure Demands Adaptability (IDA), addresses the capacity of urban supply chain systems to remain flexible and responsive to evolving demands and the dynamic nature of urban construction environments, as indicated in Cluster #7 (Philips et al., 2024). Both STT and IDA are essential for assessing the extent to which smart technologies, including AI and smart contract applications, enhance the efficiency and adaptability of construction supply chains.

Table 3: Dependent Variables from SLR

Source Cluster(s)	Variables	Explanation	Citation
Cluster #4 – Smart Contract Design Cluster #3 – AI Framework	Supply Chain Transparency and Traceability (STT)	Real-time visibility, tracking, and auditability of processes across the SC.	(Dharmapalan et al., 2021)
Cluster #7 – Urban Area	Infrastructure Demands Adaptability (IDA)	Agility and adaptability of urban SC systems to changing demands and urban dynamics.	(Philips et al., 2024)

Theory Supporting

RDT provides an appropriate theoretical lens to examine the impact of IA on the development of the CSC in China. RDT explores organisational practices by analysing power dynamics and dependency relationships that arise due to inter-organisational interactions and environmental contingencies (Ilhan, 2020). Within CSC, IA technologies—including AI, predictive analytics, and automation systems—complement existing strategic enablers, reducing over-reliance on external uncertainties by enhancing control, visibility, and responsiveness across supply chain networks (Farazi, 2024). As Chinese construction firms implement IA, they are able to mitigate uncertainties, strengthen collaborative relationships, and reposition power structures in their favour by decreasing dependence on traditional, labour-intensive practices and increasing reliance on data-driven, real-time decision-making. Accordingly, RDT supports the notion that IA adoption is not merely a technological advancement but a strategic initiative to recalibrate resource dependencies, thereby improving supply chain resilience and competitiveness. The deployment of IA technologies (AI, RPA, and CI) demonstrably enhances STT and IDA within China's construction smart supply chain.

Conceptual Framework

Drawing on the findings from the SLR concerning the identified independent and dependent variables, a conceptual research framework has been developed, as illustrated in Figure 3.

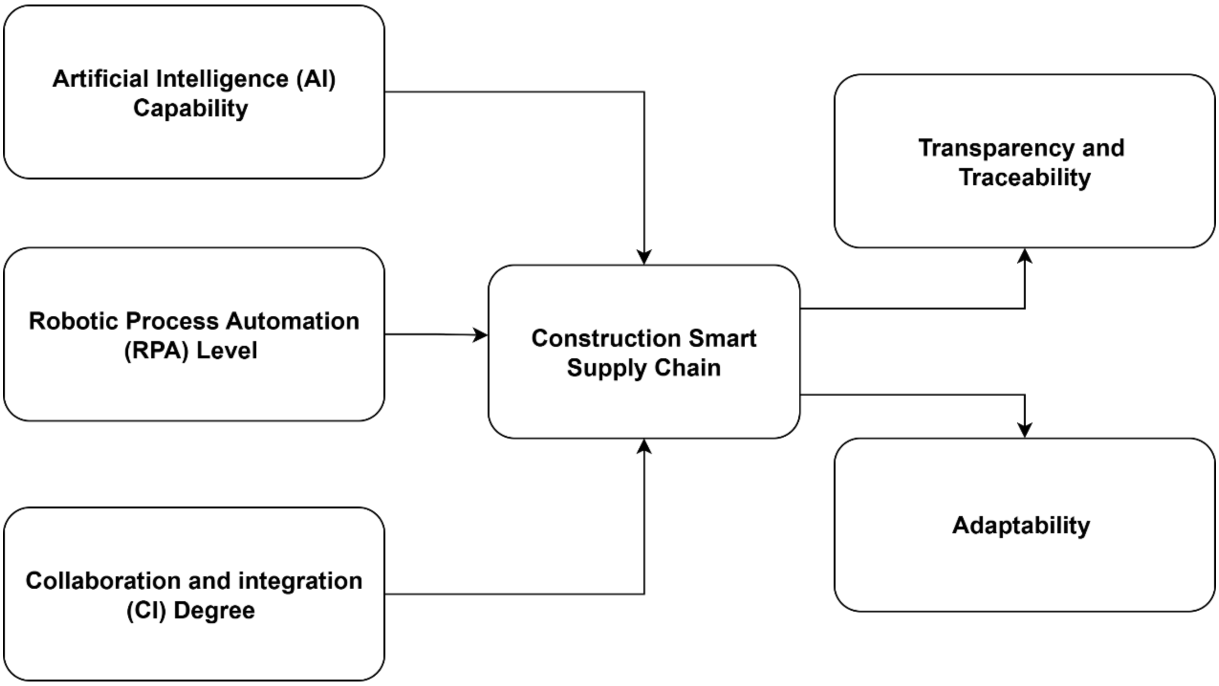

Figure 3: Conceptual Framework from SLR

The proposed framework assumes that the implementation of IA technologies serves as the primary driver for the digital and intelligent transformation of China's CSC. Its three core components operate as follows:

1. AI enhances the timeliness and accuracy of information through data analytics, intelligent forecasting, and decision-support mechanisms.
2. RPA automates repetitive processes, increases execution efficiency, and reduces the incidence of human error.
3. CI facilitates the exchange of information, coordination across platforms, and process collaboration among all SC participants, thereby improving system responsiveness and flexibility.

Collectively, these IA components contribute to SC outcomes by promoting STT, which enables end-to-end information visualisation; supporting traceability of material flows, responsibilities, and operational histories; and strengthening IDA, allowing the system to respond rapidly and flexibly to complex conditions. While the SLR establishes a strong theoretical foundation and identifies relevant variables, it does not empirically link IA technologies to CSC outcomes in the context of China's construction sector. Quantitative investigation using econometric regression on real-world data to explore these causal relationships remains absent.

METHODOLOGY

Research Design

This study adopts a quantitative approach with a mono-method research design. It employs a deductive approach within a positivist research philosophy to examine the effect of IA on the CSC in China. The design follows a cross-sectional approach, with data collected at a single point in time to capture the current state of the phenomenon. The guiding research question is: What is the transformative impact of IA on SC smart capabilities, including visibility, traceability, and end-to-end monitoring? The research design enables the evaluation of how IA technologies, specifically AI, RPA, and CI, influence SC performance. Data are collected via a structured survey, and analysis is conducted using statistical techniques such as EFA and MLR, providing a robust assessment of the relationships between IA components and SC outcomes.

Sample and Sample Size

The study sample comprised professionals within China's construction industry, including automation specialists, project engineers, SC managers, and construction practitioners. A purposive sampling strategy was adopted to select participants with direct experience in IA, ensuring the contextual relevance of their responses. Respondents were drawn from a broad range of firms and geographical regions to capture diverse perspectives within the industry. The sample size was determined using the Krejcie and Morgan (1970) formula, resulting in the distribution of 200 questionnaires, with an anticipated minimum of 177 usable responses. A pilot study involving 30 respondents was conducted to evaluate the reliability and clarity of the survey instrument. Insights from this preliminary phase were used to refine the questionnaire, ensuring that the final instrument would generate valid and actionable data from the full sample.

Data Collection Methods

Data collection was conducted using a structured questionnaire administered to the selected participants via the Wenjuanxing platform. The questionnaire was developed based on validated theoretical models and utilised a 5-point Likert scale, ranging from "strongly agree" to "strongly disagree," to capture responses. This scale allowed participants to provide their assessments of various IA dimensions, including AI capability, RPA level, and CI degree. The survey was carefully designed to ensure clarity and precision, enabling respondents to offer accurate and meaningful insights. Online administration facilitated broad geographic coverage and allowed for efficient collection and management of the data.

Measures

The measurement strategy for this study is grounded in established theoretical models examining IA dimensions within the construction industry context. The primary variables assessed include AI capability, RPA integration, and CI adoption. The questionnaire comprised items specifically designed to capture participants' perceptions of these IA dimensions, with responses recorded on a 5-point Likert scale. To ensure measurement validity and reliability, the constructs were adapted from prior literature that had been validated in comparable settings. Subsequent reliability and validity testing confirmed that the instruments employed were suitable for the research context and capable of generating robust and meaningful data.

Data Analysis Techniques

The study employed multiple statistical techniques to ensure the validity and reliability of the findings. Descriptive statistics were first used to summarise the demographic characteristics of the sample. EFA was then conducted to identify the underlying dimensions of the IA constructs and to reduce the dataset to a more manageable form. Following this, MLR analysis was performed to examine the relationships between the identified IA dimensions and SC performance. Pre-analysis diagnostics were conducted to confirm the suitability of the data for regression analysis, including tests for normality (Shapiro-Wilk), multicollinearity (VIF < 10), and reliability (Cronbach's alpha > 0.70). Construct validity was further assessed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test, confirming the appropriateness of the data for factor analysis.

Ethical Considerations

Ethical considerations were a central concern in this study, and several measures were implemented to ensure compliance with ethical standards. All participants received clear and comprehensive information regarding the study's purpose, the voluntary nature of participation, and their right to confidentiality. Respondents remained anonymous, and no personally identifiable information was collected. All data were securely stored, accessible only to the research team. Participants were also informed that they could withdraw from the study at any point without any consequences. Overall, the study upheld ethical integrity by safeguarding the rights and interests of all participants throughout the data collection and analysis process.

RESULT AND DISCUSSION

Descriptive Statistics

Table 4 presents the descriptive analysis based on 218 valid questionnaires. Regarding age distribution, the majority of respondents were aged 35 to 44 years (63.8%), followed by those aged 25 to 34 years (26.6%), indicating a workforce largely composed of mid-career professionals. A small proportion were under 25 years (1.4%) or over 45 years (8.3%), suggesting minimal representation from early-career entrants or senior professionals. In terms of gender, the sample comprised 63.3% male and 36.7% female respondents, reflecting a modest gender imbalance consistent with the general demographics of the construction and SC sectors. Concerning educational attainment, the respondents demonstrated a relatively high level of academic qualification. The majority held a bachelor's degree (78.4%), with 15.6% possessing a master's degree or higher, while only 6.0% had qualifications below the junior college level. This indicates that the sample represented an educated workforce actively engaged in the IA-driven transformation of CSC.

This distribution of experience levels reflects a balanced representation of both seasoned professionals and those actively developing expertise in the digital transformation of the construction sector. Project Engineers constituted the largest professional group (45.9%), followed by SC Managers (27.1%) and Construction Practitioners (26.6%). Notably, IT or Automation Specialists represented only 0.5% of the sample, suggesting a potential shortage of specialised technical expertise for on-site IA implementation. Respondents were recruited from a wide spectrum of industry sectors. The largest share came from Internet or IT development companies (32.1%), indicating strong participation from technology-oriented organisations. This was followed by logistics or SC firms (24.8%), construction companies (22.0%), and smaller groups from scientific research institutions (8.7%) and contractors or suppliers (8.3%).

Table 4: Basic Information Statistics

Variable		Frequency	Percentage
Age	Under 25	3	1.4
	25~34	58	26.6
	35~44	139	63.8
	45~54	18	8.3
	Over 55	0	0
Gender	Male	138	63.3
	Female	80	36.7
Education	Below Junior College Degree	13	6.0
	Bachelor Degree	171	78.4
	Master Degree and Above	34	15.6
Industry Experience	3 Years and Below	7	3.2
	3-5 Years	55	25.2
	6-10 Years	127	58.3
	10 Years and Above	29	13.3
Current Position	Construction Practitioners	58	26.6
	Supply Chain Managers	59	27.1
	Project Engineers	100	45.9
	IT or Automation Specialists	1	.5
Industry	Construction Companies	48	22.0
	Supply Chain/Logistics Companies	54	24.8
	Internet/IT Development Companies	70	32.1
	Suppliers/Contractors	18	8.3
	Professional Service Companies	9	4.1
	Scientific Research	19	8.7
Total Number of Questionnaires		218	100.0

Reliability and Validity Analysis

To assess the reliability and internal consistency of the questionnaire, Cronbach's alpha values were calculated for all constructs. Following the guidelines proposed by Peterson (1994), a Cronbach's alpha exceeding 0.7 is considered acceptable, whereas values above 0.9 indicate high reliability. Table 5 indicates that all constructs demonstrated acceptable reliability levels. Specifically, the AI construct comprised four items and yielded a Cronbach's alpha of 0.761, reflecting a satisfactory level of internal consistency. Other constructs, including RPA, CI, STT, and IDA, exhibited alpha values exceeding 0.85, ranging from 0.869 to 0.893, indicating robust internal consistency across all measured variables.

Table 5: Questionnaire Reliability Analysis

Construct	No. of Items	Cronbach's Alpha (α)	Internal Consistency
Artificial Intelligence (AI)	4	.761	Acceptable
Robotic Process Automation (RPA)	4	.878	Good
Collaboration and Integration (CI)	5	.892	Good
Transparency and Traceability	4	.869	Good
Adaptability	5	.893	Good

Table 6 reports that the KMO measure of sampling adequacy was 0.905, well above the commonly accepted threshold of 0.6, indicating that the sample is suitable for factor analysis. Additionally, Bartlett's Test of Sphericity was statistically significant (Chi-Square = 2764.899, df = 231, $p < 0.001$), demonstrating that the correlation matrix is not an identity matrix. Collectively, these results support the appropriateness of applying EFA to this dataset.

Table 6: KMO and Bartlett's Test

KMO Sampling Suitability Measure		.905
Bartlett's Test of Sphericity	Approximate Chi-Square	2764.899
	Degrees of Freedom	231
	Significance	.000

Exploratory Factor Analysis

To evaluate the overall structure of the questionnaire, an EFA was conducted using PCA with Varimax rotation. Table 7 shows that a five-factor solution was extracted, collectively explaining 70.593% of the total variance, with the first factor accounting for the largest proportion (36.784%) and each subsequent factor contributing progressively smaller amounts (e.g., 10.127%, 9.014%, etc.). The "Extraction Sums of Squared Loadings" indicates that only these five factors were retained, as their eigenvalues exceeded 1, in line with the Kaiser criterion, while the remaining 17 components (6 to 22) had eigenvalues below 1 and were therefore excluded, each explaining less variance than an individual original variable. Figure 4 presents the scree plot used in EFA to determine the number of factors to retain for analysis.

Table 7: The Total Variance Explained by the Scale

Element	Total	Percentage of Variance	Cumulative %
1	8.093	36.784	36.784
2	2.228	10.127	46.912
3	1.983	9.014	55.926
4	1.640	7.453	63.378
5	1.587	7.214	70.593
6	.714	3.243	73.836
7	.611	2.779	76.615
8	.521	2.370	78.986
9	.489	2.221	81.206
10	.471	2.139	83.346
11	.459	2.086	85.432
12	.411	1.870	87.302
13	.385	1.750	89.052
14	.369	1.679	90.731
15	.337	1.533	92.264
16	.328	1.489	93.753
17	.302	1.375	95.128
18	.287	1.304	96.432
19	.244	1.107	97.539
20	.194	.880	98.420
21	.186	.843	99.263
22	.162	.737	100.000

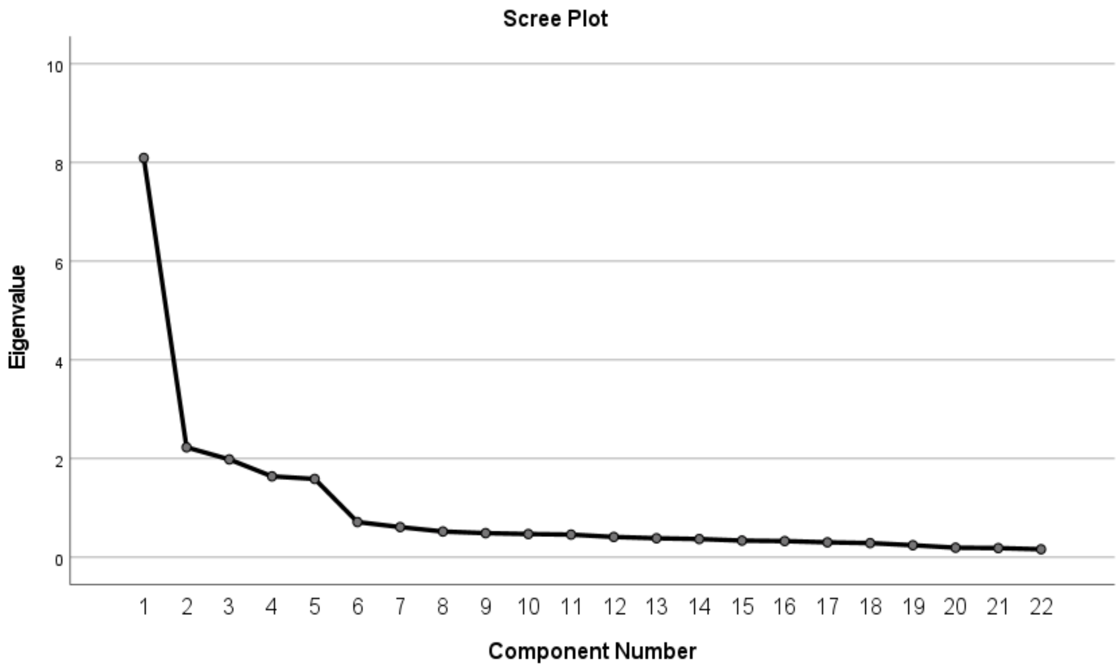

Figure 4: Scree Plot

Table 8 further confirmed the factor structure. All items exhibited strong loadings (> 0.6) on a single factor, with minimal cross-loadings, supporting both convergent and discriminant validity.

Table 8: Rotated Component Matrix[a]

	Component				
	1	2	3	4	5
Q19	.810				
Q18	.796				
Q20	.786				
Q16	.782				
Q17	.775				
Q29		.826			
Q26		.781			
Q27		.780			
Q28		.778			
Q25		.741			
Q23			.822		
Q24			.811		
Q22			.779		
Q21			.748		
Q14				.851	
Q15				.807	
Q13				.766	
Q12				.727	
Q8					.799
Q11					.779
Q9					.737
Q10					**.620**

The extracted constructs and their respective items are:

Factor 1. CI (Q16–Q20), reflecting the ability of SC actors to share real-time information, coordinate across stakeholders, and utilise collaborative platforms.
Factor 2. IDA (Q25–Q29), capturing the SC's capacity to adapt to urban project challenges, regulatory changes, and dynamically scale operations.
Factor 3. STT (Q21–Q24), representing visibility into SC operations, material tracking, and responsiveness to disruptions.
Factor 4. RPA level (Q12–Q15), emphasising the automation of routine tasks, minimisation of human error, and enhanced process efficiency.
Factor 5. AI capability (Q8–Q11), highlighting the deployment of AI technologies for predictive analytics.

Correlation Analysis

Correlation analysis was conducted to provide a foundational understanding of the bivariate relationships among the key constructs under study. This preliminary diagnostic assessment is essential, as it not only confirms the anticipated interconnections within the conceptual framework but also identifies potential multicollinearity issues prior to conducting more complex multivariate analyses, such as regression. The observed relationship strengths, ranging from moderate to strong, offer initial empirical support for the hypothesized links in the research model. Table 9 presents the correlation analysis based on all 218 observations. All variables exhibited statistically significant positive relationships. The strongest associations were observed between CI and IDA (r = 0.493) and between RPA and STT (r = 0.486). The weakest, yet still statistically significant, relationship was found between AI and CI (r = 0.228). All p-values reported were either 0.000 or 0.001, indicating that these correlations are highly significant.

Table 9: Correlation Test Results

Artificial Intelligence (AI)	Robotic Process Automation (RPA)	Collaboration and Integration (CI)	Supply Chain Transparency and Traceability (STT)	Infrastructure Demands Adaptability (IDA)	
Artificial Intelligence (AI)	1				
	218				
Robotic Process Automation (RPA)	.356**	1			
	.000				
	218	218			
Collaboration and Integration (CI)	.228**	.425**	1		
	.001	.000			
	218	218	218		
Supply Chain Transparency and Traceability (STT)	.299**	.486**	.444**	1	
	.000	.000	.000		
	218	218	218	218	
Infrastructure Demands Adaptability (IDA)	.351**	.430**	.493**	.433**	1
	.000	.000	.000	.000	
	218	218	218	218	218

Regression Analysis

Table 10 presents the results of the regression analysis, conducted to move beyond measuring simple associations and to model the causal relationships between the independent and dependent variables. This analysis is critical as it quantifies the extent to which variations in the key constructs (AI, RPA, CI) predict changes in the outcome variables. Moreover, it identifies which constructs exert a statistically significant unique influence while controlling for the effects of other variables, offering actionable insights into the primary drivers of the observed phenomena. Table 10 summarises the impact of IA technologies on STT within China's construction sector, as assessed through MLR analysis. SC performance indicators, including STT, were treated as the dependent variable, while AI, RPA, and CI served as the independent variables. The model summary (Table 11) reported an R of 0.564, corresponding to an R^2 of 0.318, indicating that approximately 31.8% of the variance in STT is explained collectively by the effects of AI, RPA, and CI.

Table 10: Regression Analysis Summary Results Table

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.564[a]	.318	.308	.91655

a. Predictors: (Constant), Artificial Intelligence (AI), Collaboration and Integration (CI), Robotic Process Automation (RPA)

Table 11 establishes the overall significance of the regression model through an ANOVA test. ANOVA assesses whether the set of independent variables—AI, RPA, and CI—collectively exert a statistically significant effect on the dependent variable, STT. It evaluates whether the variance in STT can be explained by the regression model beyond what would be expected by chance. In this study, the ANOVA result ($F = 33.243$, $p < 0.001$) confirmed the statistical validity of the regression model, indicating that at least one IA dimension significantly predicts SC performance outcomes. This finding supports the theoretical proposition that IA technologies, considered as an integrated construct, enhance traceability and transparency within China's construction smart supply chain.

Table 11: ANOVA Results

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	83.778	3	27.926	33.243	< .001[b]
	Residual	179.774	214	.840		
	Total	263.552	217			

Table 12 demonstrates that RPA and CI are significant positive predictors of STT, with RPA ($\beta = 0.326$, $p < 0.001$) exhibiting a slightly stronger influence than CI ($\beta = 0.279$, $p < 0.001$). AI showed a positive but marginally non-significant effect ($\beta = 0.119$, $p = 0.051$). The model intercept was also significant ($p = 0.006$), indicating that the baseline level of STT differs statistically from zero.

Table 12: Multiple Regression Findings

Model		UC		SC	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.859	.307		2.799	.006
	Artificial Intelligence (AI)	.157	.080	.119	1.961	.051
	Robotic Process Automation (RPA)	.309	.062	.326	4.995	< .001
	Collaboration and Integration (CI)	.276	.062	.279	4.452	< .001

a. Dependent Variable: Supply Chain Transparency and Traceability (STT)

DISCUSSION

This study investigated how the performance of China's construction smart supply chain can be enhanced through the application of IA, encompassing AI, RPA, and CI. The analysis focused on STT, a primary outcome variable representing the level of real-time transparency, operational clarity, and accountability across the SC. The MLR model demonstrated that IA technologies collectively explained 31.8% of the variance in STT ($R^2 = 0.318$, $p < 0.001$), thereby validating the hypothesis that IA adoption can improve SC performance. This finding supports the theoretical framework developed from the SLR and underpinned by RDT, indicating that organisations strategically leverage technological capabilities to reduce uncertainty, enhance control, and improve visibility and coordination within SC networks.

Among the IA dimensions, RPA emerged as the strongest predictor ($\beta = 0.326$, $p < 0.001$), indicating that automating repetitive, low-value tasks such as material handling, data entry, and scheduling generates substantial benefits in terms of accuracy, minimising human error, and accelerating information flow. The application of RPA directly improves SC traceability and STT, particularly within SC and site management contexts, where inconsistent data access and delays are prevalent challenges. CI also exhibited a significant positive impact ($\beta = 0.279$, $p < 0.001$), underscoring the critical role of real-time communication, cloud-based platforms, and stakeholder coordination in supporting transparent and efficient SC operations. By enabling timely information sharing among departments, contractors, and external suppliers, CI enhances traceability and facilitates management of project variations. This finding highlights that sociotechnical integration, rather than automation alone, is a key driver of smart SC competencies.

AI, although positively related to STT ($\beta = 0.119$, $p = 0.051$), did not reach conventional statistical significance thresholds. This suggests that despite its recognised predictive and analytical potential, AI implementation within China's construction SC remains limited or uneven, potentially due to inadequate data infrastructure, high implementation costs, insufficient skilled personnel, or resistance to integrating new technologies within traditional, labour-intensive practices. Nevertheless, the marginal effect observed implies that AI's influence is likely to grow as systems are increasingly embedded in project planning, risk management, and adaptive decision-making processes. Correlation analysis further reinforced the positive interrelationships among IA dimensions, STT, and IDA, illustrating IA's broader role in enhancing SC flexibility and resilience. Notably, CI displayed the strongest correlation with IDA ($r = 0.493$, $p < 0.01$), reflecting its capacity to improve responsiveness within urban constraints and to adapt to evolving infrastructure demands. Collectively, these results indicate that IA, particularly RPA and CI, has shifted from peripheral to central importance in the digitalisation of China's construction SC. While AI currently exerts a smaller material effect, its trajectory suggests a growing strategic role, positioning it as a potential key enabler of intelligent logistics and adaptive planning in the future.

The findings align with prior literature demonstrating the transformative effects of digital technologies on SC performance. Earlier studies (Chenna, 2024; Shamsuzzoha & Pelkonen, 2025) highlighted RPA's utility in automating material handling and operational SC tasks. The current study empirically confirms these observations, showing that RPA exerts a strong direct effect on STT in practical construction settings. Similarly, the positive influence of CI corresponds with prior research (Cui et al., 2024; Yang et al., 2022) emphasising the value of collaborative platforms and integrated information flows for enhancing SC agility and responsiveness. By incorporating CI into a regression model, this study extends existing work, quantifying its unique contribution to overall IA impact.

Conversely, AI's limited effect contrasts with optimistic projections in prior studies (Pan & Zhang, 2021; Shakibaei, 2024) that forecasted AI dominance in construction intelligence. This discrepancy likely arises from low adoption of advanced AI models onsite and the absence of a unified data infrastructure, limiting AI's ability to support real-time decision-making. Despite its potential, AI's practical impact in China's construction SC remains constrained. Finally, the study provides empirical validation of RDT within the context of the digital construction SC. By demonstrating how IA technologies modify resource control and reduce dependence on external contingencies, the research confirms RDT's relevance in explaining the dynamics of digital transformation in project-based industries. IA adoption emerges not merely as a technological upgrade but as a strategic mechanism for reshaping inter-organisational dependencies, thereby enhancing SC resilience, transparency, and adaptability.

CONCLUSION

This study provides empirical confirmation that IA, comprising AI, RPA, and CI, is fundamentally transforming China's construction smart supply chains. Based on insights from the SLR and rigorous quantitative analysis, the findings demonstrate that RPA and CI are the primary drivers enhancing STT and IDA, while AI's current impact remains limited but holds potential for future expansion as integration within core SC processes increases. By combining EFA and MLR, the study validates a performance framework that directly links IA adoption with improved outcomes in CSC. From a theoretical standpoint, the research extends RDT by illustrating how IA reshapes organisational interdependencies and mitigates external uncertainties through enhanced digital coordination and operational autonomy. Practically, the study provides industry stakeholders with a reliable diagnostic framework to evaluate and optimise digital transformation strategies within construction logistics. At a time when resilience, adaptability, and sustainability are critical, IA adoption emerges not merely as a technological enhancement but as a strategic imperative for developing smarter, more responsive, and future-ready construction SCs.

LIMITATIONS AND FUTURE RESEARCH

Although the study identifies significant associations, it does not establish definitive causal links between IA adoption and CSC outcomes. Consequently, longitudinal research is recommended to monitor the progression of these effects over time and strengthen causal inferences. In addition, the non-significant impact of AI, likely due to its early-stage and uneven deployment within the industry, highlights a critical avenue for further inquiry. Future studies should consider qualitative or mixed-methods approaches to examine in depth the specific obstacles—such as limitations in data infrastructure, implementation costs, skill shortages, and organisational resistance—that impede broader AI integration. Lastly, while RDT proved useful as a theoretical lens, combining it with complementary frameworks, such as Dynamic Capabilities or the Technology-Organisation-Environment (TOE) model, may provide a more comprehensive understanding of the technological and organisational enablers necessary for effective digital transformation within the CSC.

REFERENCES

Adesoga, T. O., Tolulope Olusola, A., Kenneth Chukwujekwu, N., Ummulikhaeri Temitope, I.-L., Emmanuel Ayobamidele, I., & Daniel Ikechukwu, E. (2024). The Rise of the "Smart" Supply Chain: How Ai and Automation Are Revolutionizing Logistics. *International Journal of Science and Research Archive*, *12*(2), 790-798. https://doi.org/10.30574/ijsra.2024.12.2.1304

Adeusi, T. S., & Onah Louis, K. (2024). Examining the Integration of Artificial Intelligence in Automated Building Construction and Design Optimization. *GSC Advanced Research and Reviews*, *21*(3), 395-405. https://doi.org/10.30574/gscarr.2024.21.3.0514

AlRushood, M. A., Rahbar, F., Selim, S. Z., & Dweiri, F. (2023). Accelerating Use of Drones and Robotics in Post-Pandemic Project Supply Chain. *Drones*, *7*(5), 313. https://doi.org/10.3390/drones7050313

Attajer, A., & Mecheri, B. (2024). Multi-Agent Simulation Approach for Modular Integrated Construction Supply Chain. *Applied Sciences*, *14*(12), 5286. https://doi.org/10.3390/app14125286

Aziz, S., Kumar, P., & Khan, A. B. (2024). Assessing the Impact of Digital Supply Chain Management on the Sustainability of Construction Projects. *Review of Business and Economics Studies*, *12*(3), 60-73. https://doi.org/10.26794/2308-944x-2024-12-3-60-73

Benjamin, O. O., Azubuike Chukwudi, O., & Sanni Ayinde, A. (2024). Optimizing Construction Supply Chains through Ai: Streamlining Material Procurement and Logistics for Project Success. *GSC Advanced Research and Reviews*, *20*(1), 147-158. https://doi.org/10.30574/gscarr.2024.20.1.0258

Bhattacharya, S., & Chatterjee, A. (2021). Digital Project Driven Supply Chains: A New Paradigm. *Supply Chain Management: An International Journal*, *27*(2), 283-294. https://doi.org/10.1108/scm-12-2020-0641

Cataldo, I., Banaitis, A., Samadhiya, A., Banaitienė, N., Kumar, A., & Luthra, S. (2022). Sustainable Supply Chain Management in Construction: An Exploratory Review for Future Research. *Journal Of Civil Engineering And Management*, *28*(7), 536-553. https://doi.org/10.3846/jcem.2022.17202

Chenna, K. (2024). The Convergence of Sap Pp, Rpa, and Ibp: A Comprehensive Analysis of Integration Benefits and Challenges in Modern Manufacturing. *International Journal For Multidisciplinary Research*, *6*(6). https://doi.org/10.36948/ijfmr.2024.v06i06.30211

Cui, L., Wang, Z., Liu, Y., & Cao, G. (2024). How Does Data-Driven Supply Chain Analytics Capability Enhance Supply Chain Agility in the Digital Era? *International Journal of Production Economics*, *277*, 109404. https://doi.org/10.1016/j.ijpe.2024.109404

Dalsaniya, A., & Kishan, P. (2022). Enhancing Process Automation with Ai: The Role of Intelligent Automation in Business Efficiency. *International Journal of Science and Research Archive*, *5*(2), 322-337. https://doi.org/10.30574/ijsra.2022.5.2.0083

Dharmapalan, V., O'Brien, W. J., & Morrice, D. J. (2021). Defining Supply Chain Visibility for Industrial Construction Projects. *Frontiers in Built Environment*, *7*. https://doi.org/10.3389/fbuil.2021.651294

Farazi, M. Z. R. (2024). Designing Circular Supply Chains with Digital Technologies for Competitive Sustainability: An Operation Management Perspective. *International Journal of Science and Research Archive*, *13*(1), 2346-2359. https://doi.org/10.30574/ijsra.2024.13.1.1928

Haloul, M. I. K., Khairol Anuar bin, M., Elianddy bin, E., Azfanizam binti, S., Bilema, M., & Ahmad, M. (2024). A Systematic Review of the Project Management Information Systems in Different Types of Construction Projects. *UCJC Business and Society Review (formerly known as Universia Business Review)*, *21*(80). https://doi.org/10.3232/ubr.2024.v21.n1.08

Ilhan, A. (2020). An Evaluation of the Changing Nature of Power-Dependence Relations in Organizations within the Context of the Resource Dependence Theory. *International Review of Management and Business Research*, *9*(4), 165-179. https://doi.org/10.30543/9-4(2020)-15

Ji, W. (2024, 2024/01/29). *Analysis and Research on the Creation of Smart Supply Chain System Based on Information Technology* Proceedings of the 2024 6th Asia Pacific Information Technology Conference, http://dx.doi.org/10.1145/3651623.3651626

Liu, K., Meng, Q., Kong, Q., & Zhang, X. (2022). Review on the Developments of Structure, Construction Automation, and Monitoring of Intelligent Construction. *Buildings*, *12*(11), 1890. https://doi.org/10.3390/buildings12111890

Maatar, O., Trost, R., De Bruyne, I., Van Dromme, H., & Berroir, F. (2022). Smart Logistics for Urban Construction Sites (Ccc). *IOP Conference Series: Earth and Environmental Science*, *1078*(1), 012046. https://doi.org/10.1088/1755-1315/1078/1/012046

Mandala, V., & Dolu Surabhi, M. (2024). Intelligent Engines: Revolutionizing Manufacturing and Supply Chains with Ai. *International Journal of Innovative Science and Research Technology (IJISRT)*, 489-502. https://doi.org/10.38124/ijisrt/ijisrt24apr1221

Nielsen, I. E., Piyatilake, A., Thibbotuwawa, A., Silva, M. M. D., Bocewicz, G., & Banaszak, Z. A. (2023). Benefits Realization of Robotic Process Automation (Rpa) Initiatives in Supply Chains. *IEEE Access*, *11*, 37623-37636. https://doi.org/10.1109/access.2023.3266293

Pan, Y., & Zhang, L. (2021). Roles of Artificial Intelligence in Construction Engineering and Management: A Critical Review and Future Trends. *Automation in Construction*, *122*, 103517. https://doi.org/10.1016/j.autcon.2020.103517

Parshuramkar, P. K., Inamdar, U., Sonar, N. K., & Mahakalkar, M. V. (2024). Building Resilient Supply Chains with Intelligent Automation. *Interantional Journal Of Scientific Research In Engineering And Management*, *08*(09), 1-6. https://doi.org/10.55041/ijsrem37541

Pessot, E., Zangiacomi, A., & Fornasiero, R. (2022). Unboxing the Hyper-Connected Supply

Chain: A Case Study in the Furniture Industry. *Production Planning & Control*, *35*(6), 580-598. https://doi.org/10.1080/09537287.2022.2110958

Peterson, R. A. (1994). A Meta-Analysis of Cronbach's Coefficient Alpha. *Journal of Consumer Research*, *21*(2), 381. https://doi.org/10.1086/209405

Philips, A. A., Bharadwaj, T., & Similoluwa Blossom Adesuwa, O. (2024). Achieving Housing Affordability in the U.S. Through Sustained Use of Ai and Robotic Process Automation for Prefabricated Modular Construction. *African Journal of Advances in Science and Technology Research*, *15*(1), 122-134. https://doi.org/10.62154/53t99n63

Shakibaei, R. (2024). Artificial Intelligence in the Effective Execution Process of Construction Projects in the Future. *Journal of Economics, Management and Trade*, *30*(6), 75-87. https://doi.org/10.9734/jemt/2024/v30i61215

Shamsuddoha, M., Khan, E. A., Chowdhury, M. M. H., & Nasir, T. (2025). Revolutionizing Supply Chains: Unleashing the Power of Ai-Driven Intelligent Automation and Real-Time Information Flow. *Information*, *16*(1), 26. https://doi.org/10.3390/info16010026

Shamsuzzoha, A., & Pelkonen, S. (2025). A Robotic Process Automation Model for Order-Handling Optimization in Supply Chain Management. *Supply Chain Analytics*, *9*, 100102. https://doi.org/10.1016/j.sca.2025.100102

Vignesh, S., & Prabakaran, M. P. A. (2024). Optimizing Supply Chain Management Operations in Construction: A Systematic Review of Scm Trends, Challenges, and Innovations. *International Journal of Research Publication and Reviews*, *5*(2), 2892-2897. https://doi.org/10.55248/gengpi.5.0224.05060

Yang, N., Ding, Y., Leng, J., & Zhang, L. (2022). Supply Chain Information Collaborative Simulation Model Integrating Multi-Agent and System Dynamics. *Promet - Traffic & Transportation*, *34*(5), 711-724. https://doi.org/10.7307/ptt.v34i5.4092

Yusoff, M. S. B., Arifin, W. N., & Hadie, S. N. H. (2021). Abc of Questionnaire Development and Validation for Survey Research. *Education in Medicine Journal*, *13*(1), 97-108. https://doi.org/10.21315/eimj2021.13.1.10

Zhang, Z., & Huang, Z. (2022). Design and Application of Logistics Robot Based on Rpa. *Frontiers in Computing and Intelligent Systems*, *1*(1), 66-75. https://doi.org/10.54097/fcis.v1i1.1464