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Efficiency in real estate development: Is management or robotics the key?

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ABSTRACT

This study examines the impact of construction robotics (CR) and agile project management (APM) principles on operational efficiency in Chinese commercial residential projects (CRPs). By analyzing 107 CRPs across 21 provinces, including 30 using CR technology, we employ a novel methodology that combines superefficiency SBM-DEA, APM frameworks, and Tobit regression models. The results show that CR implementation improved work efficiency by 2.59% on average. Operational efficiency varied regionally, with the eastern area (mean 0.3963) outperforming the central (0.3651) and western (0.3790) areas. The provinces of Jiangsu and Shanghai demonstrated the highest efficiencies. APM factors significantly influence efficiency: top management commitment negatively (−0.9432) and product owner involvement positively (0.2266). CR implementation in the main structural phase showed the strongest positive correlation (0.0438). Three of the nine typical CR technologies on the project duration's critical path were the most popular among the contractors. The study identified potential improvements in interim payments and inventory balance efficiency. The findings extend APM theory to real estate development, refine technology adoption models in construction, and reveal tensions between contractor priorities and overall project efficiency. Practical implications include recommendations for targeted CR implementation, management restructuring, and policy support. Future research should explore longitudinal effects, broader geographic scopes, and potential mediating variables in CR and APM dynamics in real estate development.

1. Introduction

The construction sector, characterized by high manual labor reliance and minimal automation, faces challenges, including labor shortages, productivity inefficiencies, and safety concerns (Ling et al., 2022; Melenbrink et al., 2020). Real estate stakeholders aim to increase investment efficiency by delivering quality houses more quickly. Technological advancements, particularly construction robotics, offer a potential solution. Advancements in servo motors, controls, sensors, and cost reductions have made the construction of robots viable (Saidi et al., 2016). This phenomenon has generated substantial worldwide endeavors in research and development (R&D), with prospective implications in the fields of architecture, engineering, and construction (AEC).

Currently, there is significant research in China on construction robotics (CR) technology, including welding, masonry, cleaning, concrete pouring, and task handling. Robotic construction research has demonstrated several advantages in these demanding application domains, including improved work efficiency, enhanced safety measures, decreased construction duration and costs (Borja García de Soto et al., 2018), and enhanced quality control (Castro-Lacouture, 2009). However, CR adoption remains limited, with anticipated benefits unrealized and operational efficacy not substantially enhanced. This challenge persists amid increasing demands for efficiency and quality in construction. Research has explored various aspects, including business risks and the construction limitations of robotics (Buchli et al., 2018; Davila Delgado et al., 2019).

While scholars in the construction field have investigated determinants of CR adoption (Pan & Pan, 2020b) and adoption barriers (Law et al., 2022), there remains a gap in understanding commercial residential project (CRP) operational efficiency improvements after CR implementation from the perspective of real estate developers. This study aims to address this gap by examining

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whether CR can increase operational efficiency in real estate development and identifying influential management factors. To this end, we formulate one primary research question (RQ) with four supporting subquestions:

RQ: How do current CR technologies, coupled with China's project management methodology, improve CRP development and construction efficiency?

1) : What is the current state of operational efficiency in China's CRP, and how can it be enhanced?
2) How does CR technology implementation influence CRP work efficiency?
3) : How does the integration of technical and nontechnical elements impact CRP operational efficiency?
4) : Which subprojects can improve productivity in project-specific construction through CR implementation?

To address these questions, we studied 107 diverse Chinese commercial residential developments via CR, each of which was managed by a distinct project team. We collected key operational metrics, including employee count, land area, actual cost of work performed (ACWP), contractor payments, housing units sold, income, and project duration. We developed a nontechnological management capability assessment model on the basis of the Agile Project Management framework (F. Tripp & Armstrong, 2018). This study contributes to the CR and CRP development operational efficiency literature by providing an in-depth analysis of the impact of CR on the operational efficiency of China's CRPs. By examining CRPs across 21 Chinese provinces, with and without CR implementation, we offer insights into regional variations and practical implications of CR adoption in a major real estate market.

The remainder of this research is structured as follows: Section 2 reviews the literature on CR types, DEA methodologies, and research scales. Section 3 details the methodology, focusing on the analytical process and nontechnical agile management assessment. Section 4 discusses the results of each methodological stage within the relevant literature. Section 5 concludes with key findings, limitations, and future research directions.

2. Literature review

2.1. Overview of construction robotics technology

Ma et al. (2022) collected 183 construction robot documents, which have been widely employed in the sector in recent years, into 12 categories: concrete, welding, masonry, spraying, installing, surveying, plastering, inspecting, renovating, recycling, lifting steel, and handling robots. Davila Delgado et al. (2019) reported that the primary tasks that stakeholders want to automate are concrete construction, surveying and monitoring, drilling, excavation, and demolition.

Recent advancements have led to more integrated CR systems. For example, the China Bright Dream Group used its own "BIM + FMS + WMS + CR" collaboration system for the first time, having run through the end-to-end intelligent construction ecological practice in the building stage and initially building a complete full-cycle construction closed loop. This means that CR technology has enabled 22 types of CRs to conduct such autonomous construction work as assembly line production through a scientific arrangement of construction processes in specific construction stages (Duan, Feng, CHEN, CHEN, & LUO, 2022). This development highlights the potential for CR to create a complete full-cycle construction closed loop.

This study focuses on nine frequently used CRs in the Chinese construction industry, as shown in Appendix Table A, identified through a comprehensive review of industry reports, academic literature, and government documents. This classification aligns with categories recognized by the China Construction Industry Association (CCIA) and the Ministry of Housing and Urban–Rural Development in their intelligent construction guidelines (Source: www.mohurd.gov.cn).

2.2. Operational efficiency in the real estate sector

2.2.1. Work vs. operational efficiency in CRPs

This study distinguishes between work efficiency and operational efficiency in the context of CR and CRP. Work efficiency, as defined by Bock (2015), refers to the effectiveness and productivity of individual tasks or activities in the construction process. It is typically measured in terms of time, cost, or resource utilization for specific activities (Liu et al., 2024), distinguishing it from manufacturing efficiency generated by stationary robots on assembly lines (Barosz et al., 2020; Everett John & Slocum Alexander, 1994).

In contrast, operational efficiency in CRPs encompasses the project's overall effectiveness in resource utilization throughout its lifecycle, from planning to sales. It considers multiple inputs (labor, capital, and time) and outputs (revenue, units sold, and project completion) at the project level (Caves et al., 1982). Kim et al. (2003) measure operational efficiency in terms of flexibility, consistency, productivity, and cycle time, with a focus on improvements in customer performance. Crucially, the operational efficiency of CRPs can be influenced by various factors, including technological innovations such as CR. While CR aims primarily to increase the work efficiency of specific tasks, its impact on overall operational efficiency is more complex and warrants further investigation. This study posits that improvements in work efficiency through CR implementation may contribute to enhanced operational efficiency in CRPs, but this relationship is neither direct nor proportional. Understanding this nuanced relationship is vital for assessing the true value of CR adoption in the real estate sector and forms a central focus of our research.

While improvements in work efficiency, such as those potentially offered by CR, can contribute to CRP operational efficiency, the relationship is not always direct or proportional. This distinction is crucial for understanding the complex dynamics between technological adoption and overall project performance in the real estate sector. By clarifying these concepts, we lay the groundwork for exploring whether the use of CR in the CRP can improve operational efficiency, which is a key focus of this study.

2.2.2. Overview of data envelopment analysis applications

To assess operational efficiency in the context of CRPs, this study employs data envelopment analysis (DEA), a technique developed by Charnes et al. (1978). DEA uses a linear programming model to evaluate the relative efficiency of decision-making units (DMUs) by considering multiple inputs and outputs simultaneously (Zhang et al., 2022). This nonparametric method is particularly suitable for the real estate sector, where projects often involve complex interactions between various inputs (e.g., labor, capital, and time) and outputs (e.g., revenue, units sold, and project completion) (Yu Sun, 2021).

In the real estate context, DEA has been applied to evaluate the efficiency of CRP development firms (Hung Chiang et al., 2013; Ling Chen & Liang, 2015), assess the performance of real estate investment trusts (REITs) (Chuweni, 2018), and analyze the efficiency of construction projects (Muhammad Ridhuan Bos et al., 2019; Qiang Chen et al., 2010). These applications demonstrate the versatility of DEA in capturing the complex dynamics of operational efficiency in the real estate sector, making it an appropriate methodological choice for this study's examination of the impact of CR on CRP efficiency.

DEA's ability to handle multiple inputs and outputs makes it well suited for capturing the multifaceted nature of operational efficiency in CRPs, as opposed to the more narrowly defined work efficiency. Unlike traditional ratio analyses, DEA provides a comprehensive efficiency score that accounts for all relevant factors simultaneously. This approach allows for a more nuanced understanding of how various elements, including the implementation of CR, contribute to overall project efficiency. To provide a comprehensive understanding of how DEA has been applied in real estate efficiency studies, Table 1 summarizes key research in this field. It highlights the various input and output indicators used, as well as the specific DEA methodologies employed across different studies.

2.2.3. Superefficiency SBM-DEA model

By building upon traditional DEA applications in real estate efficiency studies, researchers have developed more advanced methodologies to address limitations in classic DEA models. One significant advancement is the superefficiency Slack-Based Measure DEA (superefficiency SBM-DEA) model, introduced by Tone (2001). This model overcomes two key limitations of traditional DEA approaches: the radial nature of classic DEA-CCR and DEA-BCC models, which can compromise efficiency calculation accuracy, and the inability to differentiate between efficient DMUs that all score 1 in traditional models.

The superefficiency SBM-DEA model has proven particularly valuable in the complex realms of real estate and construction. For example, (Zhu et al., 2019b) employed this model to evaluate urban land resource use efficiency, considering both expected and unexpected outputs. Similarly, Wang et al. (2020) utilized the superefficiency SBM-DEA model in combination with other econometric approaches to assess the capital operation efficiency of real estate enterprises in Vietnam. These applications demonstrate the model's versatility and effectiveness in capturing the multifaceted nature of efficiency in the real estate sector.

Furthermore, the integration of the superefficiency SBM-DEA model with regression techniques, such as Tobit regression, has enabled researchers to explore macrodrivers of operational efficiency in the real estate sector. This combined approach offers valuable insights for policy formulation aimed at improving operational quality and fostering sustainable development in the construction and real estate industries (Deng et al., 2020; Shao & Li, 2018; Yang & Fang, 2020).

The superefficiency SBM-DEA model, therefore, represents a significant advancement in the application of DEA to real estate efficiency studies. Its ability to provide more nuanced efficiency scores and rank efficient DMUs makes it particularly well suited for assessing the complex operational dynamics of CRPs, especially when considering the impact of technological innovations such as CR.

2.2.4. Gap analysis

Despite the extensive application of DEA and its advanced variants, such as the superefficiency SBM-DEA model in real estate efficiency studies, several notable gaps persist in the current literature:

1). *Limited integration of technological innovations*: While DEA has been widely used to assess operational efficiency in real estate, few studies have explicitly considered the impact of emerging technologies such as CR on efficiency metrics. The

Table 1
Existing indicators for evaluating efficiency performance.

Authors	Input	Output	Indicator Category	Methodologies
Jiang et al. (2010)	Gross investments, Land use, Employees number	Gross revenue, Sales amounts	Economic, Resource	CCR
Wong et al. (2012)	Capital, Assets value, Operation costs, Employees number	Revenue, Profit	Economic, Resource	CCR, SBM
Li et al. (2014)	Total assets, Total operating costs	Operating income, Net profit, Earnings per share	Economic	CCR, SBM
Wang et al. (2015)	Total assets, Prime operating cost, Variable costs	Prime revenue, Net profit	Economic	BCC
Chen and Liang (2015)	Business cost, Total assets, Employees number	Business income, Gross profit, Return on equity	Economic, Resource	CCR, BCC
Ahmed and Mohamad (2017)	Management fees, Operating expenses, Interest expenses	Total assets, Net assets value, Total revenue	Economic	Malmquist model
Zhou et al. (2019)	Labor, Capital, Energy Consumption	Industrial Economic, Carbon Emissions	Economic, Resource, Social	Superefficiency SBM
Atta Mills et al. (2021)	Assets, Capital, Operating cost, Employees number	Revenue, Gross profit, Return on equity	Economic, Resource	SBM, Regression model
Yang and Fang (2020)	Total Assets, Number of Patent, Number of Employee	Total Income, Net Income, Return on Total Assets, Green Credit Index, CO_2 Emission	Economic, Resource, Commercial, Social	SBM
Wang et al. (2021)	Total assets, Cost of sales, Cost of goods sold	Total revenue, Gross profit	Economic, Commercial	Malmquist model
Liu et al. (2022)	Number of employees, Completed Investment, Floor Space of Building Stared	Floor Space of Building Completed, Area of Commercialized Hosing Sold, Value of Commercialized Housing Sold, Area of Commercialized Housing Unsold	Resource, Commercial	SBM
Liu et al. (2022)	National Subsidy, Local Subsidy,	GDP, Green Coverage, Build-up Areas, Regenerated Residential Unites	Economic, Environmental, Social	Superefficiency SBM
Wang et al. (2022)	Capital, Costed Time, Dynamic payback period, GDP	Renovated Area, Annual Energy Saving, Government regulation	Economic, Time	3-stage DEA model
Fukuyama and Tan (2023)	land areas purchased, completed housing area,	sales area for commodity housing, residential commodity houses' sales area	Resource, Commercial	DEA model

Notes: CCR: Charnes—Cooper—Rhodes, SBM: slack-based measure, BBC: Banker—Charnes—Cooper.

potential of CR to transform both work efficiency and overall operational efficiency in CRPs remains largely unexplored within the DEA framework. Additionally, our literature review identified a notable lack of research employing the use of superefficiency SBM-DEA models within the field of robotics. Instead, there is a significant surplus of studies that focus on examining companies' continuity efficiency (Jiang et al., 2021).

2). *Insufficient distinction between work and operational efficiency*: Existing studies often fail to clearly differentiate between work efficiency (task-level productivity) and operational efficiency (project-level effectiveness) in the context of CRPs. This distinction is crucial when evaluating the impact of technological interventions such as CR, which may have different effects at these two levels.

3). *Scarcity of longitudinal studies*: Most existing research provides snapshot analyses of efficiency at a given point in time. There is a lack of longitudinal studies examining how efficiency evolves over the lifecycle of a specific CRP, particularly in relation to the adoption and integration of new technologies.

By addressing these gaps, this literature review aims to contribute to a more comprehensive understanding of operational efficiency in real estate development, particularly in the context of technological innovation and adoption.

2.3. Agile project management framework

2.3.1. Introduction to agile project management

Managing changing requirements and complexity is important in enhancing the success of real estate projects. Through the theoretical lens of APM theory, a project team's functioning in an agile project setting can be explained (Radhakrishnan et al., 2022). The concept of APM originated in the field of software development, where it has made a progressively significant contribution (Sheffield & Lemétayer, 2013). According to project developers, significant transformations in customer needs and increases in collaborative efforts across different companies are anticipated. The need to adopt a flexible and customer-centric approach in the real estate development process is becoming apparent. As a result, new theory frameworks, such as the APM, are also becoming increasingly relevant for the real estate sector. APM theory is characterized by the iterative and incremental delivery of project requirements throughout its life cycle (Project Management Institute, 2017). Fundamentally, the theory seeks to demonstrate key principles and conduct encompassing trust, adaptability, empowerment, and collaboration.

Many researchers have recognized the significance of four fundamental values in agile projects. Indeed, the Agile Alliance proposed "The Agile Manifesto" (Beedle and van Bennekum, 2001), which encompasses the values of individuals and interaction, the development of working software, a very high level of customer collaboration, and frequent responses to changes in requirements (State of Agile Report, 2022).

2.3.2. APM in real estate development

The real estate sector is increasingly recognizing the need for flexible and customer-centric approaches in project development. Pfnür and Wagner (2020) anticipate significant transformation in customer needs and an increase in collaborative efforts across different companies in the real estate industry. This evolving landscape makes APM particularly relevant for real estate development. Andújar-Montoya et al. (2015) applied the APM framework to the execution of construction projects, combining it with information technology to establish a customized agile management system for development projects. This system integrated principles of standardization, automation, agility, flexibility, and integration and was implemented in a case study.

The APM framework has led to significant improvements in large-scale project development applications. Klotschke et al. (2022) proposed that while APM offers significant benefits for real estate development, including enhanced flexibility, customer integration, incremental planning, and improved interdisciplinary collaboration, its implementation faces challenges such as stakeholder conflicts, regulatory constraints, and complex product adjustments, necessitating careful adaptation of APM methods for widespread application in this sector. Consequently, future research in this field should focus on developing adaptive theoretical frameworks on the basis of critical analysis of the specificities of APM implementation in real estate projects, considering the unique characteristics of adaptive approaches in development project management (Szreder et al., 2019). To better understand the factors influencing the success of agile projects, Table 2 summarized prior studies on this topic.

Table 2 highlights several recurring topics related to agile project success factors, including team capability, customer involvement, the organizational environment, and the project management process. The diversity of success factors identified in these studies reflects the complex and multifaceted nature of agile project management. It also suggests that the application of APM principles may need to be tailored to specific contexts, such as real estate development projects.

Building upon these insights from prior studies, several studies have explored the application framework of APM principles in widespread projects. For example, Russo (2021) proposed a hierarchical and plan-driven model of agile project command and control systems, which consisted of the following eight aggregate dimensions:

(1). Mission critical requirements implementation velocity (MC);
(2). Time, budget, and security constraints (TBS);
(3). Top management commitment (TM);
(4). Product owner involvement (PO);
(5). Scrum master leadership (SM);
(6). Developers' social skills (DS);
(7). Developers' technical skills (DTs);
(8). Project success (PS).

This study constructed a scale (see the Supplement), using the abovementioned system, to evaluate the project management team's ability to manage CRPs. The outcomes of this survey were then used to evaluate the impact of project management factors on the basis of the APM framework.

2.4. Consumption quantity quota, duration quota, and cost index

In China, the consumption quantity quota (CQQ) (First Batch of Intelligent construction quota, 2023) refers to an officially sanctioned database that breaks down production into numerous standardized elemental processes. These processes are characterized by specific technical routines, quality standards, and a defined range of applications. The quota system prescribes the average consumption of manpower, materials, and machine shifts for each elemental process. Furthermore, in addition to using CQQ, Chinese AEC field technicians employ duration quotas (Guangdong Provincial Department of Housing and Urban-Rural Development, 2022), which are provided by construction authorities, to assess the time required for different project phases. Zhou and Nie (2021) defined CQQ according to the average consumption quantity

Table 2
Prior studies on the factors affecting the success of agile projects.

Authors	Methodology	Key findings	Aggregate Dimensions
Augustine et al. (2005)	Case study	Successful agile projects used practices such as self-organized project teams, simple interaction rules, and adaptive leadership.	Scrum Master leadership, Developers Social skills.
Maruping et al. (2009)	Survey methodology	A robust positive correlation has been seen between the implementation of successful agile methodologies and the quality of projects. However, it is worth noting that this correlation is statistically significant but comparatively lower in projects characterized by little alterations in requirements and teams with limited autonomy.	Developers' technical skills, Top management commitment.
Laanti et al. (2011)	Survey methodology	The benefits of a successful agile practices include improvement in quality, effectiveness, profit, and customer satisfaction.	Mission critical requirements implementation velocity, Time/Budget/ Security constraints.
Serrador and Pinto (2015)	Survey methodology	The findings indicate that the utilization of agile project management enhances the achievement of objectives related to time, budget, scope goals, and stakeholder satisfaction. Agile principles are employed in several non-IT industries, including healthcare, professional services, construction, manufacturing, real estate and retail.	Time/Budget/Security constraints.
Strode (2016)	Multiple case studies of colocated agile projects	There are three types of dependencies — knowledge, process, and resource in a successful agile project.	Scrum Master leadership
Tripp et al. (2016)	Survey methodology	The findings indicate a substantial correlation between agile project management methodologies and the perception of work satisfaction. In contrast, no discernible correlation exists between the utilization of software development methodologies and the subjective perception of job satisfaction.	Scrum Master leadership, Developers social skills.
F. Tripp and Armstrong (2018)	Survey methodology	The findings indicate that when the objective is to enhance software quality, there exists a noteworthy positive correlation between the implementation of software development-focused agile techniques and the achievement of project goals. A notable correlation exists between the implementation of project management-focused agile methods and the achievement of project success when the objective is to enhance efficiency.	Mission critical requirements implementation velocity, Time/Budget/ Security constraints.
Tam et al. (2020)	Survey methodology	The findings suggest that both team capability and customer involvement are important factors that contribute to project success.	Product Owner involvement.
Russo (2021)	Survey methodology	A comprehensive field research was undertaken to examine the implementation of Agile management in mission-critical environments for projects of significant scale. The study revealed that the commitment of stakeholders emerged as a crucial determinant of success. The objective of this change is to incorporate mission-oriented functionality that effectively decreases operating expenses and time in crucial situations.	Product Owner involvement, Top management commitment.
Radhakrishnan et al. (2022)	Survey methodology	Project success was assessed by measuring the timely completion, adherence to budget, fulfillment of requirements, and evaluating the satisfaction ratings provided by project sponsors, clients, and team members involved in the project. The researchers discovered that the amount to which project team members demonstrated adaptive performance moderated the connection between project agility and success. The findings of this study provide valuable guidance for agile project managers in facilitating the autonomy of team members to self-organize their tasks, discover efficient work approaches, and foster the creation of novel solutions.	Time/Budget/Security constraints, Product Owner involvement, Project success.

standard required by society from the total production process. Additionally, it provides regularly updated unit prices for the production factors involved in each process (Xiang, Bin Xie, & Cao, 2013). Hence, the consumption quantities provided by CQQ are of significant reference value.

Chen and Li (2017) developed a subsystem within the context of project cost statistics. This subsystem encompasses the analysis of project cost indices, the ability to query bills of quantities, and the comparative analysis of project cost indices. In their study, the cost indices pertained to the quantification of the main materials (i.e., steel, concrete, and paint) consumed per square meter for different types of buildings. These calculations and recordings were facilitated by a big data cost system. Previous researchers and official departments have contributed a wealth of pertinent databases and guidance. For example, the Ministry of Housing and Urban–Rural Development of the People's Republic of China has disseminated relevant standards (Standard for classification and measurement of construction cost index, 2018), whereas Wu (2009) research has provided indices pertaining to the costs associated with commercialized residential construction.

Furthermore, accurate estimation of the construction process duration is crucial in CRP management, as it significantly impacts a project's quality and cost. Qin (2021) proposed the implementation of quota and standard duration models (Pan et al., 2022) to forecast the anticipated completion time for each process within an existing project. This forecast is based on historical data from infrastructure projects, with particular emphasis on the duration of project processes as the primary influencing element. By employing network planning techniques, the project's Gantt chart can be analyzed, the network node diagram constructed, and the essential path of project execution can be identified. This enables the estimation of the duration range for the entire project.

2.5. Summary

In summary, many studies evaluating the efficiency of CR and CRP construction have been conducted, and substantial evidence has been found. We explored the evolving landscape of CR in CRPs, highlighting the distinction between work efficiency and operational efficiency. The literature review established DEA, particularly the superefficiency SBM-DEA model, as a robust method for assessing the multifaceted nature of operational efficiency in CRPs. Additionally, the growing relevance of the APM framework in real estate development was examined, offering potential flexibility in managing CR implementation.

Despite these advancements, significant gaps persist in the literature. These include limited integration of CR in DEA-based efficiency assessments, insufficient distinction between work and operational efficiency in CRP contexts, and a scarcity of longitudinal studies examining efficiency changes throughout CRP life cycles. This study aims to address these gaps by integrating CR considerations into a superefficiency SBM-DEA model, clearly differentiating between work efficiency and operational efficiency, and conducting a longitudinal analysis of CRP efficiency. By combining these approaches with APM principles and standardized Chinese construction metrics such as CQQ, duration quotas, and cost indices, this research seeks to provide a comprehensive understanding of whether CR implementation affects operational efficiency in CRPs.

3. Data and methods

Our research employs a multistep analytical approach, as illustrated in Fig. 1, to address the proposed research questions. The methodology integrates the following:

1). A superefficiency SBM-DEA model incorporates CRP-specific variables to evaluate operational efficiency and identify improvement areas.
2). Calculation of work efficiency improvement values for nine typical CR applications using existing CQQ and duration quotas.
3). An APM-based method to examine management control performance indicators in the studied projects.
4). A Tobit regression model uses APM eigenvalues and CR-induced work efficiency improvement values as explanatory variables to identify key factors influencing CRP operational efficiency.

This integrated approach allows for a comprehensive analysis of the interplay between CR implementation, project management practices, and operational efficiency in CRPs.

3.1. The superefficiency SBM-DEA model

In assessing a DMU's operational efficiency through the superefficiency SBM-DEA model, it is essential to note that the reference object does not encompass all decision units. Specifically, the decision unit being reviewed is omitted from the reference set during the evaluation process and is instead assessed by other decision units (Sun, 2021). For an ineffective decision unit, the efficiency value should be less than 1 so that all decision units can be fully sorted. Since the efficiency of the valid decision unit is greater than 1, the concept of superefficiency arises. In this work, we assume that every CRP is a DMU, which is named $DMU_j (j = 1,2,3\ldots n)$, with m inputs $x_i (i = 1,2,3\ldots m)$ and q_1 desirable outputs $y_{gr} (r = 1, 2, 3\ldots q_1)$. The SBM model with only desirable outputs is shown as follows:

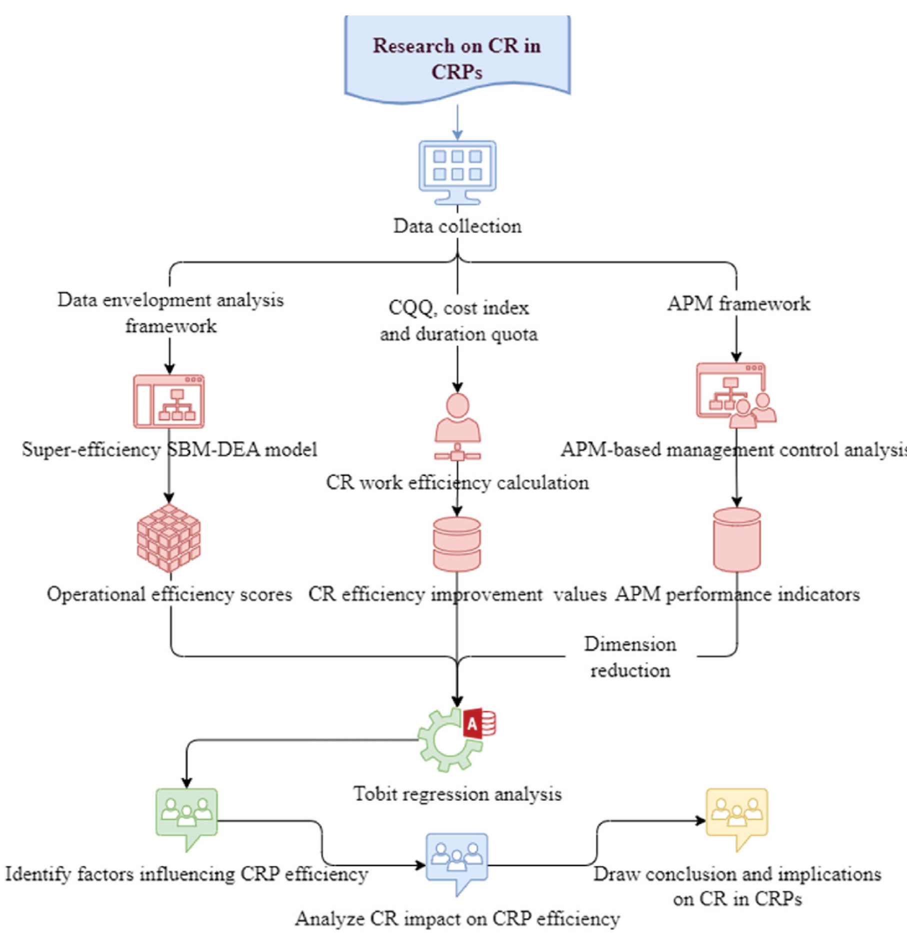


Fig. 1. Research flow chart.

$$min\ \rho_1 = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^{t,x-}}{x_{ik}}}{1 + \frac{1}{q_1}\sum_{r=1}^{q_1}\frac{s_r^{t,g+}}{y_{rk}^{g}}} \tag{1}$$

$$\text{s.t.}\begin{cases} \sum_{j=1}^{n} x_{ij}^{t}\lambda_j^t + s_i^{t,x-} = x_{ik} \\ \sum_{j=1}^{n} y_{rj}^{t,g}\lambda_j^t - s_r^{t,g+} = y_{rk}^{g} \\ \lambda, s_i^{t,x-}, s_r^{t,g+} \geq 0 \end{cases}$$

where $s_i^{x-} s_r^{g+}$ represent the adjustment variables of input slack and desirable output slack, respectively. λ is the weighting parameter vector. ρ_1^* is the objective function of the efficiency of DMU_k; $0 < \rho_1^* < 1$ indicates that the current DMU_j does not achieve the optimal efficiency in interval t. If $\rho_1^* = 1$, DMU_j achieves the optimal efficiency in interval t.

One drawback of the SBM model with undesirable outputs is that the calculated efficiency value can only be kept in the interval of [0, 1]. To address this issue, we use the Super-SBM model with undesirable outputs, which is based on Lin and Xie (2022), and the corresponding formula is as follows:

$$min\ \rho_2 = \frac{1 + \frac{1}{n}\sum_{i=1}^{m}\frac{s_i^{t,x-}}{x_{ik}}}{1 - \frac{1}{q_1}\sum_{r=1}^{q_1}\frac{s_r^{t,g+}}{y_{rk}^{g}}} \tag{2}$$

$$\text{s.t.}\begin{cases} \sum_{j=1, j\neq k}^{n} x_{ij}^{t}\lambda_j^t - s_i^{t,x-} \leq x_{ik} \\ \sum_{j=1, j\neq k}^{n} y_{rj}^{t,g}\lambda_j^t + s_r^{t,g+} \geq y_{rk}^{g} \\ 1 - \frac{1}{q_1}\sum_{r=1}^{q_1}\frac{s_r^{t,g+}}{y_{rk}^{g}} > 0 \\ \lambda, s_i^{t,x-}, s_r^{t,g+} \geq 0 \end{cases}$$

where ρ_2^* is the objective function of the efficiency of DMU_k; note that the optimal value of Equation (2) is greater than or equal to 1. That is, $\rho_2^* \geq 1$. The superefficiency for DMU_k will be 1 even if DMU_k is inefficient. To determine whether DMU_k is inefficient or efficient, both Equations (1) and (2) are then used to calculate its superefficiency.

3.2. Indicator system of operational efficiency

According to the principles of accessibility and representativeness, we selected several appropriate input and output indicators of the real estate sector, as shown in Table 3. Four indicators, namely, "number of employees," "land area occupied from the start of construction," "interim payments to contractors," and "development duration," were chosen as input indicators to clarify the different resources invested from real estate companies and the construction sector. In terms of output indicators, economic and commercial aspects need to be considered (Liu et al., 2022; Yang & Fang, 2020). On the economic side, the indicator "AWCP" was chosen; on the commercial side, the indicators "Number of commercialized housing units sold" and "business income" were chosen. Given the comparatively higher level of "main body responsibility" (Boya et al., 2014; Zhang et al., 2021) that practitioners in the Chinese real estate business often have in comparison with their counterparts in the developed world, such as Europe and North America, we deemed the abovementioned indicators to be well suited to the unique characteristics of the Chinese real estate market.

3.3. Tobit regression model

Given that the efficiency scores were greater than 0, the estimation of the ordinary least squares regression approach may have yielded biased results (Permani, 2023). We adopted the panel Tobit model to analyze the factors influencing the operational efficiency of the CRP in China. Moreover, to eliminate heteroscedasticity, we logarithmically processed all explanatory variables (Zhang & Xu, 2022); hence, we obtained the following model (see Equation 3):

$$Y^* = \begin{cases} \beta X_i + \mu, Y^* > 0 \\ 0, Y^* \leq 0 \end{cases} \tag{3}$$

where Y is the dependent variable, Y^* is the truncated dependent variable, $X_i (i = 1, 2, 3 \ldots b)$ is the independent variable, β is the regression coefficient vector, μ is the error vector, and μ is independent and obeys $\mu \sim N(0, \sigma^2)$, which we estimate from SBM and superefficiency models. Some influencing factors were selected as the independent variables. Following the Tobit regression, we analyzed the results to determine the influence direction and intensity of the independent variables on various efficiency values.

3.4. Indicator system of agile management

This subsection describes the eight aggregate dimensions that we use in our APM-based framework, which assessed the CRP management capability for the objective projects.

3.4.1. APM and its applications in CRP operational management

Building upon the literature review presented in Section 2.3, we recognize that certain elements influencing the overall factor productivity and efficiency of real estate enterprises are not amenable to direct quantification. Yang and Fang (2020) reported that, in addition to inputs and outputs, some factors influence the overall factor productivity and efficiency of real estate enterprises. Notably, certain elements are not amenable to direct quantification. A multiple-indicator Tobit model was employed to evaluate the efficiency of real estate companies. In this study, to construct the APM framework, we employed the Agile Project Success Model framework to review previous research's aggregate dimensions.

Previous researchers have presented agile methodologies that are explicitly tailored for agile projects, which diverge from the approaches employed in conventional projects. For example, Hu et al. (2009) suggested the Scrum method, which involves the product owner creating a comprehensive product backlog that includes all known requirements and team members executing each sprint task on the basis of the evolving product backlog. In corporate expeditious customer evaluation and feedback, Stapleton (1997) introduced the dynamic systems development method (DSDM), a project development approach distinguished by ongoing engagement and cooperation among all project stakeholders, with a particular emphasis on the client. This methodology aims to expedite project development processes. Palmer and Felsing (2001) presented the feature-driven development (FDD) technique, which is distinguished by the implementation of regular assessments

Table 3
Input and output indicators of the real estate sector perspective.

Dimension	Indicator	Category	Description	Notation
Input Indicator	Number of employees (People)	Resource	Includes project manager, office staff and sales staff, who employed by real estate company.	NE
	Land area occupied from construction started. (m^2)	Resource	The land area that has been occupied since the start of construction activities.	LA
	Interim payments to contractors. (Million CNY)	Economic	Generally, real estate companies in China are required to make monthly interim payments to contractors.	IP
	Developed duration. (Months)	Time	Developed duration time from the start of the project to the date of the investigation.	DDU
Output Indicator	ACWP (Million CNY)	Economic	Actual Cost of Work Performed	ACWP
	Number of Commercialized Housing Sold Units (Set)	Commercial	The quantity of units of commercialized residences that have been sold.	NSU
	Business Income (Million CNY)	Commercial	The generated income derived from the sale of commercialized residential properties.	BIN

conducted by an autonomous team to verify the system's currency. Furthermore, Kanban was introduced by Heizer and Render (2004) as a strategy emphasizing inventory scheduling and timely replenishment.

On the basis of the qualitative research and comparisons conducted, we confirmed the applicability and comprehensiveness of the eight aggregated characteristics proposed by Russo (2021) in assessing the significance of command–and–control systems in achieving project success within the APM-based paradigm. Hence, we constructed measurement scales in accordance with this paradigm to quantitatively evaluate the managerial competencies of project management teams.

3.4.2. Measurement scales

To ensure content validity and relevance to the CRP context, we conducted two rounds of expert panel review (n = 4 experts per round). This iterative process allowed us to refine the questionnaire items for clarity and face validity. The final measurement instrument consists of eight aggregate dimensions with a total of 28 items, each measured on a 7-point Likert scale using linguistic expressions to ensure consistent interpretation.

Fig. 2 illustrates the conceptual framework of our measurement scales, showing the relationships among first-order concepts, second-order themes, and aggregate dimensions. The scale is shown in the supplementary material.

The collected data were screened for outliers and missing values before descriptive statistics, reliability analysis via Cronbach's alpha, confirmatory factor analysis for construct validity, and correlation analysis between dimensions were conducted. These analyses formed the foundation for our subsequent factor regression studies, enabling us to examine the relationships between APM dimensions and CRP operational efficiency.

3.5. Work efficiency improvement

3.5.1. Cumulative work efficiency improvement from CR technology

In the context of the CRP, we consider various CR technologies as integral components of the construction production line. To quantify the cumulative work efficiency improvement due to CR technology, we employ a two-step approach adapted from the industrial production method (Dal et al., 2013).

Step 1. The work efficiency improvement for each workstation is as follows:

$$EFF_{i,imp} = \left(\frac{eff_{i,t+1} - eff_{i,t}}{eff_{i,t}}\right) \times 100\%, (\mathrm{i} = 1, 2, 3 \ldots, \mathrm{n}) \tag{4}$$

where EFF_{imp} represents the workstation efficiency improvement in the production line. $eff_{i,t}$ represents the workstation efficiency before improvement (i.e., the efficiency value of process i at time (t)). $eff_{i,t+1}$ represents the workstation efficiency after improvement (i.e., the efficiency value of process i at time $t+1$).

Step 2. The cumulative work efficiency improvement for the entire production line is calculated as follows:

To estimate the cumulative efficiency improvement, we summed the weighted efficiency improvements for all tasks with such improvements and then divided them by the number of tasks:

$$\overline{EFF_{imp}} = \frac{\sum_{i,k=1}^{n} \left[(\omega_1 + \omega_2 + \ldots + \omega_k) \times EFF_{i,imp}\right]}{n} + 1, (i, k = 1, 2, 3 \ldots, n) \tag{5}$$

$$\omega_k, \omega_k' = \frac{Workstation_i}{Entire_i}, (i, k = 1, 2, 3 \ldots, n) \tag{6}$$

where $\overline{EFF_{imp}}$ represents the cumulative efficiency improvement for the entire production line. ω_k, ω_k' represents the cost and duration weight for each workstation.

In our analysis, we integrated various CRs as key components within the CRP production line. To quantify the overall work efficiency improvement due to CR technology, we applied Equations (4)–(6).

The efficiency calculation incorporates two crucial weights: direct cost and duration. These weights are determined by the ratio of a task's direct cost and duration to the project's overall cost and timeline, respectively. To increase the precision of the duration weights and their effects on the project schedule, we employed the critical path method (CPM). This widely recognized technique identifies the project's longest path, highlighting activities that significantly influence the total timeline (Kelley & Walker, 1959). By differentiating between critical and noncritical activities, we assign a weight of 0 to the CR implementation duration on noncritical paths.

3.5.2. Calculation of cost and duration

By using the CQQ data and the CRP building cost index database, it was possible to estimate the unit cost of subprojects for buildings of different stories via the following equation (7):

$$C_i = \frac{CQ_i \times Q_i}{EC_i} \times \frac{S_i'}{S_i' + S_i''}, (i = 1, 2, 3 \ldots, n) \tag{7}$$

where C_i represents the unit cost to be measured. Q_i represents per m^3 or per m^2 of the subprocess price in the CQQ. CQ_i represents per

m^3 or per m^2 of the subprocess consumption quantity, and EC_i represents the entire unit cost to be measured. S_i' and S_i'' represent the areas of the corresponding parts of CQ_i. This payment is settled in the Chinese yuan (CNY). The “price” represents the price of construction workers, which is periodically published by the issuing authority for use in CQQ calculations. As of September 2023, the published unit price was CNY 107.00 per work day (Construction Engineering Dynamic Labor and Main Building materials Price index, 2023).

Moreover, we included a schedule that specified the duration of the CRP for various floor heights. We present a model of a 30-story CRP baseline model, as shown in the supplementary material. This Gantt chart demonstrates that, within mainland China, the critical path does not encompass interior decoration subprojects and basement floor painting works.

4. Empirical study

This section uses three stages (superefficiency SBM-DEA, UMAP-based dimensionality reduction, and Tobit regression model) to measure the work and operational efficiency performance of CR application in mainland China's CRP. We employed the proposed method with data from 21 provinces in China for July 2022 to August 2023.

4.1. Sample selection and data acquisition

The study draws upon data from a prominent listed real estate enterprise with national operations, selected for its representative status within the industry. Through collaborative efforts with project managers, the research team acquired both qualitative data via questionnaires and quantitative financial and operational metrics. The investigation encompasses 107 CRPs distributed across 21 provinces in mainland China, as illustrated in Fig. 3(a).

4.1.1. Sample representativeness

To contextualize the sample's significance, it is pertinent to consider the following metrics:

- According to the National Bureau of Statistics of China (NBSC), in 2022, Chinese real estate developers embarked on projects covering a staggering 88,1350,800 m^2.
- Our 107 CRPs account for 16,908,803.92 m^2, as shown in Fig. 3(b). Our sample represents 1.92% of the overall population of CRPs currently (in 2023) under development in China in terms of management area coverage. Statistically, a 0.43% sample area is sufficient to achieve a 95% confidence level, indicating that our sample size is robust.
- Our project distribution mirrors the broader reality. The east-central and west-central splits in our sample align closely with the NBSC's nationwide figure (Fig. 3(c)), adding another layer of credibility to our research.

4.1.2. Geographic stratification

China consists of 23 provinces, 5 autonomous regions, 4 municipalities directly under the central government, and 2 special administrative regions (collectively called provinces in the following research). The country is often categorized into three distinct regions for analytical purposes: the eastern, central, and western areas (Shuai & Fan, 2020; Zhao et al., 2016). The constituent provinces of each area are reported in Table 4.

4.1.3. Descriptive statistics

Table 5 shows the descriptive statistical information of the dataset. As shown in Table 5, the large standard deviations of the input and output variables involving funds indicate the possibility of uneven performance of the CRP in different provinces. This finding can be attributed to China's imbalanced nature of regional economic development (Johnes & Yu, 2008). The standard deviations for nonfinancial input variables are comparatively lower, indicating less variation in input resources other than financial aspects among different projects.

Following the collection of financial and human resource data for the projects, we conducted a questionnaire survey based on the APM paradigm conducted from a nontechnical perspective with the surveyed CRP project managers. These experienced managers (i.e., 107 CRP project managers), with an average of 11 years of project management experience, are shown in Table 6.

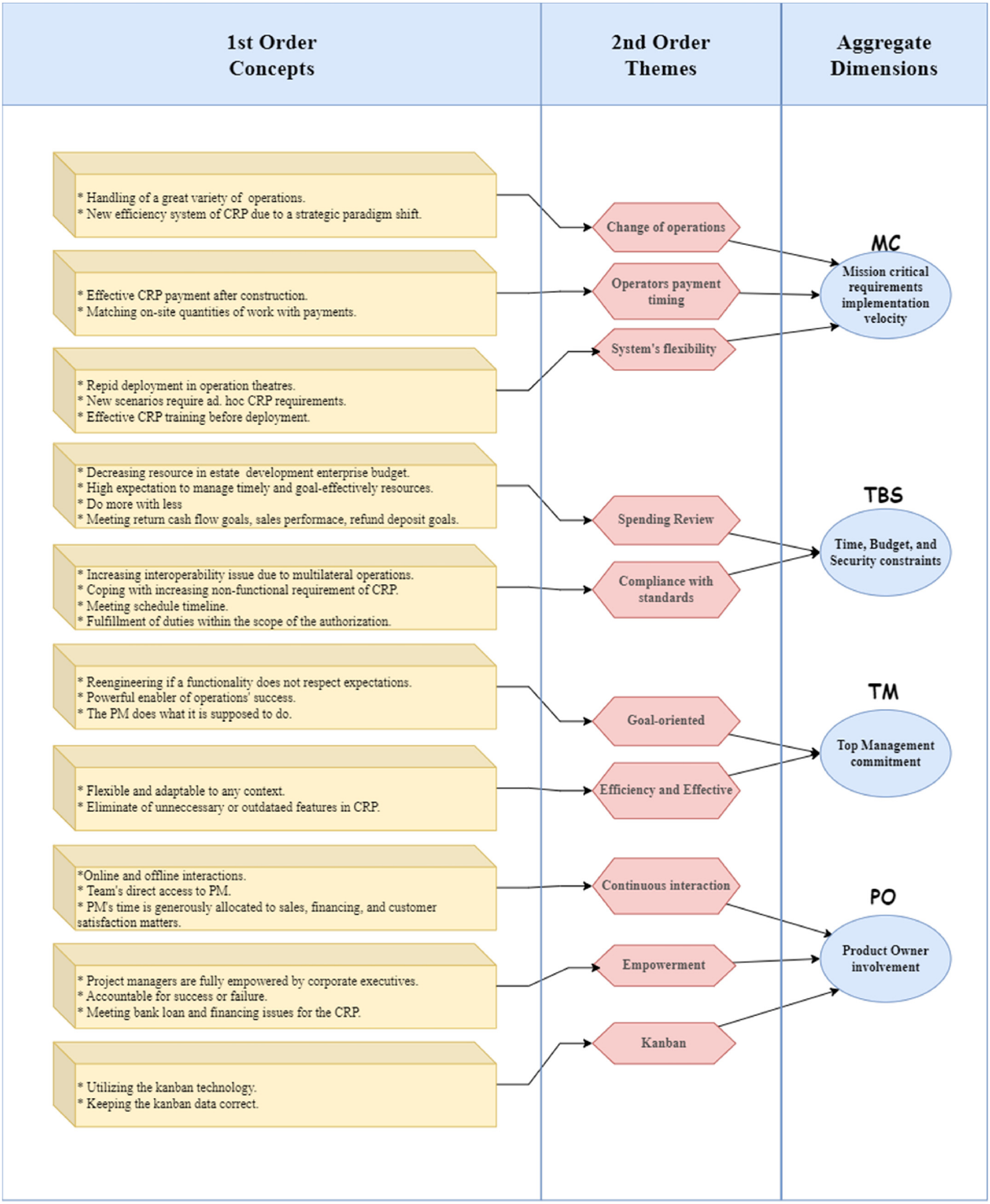
4.2. Superefficiency SBM-DEA results

The operational efficiency values for the chosen DMU were calculated via MATLAB software on the basis of the superefficiency SBM-DEA model. The resulting values are presented in Table 7, including the average efficiency values (*Mean_eff*) for each region. The comprehensive outcomes of the efficiency and slack values of all the DMUs are presented in Appendix Tables C and D, respectively. To maintain the commercial secrecy of the CRP information, DMU codes are employed to represent the name descriptions. In this subsection, our primary objective is to address the inquiries presented in Sub RQ (1).

According to the data presented in Table 7, Project AH053 in Anhui Province, Project HS019 in Shanghai, and Project GZ015 in Guizhou Province presented the highest levels of efficiency. In contrast, project SX002 in Shaanxi Province, HB052 in Hebei Province, and HN001 in Henan Province presented the least favorable efficiency rates within their respective regions. Notably, both Projects HN001 and HB052 demonstrate efficiency levels close to zero.

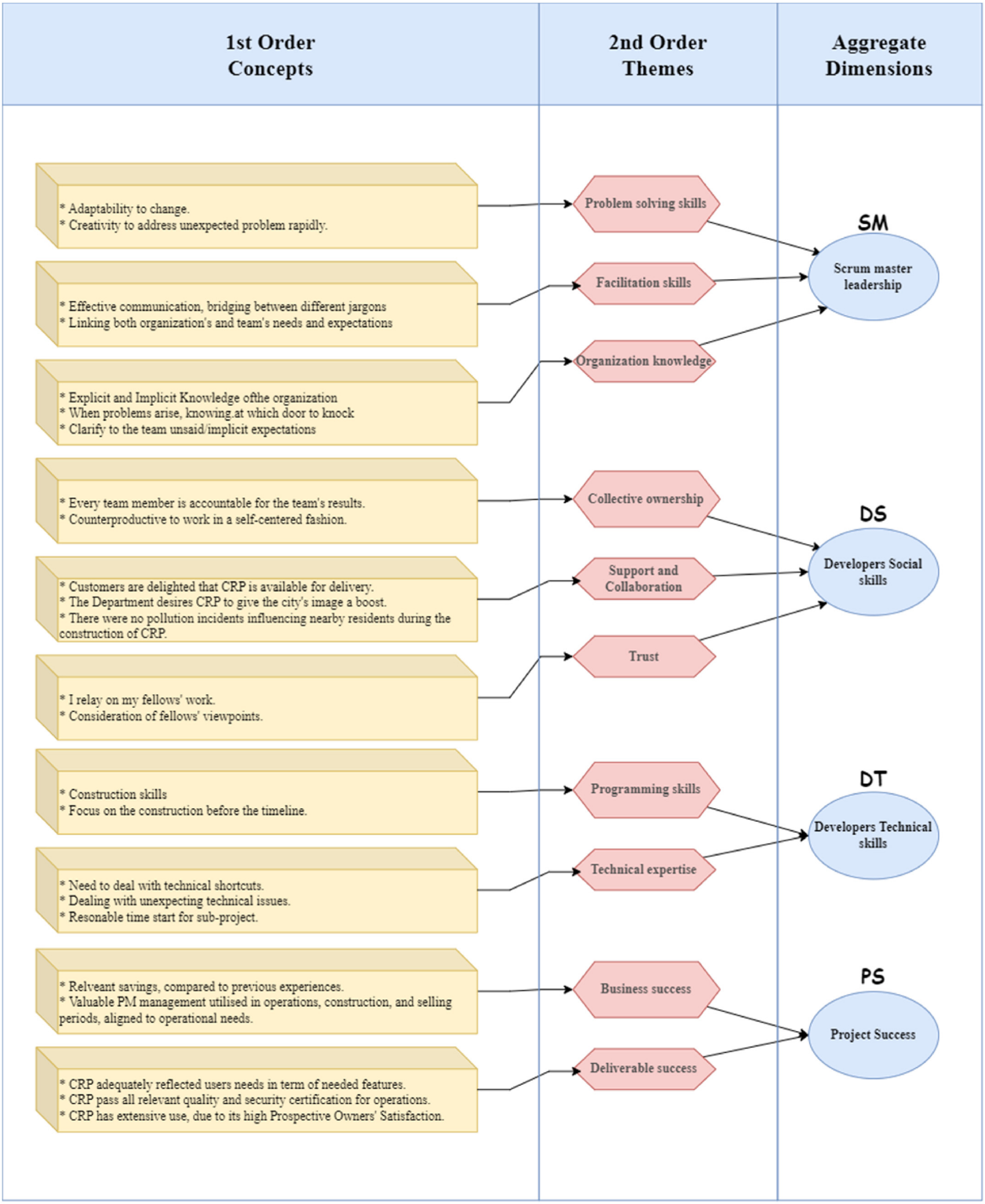
The efficiency matrix in Fig. 4(a) was derived from the DEA data. Fig. 4(a) is partitioned into four quadrants with the mean value as the demarcation line. The DMU located in the upper right corner has a high level of efficiency. The projects implemented in Jiangsu and Shanghai Provinces exhibit superior operational efficiency performance, whereas those in Guizhou Province demonstrate more balanced performance but with greater variability in their efficiency levels. The provinces have better average efficiency in the upper left corner, but the programs demonstrate comparatively lower efficiency, such as project XB029 in Gansu Province and project XX007 in Shanxi Province. Additionally, some projects can be found in Shanxi Province in southeastern China, specifically in the lower right corner. These projects exhibit higher efficiency levels, whereas provinces demonstrate lower efficiency performance. The zone of inefficiency, which is located primarily in the lower left corner, is where a significant concentration of projects may be observed. This observation highlights the existing potential for enhancing the operational efficiency of the real estate business. Given the significant regional dependence of the real estate business and the notable economic disparities among China's provinces, we employed a trend line and confidence intervals to identify a threshold of the CRP, as shown by the red line in Fig. 4(a). If the operational efficiency value aligns more closely with the trend line, it indicates a greater harmonization of stakeholder interests in accordance with the prevailing economic conditions.

Furthermore, we conducted a back-testing analysis to determine the ideal number of clusters, which was found to be three on the basis of the elbow curve method (see Fig. 4(b)). This approach



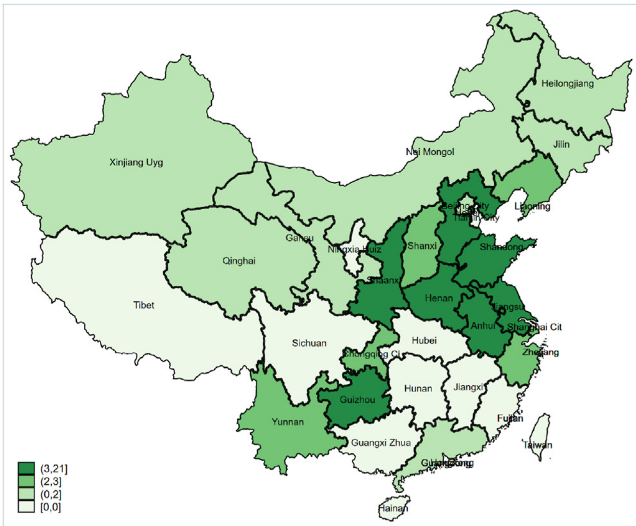
(a). Conceptual framework for MC, TBS, TM, and PO

Fig. 2. Conceptual framework for APM-based measurement scales in CRP management.

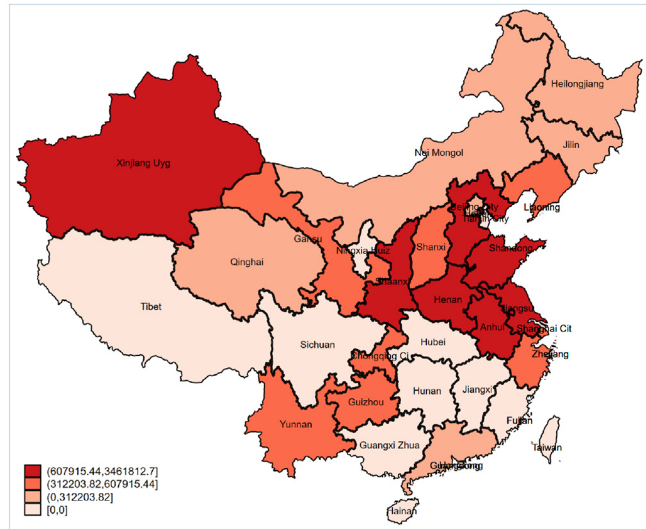


(b) Conceptual framework for SM, DS, DT, and PS

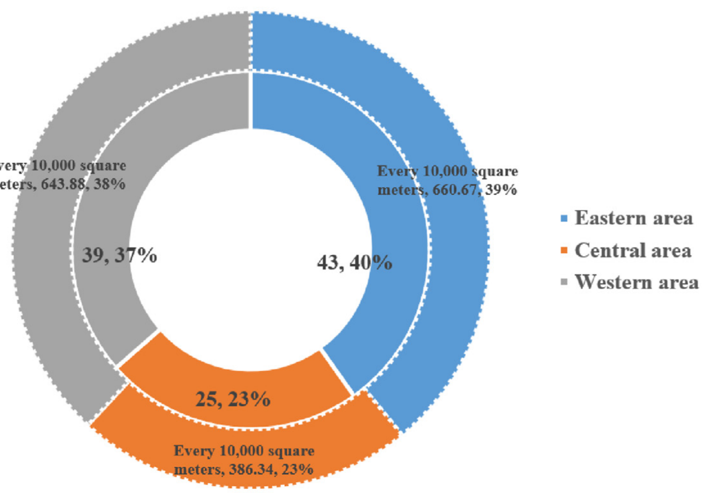
Fig. 2. (*continued*).



(a). The sample is geographically distributed in China, by number.



(b). The sample is geographically distributed in China, by areas.



(c). The sample is distributed in China, by regions.

Fig. 3. The sample distribution in China was investigated in this study.

Table 4
Three regions in mainland China.

Areas	Provinces, Autonomous regions, or Municipality
Eastern area	Beijing, Shanghai, Tianjin, Guangdong, Shandong, Hainan, Zhejiang, Jiangsu, Fujian, Hebei, and Liaoning
Central area	Jiangxi, Heilongjiang, Jilin, Anhui, Hunan, Henan, Hubei, and Shanxi
Western area	Sichuan, Inner Mongolia, Ningxia, Guizhou, Guangxi, Shaanxi, Yunnan, Gansu, Xinjiang, Qinghai, Tibet, and Chongqing

demonstrates that, by employing the K-means algorithm, it is possible to effectively partition the dispersed data points into three distinct regions, thus facilitating a more streamlined examination.

According to the SBM-DEA framework and slack improvement, the CRP provides insights into the direction of operational efficiency enhancement. This is illustrated in Fig. 4(c), and the detailed data are shown in Appendix Table C, D. Our findings reveal varying potentials for improvement across different variables:

- *Limited improvement potential*: Number of employees (NE), land area (LA), duration of development and unit sales (DDU), and actual cost of work performed (ACWP).
- *Significant improvement potential*: Interim payment (IP), number of sales units (NSU), and balance of inventory (BIN).

Operational efficiency improvements are typically achieved through extensive commercial negotiations with contractors prior

Table 5
Descriptive statistics for the dataset (07.2022–08.2023).

Region	Variable and Units		N	Mean	Std.dev	Min	Max
Central area	Input	Number of employees (People)	25	24.48	12.68	4	58
		Land area occupied from construction started. (Square meters)	25	8.282	9.115	0.51	43.37
		Interim payments to contractors. (Million CNY)	25	114.8	72.9	27.96	322.5
		Developed duration (Months)	25	40.36	18.64	17	89
	Output	ACWP (Million CNY)	25	138.2	85.91	34.8	393.6
		Number of Commercialized Housing Sold Units (Set)	25	327.5	211.4	0	749
		Business Income (Million CNY)	25	248.6	153.2	0	517.1
Eastern area	Input	Number of employees (People)	43	25.88	19.4	5	120
		Land area occupied from construction started. (Square meters)	43	16.61	36.23	0.352	240.4
		Interim payments to contractors. (Million CNY)	43	174.4	177.5	15.16	955.1
		Developed duration (Months)	43	40.12	28.38	20	155
	Output	ACWP (Million CNY)	43	182.6	170.3	12.13	1059
		Number of Commercialized Housing Sold Units (Set)	43	376.8	403.2	0	1981
		Business Income (Million CNY)	43	681.5	1109	12.49	4883
Western area	Input	Number of employees (People)	39	25.87	16.1	4	78
		Land area occupied from construction started. (Square meters)	39	13.98	9.434	1.33	41.53
		Interim payments to contractors. (Million CNY)	39	833	2124	19.51	10710
		Developed duration (Months)	39	40.8	16.82	13	74
	Output	ACWP (Million CNY)	39	781.5	1874	24.18	9369
		Number of Commercialized Housing Sold Units (Set)	39	341.1	264.6	0	1275
		Business Income (Million CNY)	39	371.4	522.4	0	2353

Table 6
Sample characteristics (N = 107).

Feature	Distribution	Frequency	Percent
Gender	Female	0	0.00%
	Male	107	100.00%
Age	26–35	4	3.74%
	36–40	22	20.56%
	40–45	32	29.91%
	46–50	34	31.78%
	Over 50	15	14.02%
Working experience	1–5 years	2	1.90%
	6–10 years	24	22.86%
	More than 10 years	79	75.24%
Agile experience	1 year or less	30	28.04%
	2–4 years	47	43.93%
	5–7 years	28	26.17%
	More than 7 years	2	1.87%

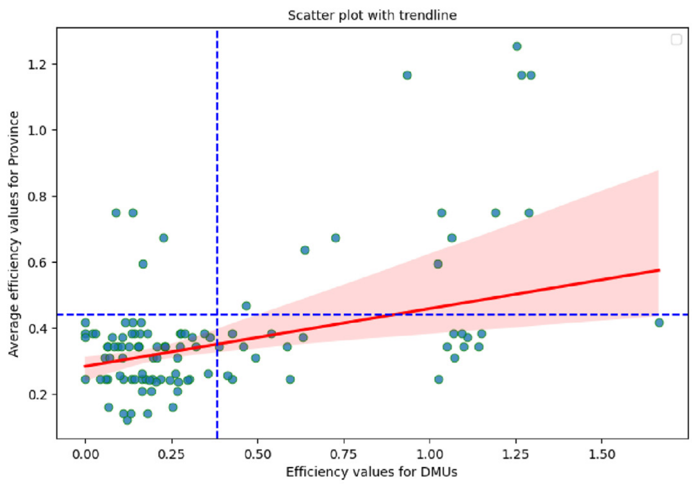
to finalizing lump-sum contracts. Project managers commonly establish mutually agreed-upon terms regarding the timing and amounts of interim payments. However, our investigation reveals that PMs often use these conditions as negotiating tools, which can inadvertently impact CRP operational efficiency. For example, projects in Guizhou and Zhejiang Provinces demonstrate potential for efficiency enhancement through optimized process payment allocations to contractors. This underscores the importance of balanced negotiation strategies that consider both short-term financial objectives and long-term operational efficiency.

Additionally, China's presale system in real estate development has created a notable disparity between the NSU and BIN variables. This system introduces a temporal gap between the sale of commercialized residential housing units and the return of funds to real estate companies, necessitating careful financial planning and

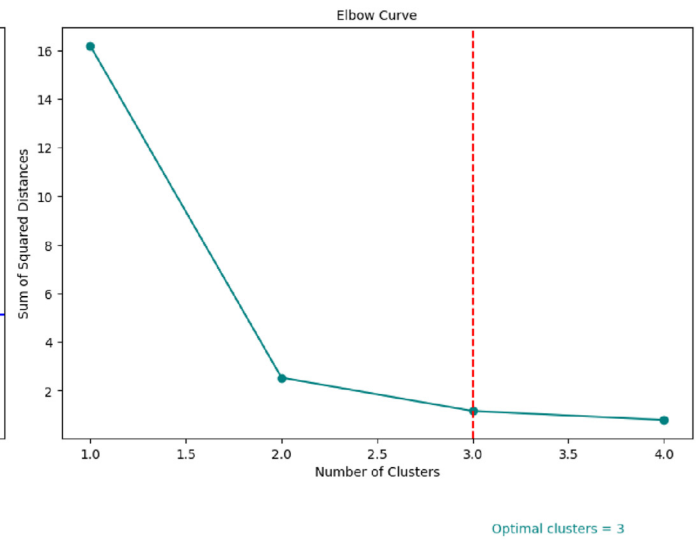
Table 7
107 DMU values in their respective regions and provinces.

Region	Region *Mean_eff*	Province	Province *Mean_eff*	*Max_DMU*	*Max_eff*	Rank	*Min_DMU*	*Min_eff*	Rank
Central area	0.3651	Anhui	0.416	AH053	1.666	1	AH025	7.31E-06	104
		Heilongjiang	0.121	DB005	0.121	82	DB005	0.1207	82
		Henan	0.244	YX016	1.026	17	HN001	1.40E-06	107
		Shanxi	0.672	XX012	1.064	14	XX007	0.2263	53
		Jilin	1.253	DB007	1.253	5	DB007	1.2527	5
Eastern area	0.3963	Beijing City	0.468	BJ008	0.468	27	BJ008	0.4683	27
		Guangdong	0.237	GQ003	0.269	44	GQ009	0.2048	57
		Hebei	0.371	HB030	1.109	9	HB052	4.15E-06	106
		Jiangsu	0.383	SB029	1.150	7	HS037	6.11E-06	105
		Liaoning	0.261	DB003	0.357	34	DB021	0.1647	68
		Shandong	0.309	LD002	1.073	12	LD003	0.0553	100
		Shanghai City	1.164	HS019	1.292	2	HS015	0.9332	19
		Zhejiang	0.207	ZJ006	0.267	45	ZJ003	0.1650	66
Western area	0.3790	Chongqing City	0.141	CQ002	0.180	62	CQ014	0.1108	85
		Gansu	0.595	XB008	1.024	18	XB029	0.1661	65
		Guizhou	0.749	GZ015	1.289	3	GZ011	0.0899	91
		Nei Mongol	0.257	BJ018	0.413	31	BJ013	0.1007	89
		Qinghai	0.637	XB026	0.637	21	XB026	0.6366	21
		Shaanxi	0.344	SX023	1.141	8	SX002	0.0646	97
		Xinjiang Uygur	0.161	XB019	0.254	48	XB021	0.0668	95
		Yunnan	0.243	YN004	0.296	39	YN001	0.1874	61

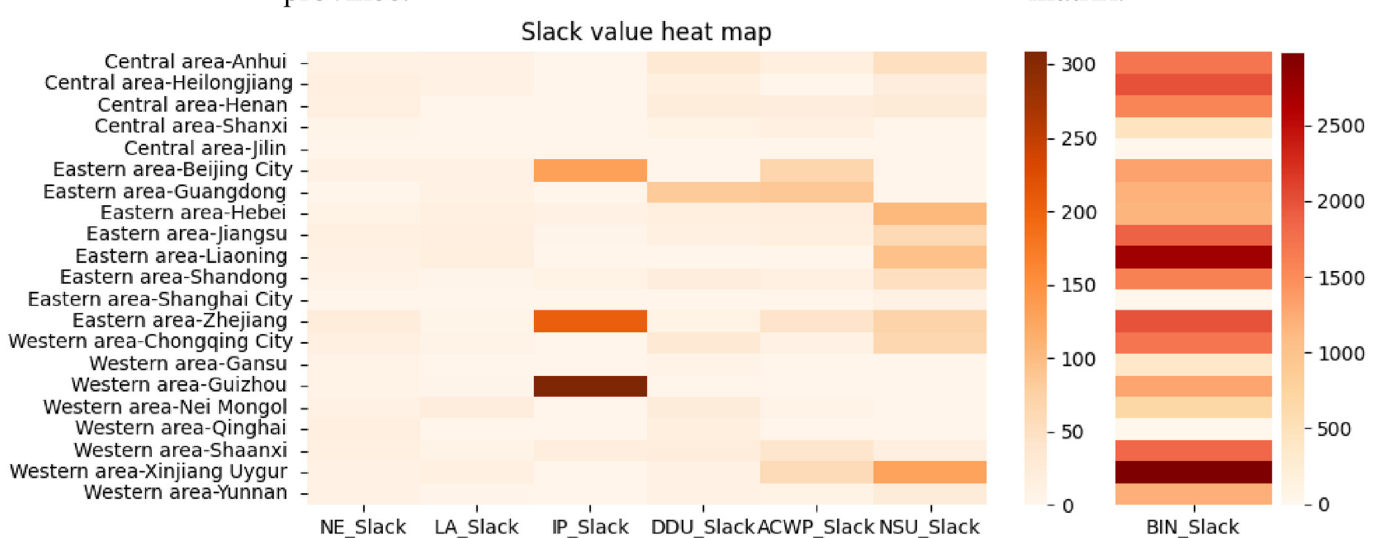
Note: *eff* represents the operational efficiency of the CRP.



(a). Synthesize evaluation matrix for project and province.



(b). Optimal clusters for project and province matrix.



(c). Heatmap of relaxation improvement for each input and output variable.

Fig. 4. Results of the application of the superefficiency SBM model.

cash flow management throughout the project lifecycle.

4.3. The work efficiency improvement value of the CR is calculated

This subsection addresses the inquiries presented in Sub RQ (2). Among a total of 107 CRP samples investigated, 30 projects included CR technology to varying degrees. According to Fig. 5, our investigation revealed the presence of 9 prevalent types of construction robotics in the investigated projects, amounting to a collective total of 99 occurrences in 30 samples.

For projects that did not use CR technology, we considered their work efficiency value to be 1, indicating no improvement. The average work efficiency improvement via CR technology was modest, with a slight increase of 1.026. Notably, projects in Anhui Province (central area) exhibited the most substantial average work efficiency improvements, with a value of 1.104, exceeding the averages of 1.067 in Shandong Province (eastern area) and 1.042 in Yunnan Province (western area).

To calculate the duration weights in our proposed cumulative work efficiency improvement model, we determine a standard duration model by using the duration quota (Guangdong Provincial Department of Housing and Urban-Rural Development, 2022) as the model's base value. After thorough discussion with the experts (107 project managers of the CRP), we established a Gantt chart for a 30-story CRP model with a standard duration model of 475 working days:

(1). *Basement structure construction*: 93 working days;
(2). *Aboveground main structure construction*: 144 working days;
(3). *Standard floor reinforced concrete construction*: 7 working days per floor.

The Gantt chart (available in supplementary materials in Microsoft Project format) revealed that the CR used in the main

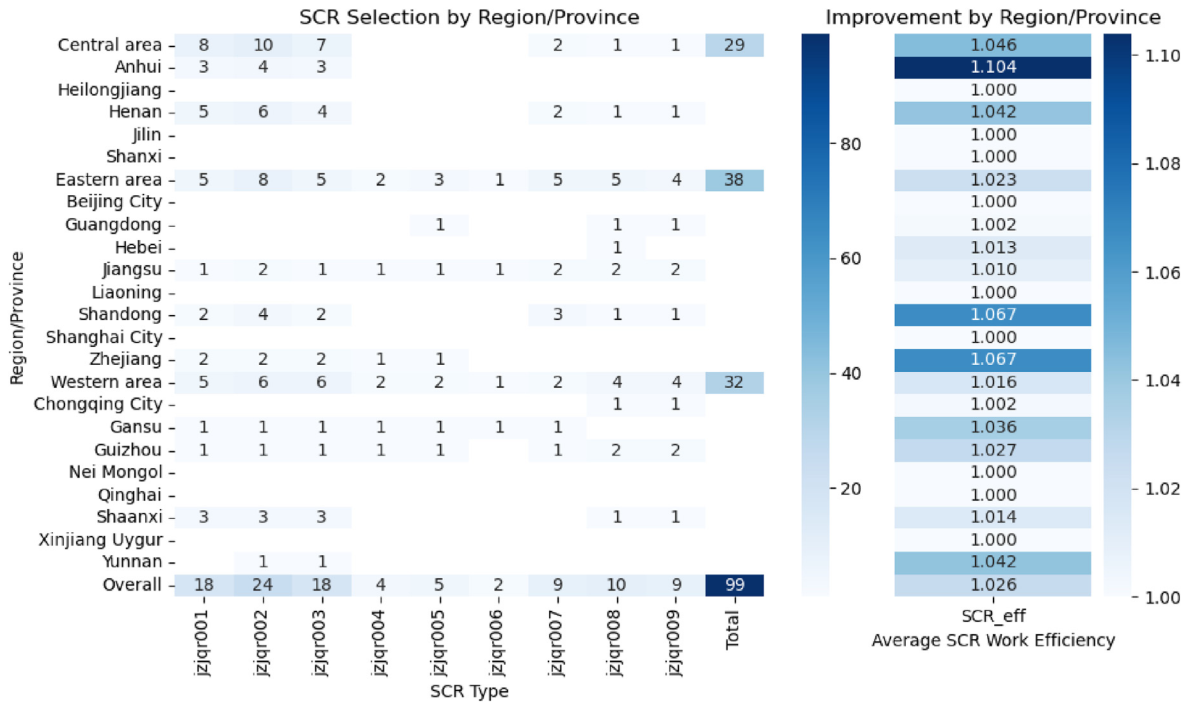
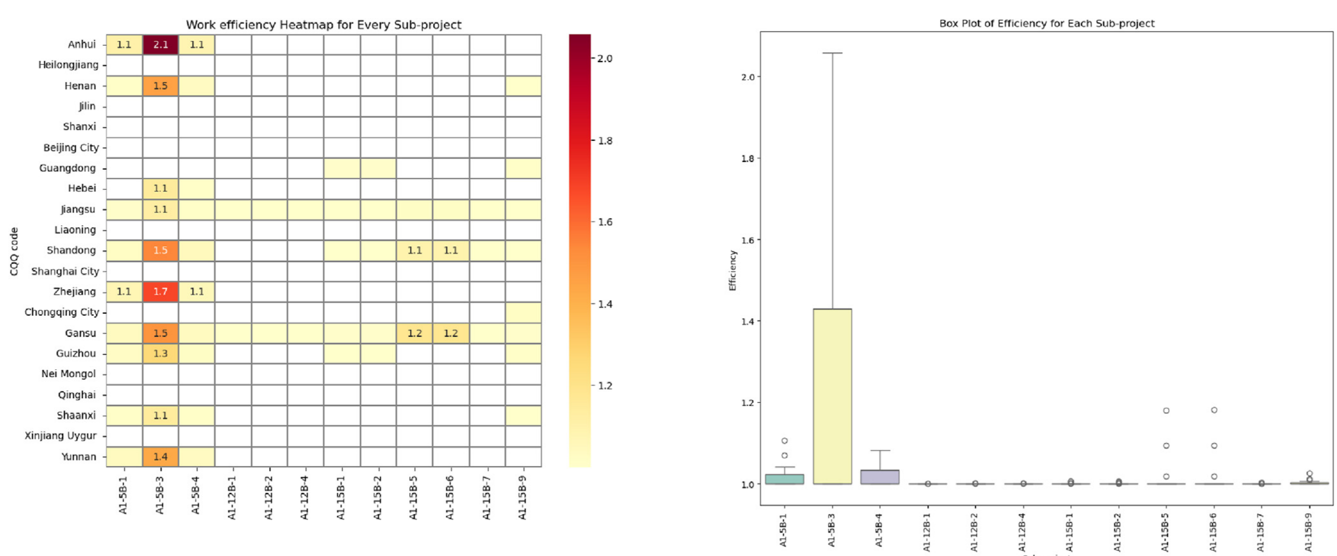


Fig. 5. CR selection and efficiency improvement by region or province.

structure construction stage, such as jzjqr001~jzjqr003, followed a critical path. Consequently, the duration weight of the main structure construction stage was $\omega_k' > 0, (k = 1,2,3 \ldots n)$. However, in the interior finishing and basement construction stages, since they were not on the critical path, their efficiency weight was $\omega_k' = 0$, $(k = 1,2,3 \ldots n)$.

The cost weights ω_k were determined via the CQQ guidelines (Guidelines for Evaluation of Intelligent Construction, 2023). The work efficiency improvement values of the 12 subprojects were calculated via the suggested model, as shown in Fig. 6. The most significant improvement was observed in subproject CQQ code A1-5B-3 (“construction of cast-in-place concrete slabs, including flat slabs, slabs with beams and slabs without beams by robot included robot feeder”), which was achieved through the collaborative use of jzjqr001 and jzjqr002. Fig. 7 presents the weight calculation results, indicating that the cost weight ω_k for the main structure



(a). The heatmap of work efficiency improvement of subprojects involving CR in each region or province.

(b). The box plot of work efficiency improvement of subprojects involving CR.

Fig. 6. Visualization of the work efficiency improvement.

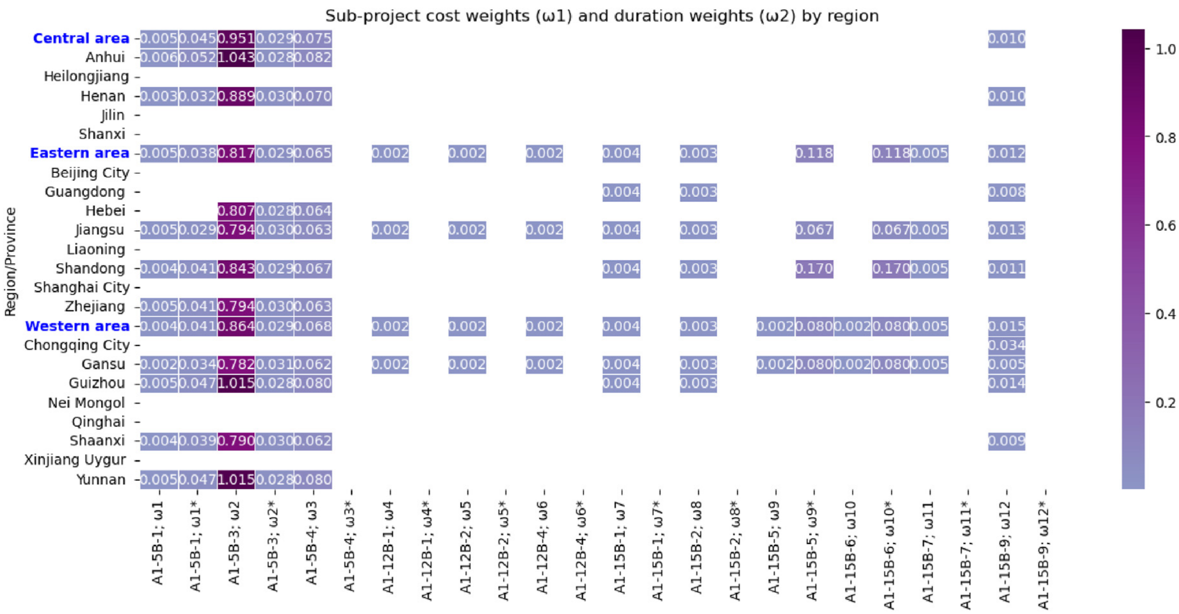


Fig. 7. The cost and duration weight of the subproject by region and province.

construction stage exceeded that of the other construction stages.

Contractors tend to prefer CR models that effectively improve work efficiency and reduce costs. The popularity of the CR models jzjqr001 to jzjqr003 was greater than that of jzjqr004 to jzjqr007 because of these factors. In the case study of Jiangsu Province's HS060 (a 34-story CRP), implementing all 9 typical CRs yielded a work efficiency enhancement of 1.065 times compared with projects without CR. However, it is important to note that improved work efficiency does not necessarily translate to increased operational efficiency from the real estate business perspective. This discrepancy highlights the ongoing challenge of achieving mutually beneficial outcomes for both real estate companies and contractors.

4.4. APM scale development and survey

The following subsections seek to address the inquiries presented in Sub RQ (3).

4.4.1. Survey data tests

The participants were asked to complete a questionnaire specifying the 8 aggregate dimensions and 28 subquestions of the APM. The development of the questionnaire was based on the APM paradigm (see Appendix Table B), and the survey questionnaire is depicted in the supplementary material. All of these subquestions provided a comprehensive overview of the items employed to delineate each dimension, as well as the references used to formulate the questions. Constructs were measured through unidimensional items in the form of a level of agreement on a 7-point Likert scale.

To identify the minimum sample size, we run an a priori power test via G*Power software (Faul et al., 2009). According to the statistical power analyses suggested by Cohen (2016) and implemented by Hair et al. (2017) in the form of statistical power, such power should not be lower than 80%. Hence, in this analysis, with its suggestions of an effect size of 20%, significance of 5%, and a power of 90%, the minimal size for 8 predictors was 104, as shown in Fig. 8. Hence, we deemed the sample size to be sufficient.

We performed a scale reliability statistic to assess the overall

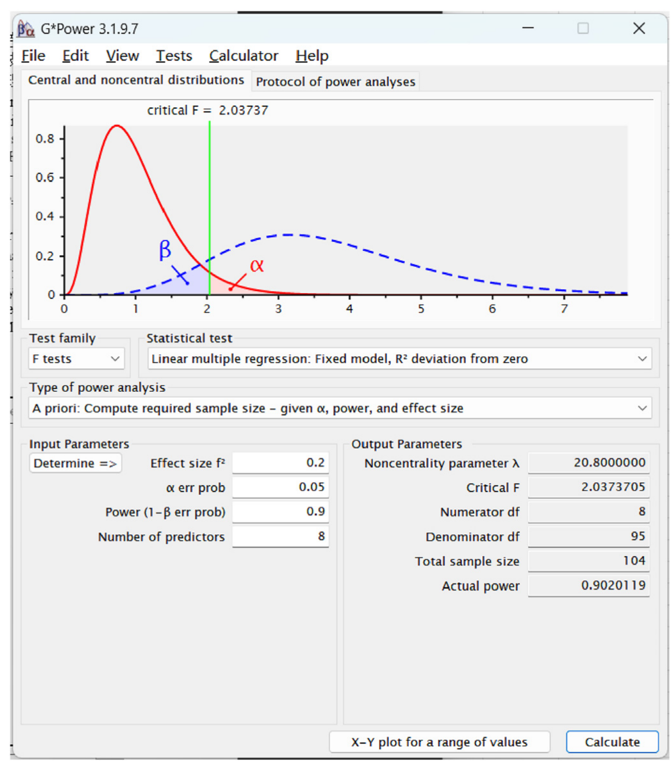


Fig. 8. The sample size estimation was based on a statistical power of 90%.

Table 8
Scale reliability statistics.

Estimate	McDonald's ω	Cronbach's α	Guttman's λ2
Posterior mean	0.9824	0.9694	0.9759
95% CI lower bound	0.9458	0.9501	0.9536
95% CI upper bound	0.9817	0.9811	0.9862

quality of our measurement instrument, as shown in Table 8. The results confirmed exceptionally high reliability (all above 0.9) for all relevant coefficients (McDonald's ω, Cronbach's α, and Guttman's λ2), suggesting a robust instrument.

4.4.2. Dimension reduction

The questionnaire data include many variables to analyze the factors influencing operational efficiency in real estate development projects. To effectively utilize these results in our regression model, dimensionality reduction is crucial. This approach mitigates multicollinearity and condenses multiple subquestions into essential components (Shrestha, 2021). By transforming the raw data through these techniques, we ensure that our regression model remains robust, interpretable, and suitable for rigorous statistical analysis.

To achieve this goal, we initially considered principal component analysis (PCA) for dimensionality reduction. However, despite a satisfactory Kaiser–Meyer–Olkin (KMO) test result of 0.9363, Bartlett's sphericity test indicated weak linear relationships between variables (mean SMC = 0.6650, SD = 0.2992).

Further analysis of the scree plot Fig. 9(a) and component loading scatter plots (Fig. 9(b)) revealed that PCA did not adequately capture the complex relationships in our data, failing to align with our proposed 8 aggregated dimensions. Although PCA works best in straightforward relationships between variables, our data had more complex connections that PCA could not capture well. Yousuff and Babu (2023) noted the limitations of PCA in their research. This was another reason we decided that PCA might not be the most suitable method for our specific data.

Given these constraints, we opt for uniform manifold approximation and projection (UMAP), a nonlinear method of reducing dataset dimensionality. To validate this choice, we employed the trustworthiness metrics developed by Stasis et al. (2016), which use rank order to quantify the proximity between a given point i and k-nearest neighbors inside a space of high dimensionality. These metrics assess the degree to which each rank undergoes changes within a space of lower dimensionality. The measure assesses the degree to which the low-dimensional representation of the dataset maintains the local structure of the original dataset. For n samples, if these k neighbors are also placed close to point i in the low-dimensional space, the map can be considered trustworthy, as shown in Equation (8).

$$T(k) = 1 - \frac{2}{nk(2n-3k-1)} \sum_{i=1}^{n} \sum_{j \in U_i^{(k)}} (r(i,j) - k) \tag{8}$$

where $r(i,j)$ represents the rank in distance of sample i to j in the high dimension space $U_i^{(k)}$.

UMAP demonstrated superior performance, as shown in Fig. 10, with trustworthiness scores exceeding 0.9 across all dimensions (mean = 0.9466), surpassing the 0.8 threshold suggested by Zhou et al. (2022) and Rodrigues et al. (2019) for trustworthy dimensionality reduction.

To ensure reproducibility and robustness, we conducted a sensitivity analysis on UMAP's key parameters: *n_neighbors* and *min_dist*. We calculated the Jaccard indices across various parameter settings:

- *n_neighbors*: 10, 15, 20
- *min_dist*: 0.1, 0.3, 0.5, 0.7, 0.9

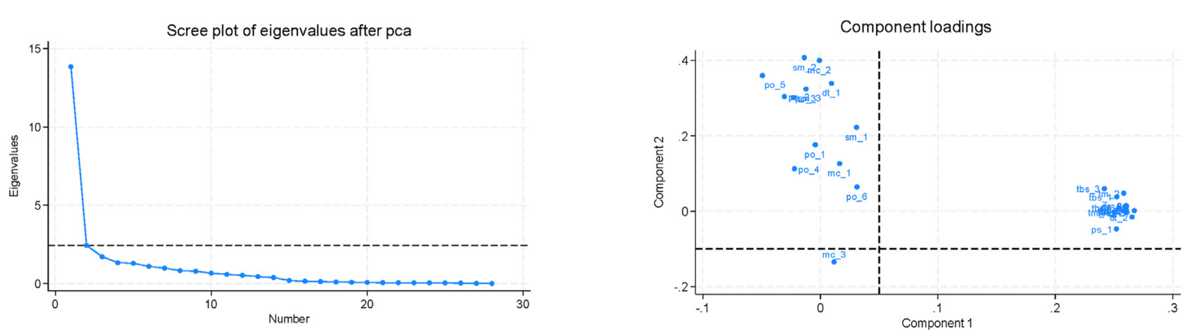
As shown in Fig. 11, UMAP consistently produced stable results across a range of parameter settings. Although certain categories, such as the MC, showed slight fluctuations in the Jaccard similarity indices (Ivchenko & Honov, 1998) under specific parameter conditions, these variations remained within acceptable limits and did not significantly impact UMAP's overall performance. For example, for the PS variable, the Jaccard similarity indices remained stable, ranging from 0.3983 to 0.4614 across all the parameter combinations, confirming UMAP's reliability. This analysis supports the conclusion that UMAP provides consistent and reliable dimensionality reduction results across a broad spectrum of parameters, making it a versatile and dependable method for various datasets and applications. Table 9 shows the questionnaire scores after dimensionality reduction and min−max standardization, which were then used in the following regression analysis.

4.4.3. Tobit regression

Following the construction of operational efficiency metrics for 107 CRPs and the examination of work efficiency improvements through CR. We conduct a Tobit regression analysis to investigate the relationship between operational efficiency and our proposed APM-based management assessment factors.

The operational efficiency value (*eff*) is used as the dependent variable, and the 8 APM assessment indicators are used as the independent variables. To ensure the robustness of our model, we first calculate variance inflation factors (VIFs) for the independent variables. All the VIF values were less than 10 (mean VIF = 1.870), indicating no significant multicollinearity (Table 10).

A correlation matrix (Table 11) was constructed including the dependent variable (*eff*), the 8 APM indicators, and the work efficiency after using CR technology (*ROBOT_EFF*). This analysis revealed weak correlations between *ROBOT_EFF* and other variables in the real estate sector context.



(a) (b)

Fig. 9. Scree plot and scatter plots generated via the PCA method.

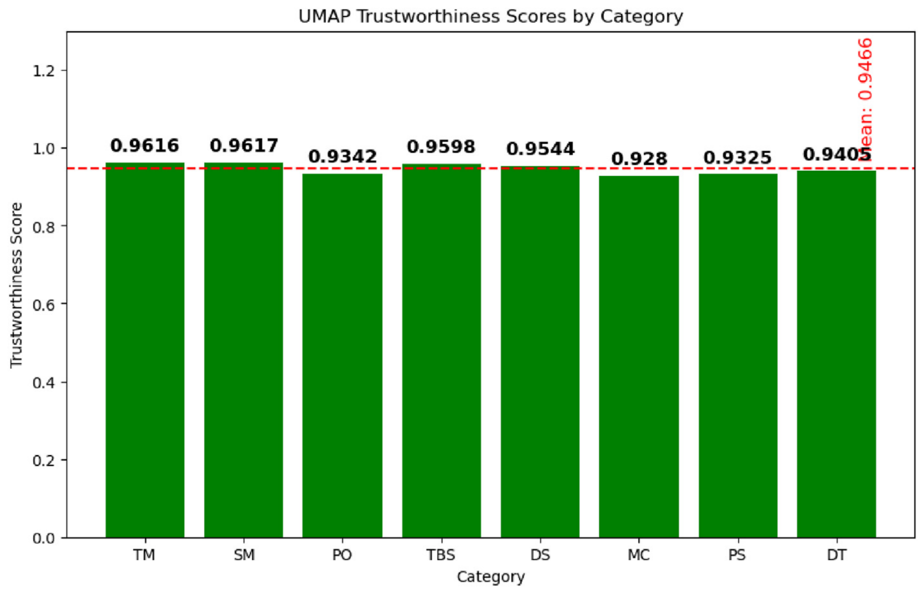


Fig. 10. UMAP trustworthiness scores for 8 aggregate dimensions.

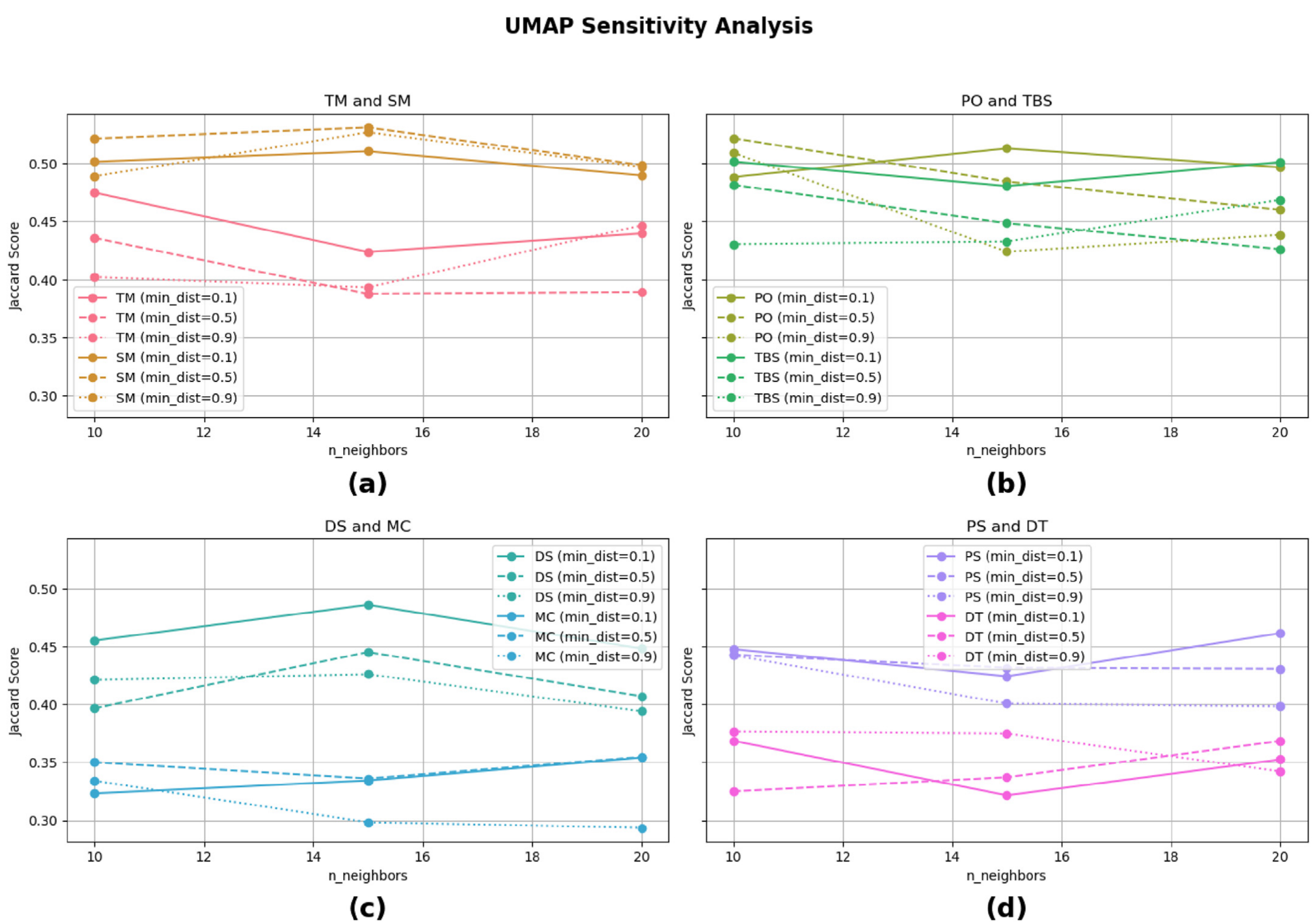


Fig. 11. UMAP sensitivity analysis for different variables.

Table 9
Descriptive statistics of questionnaire scores after dimensionality reduction and min−max standardization.

Variable	Obs.	Mean	Std.dev.	Min	Max
TM	107	0.5578	0.3053	0	0.8783
SM	107	0.5806	0.2789	0	0.9599
PO	107	0.4778	0.1448	0.1723	0.7602
TBS	107	0.4851	0.2354	0.0851	0.9944
DS	107	0.2250	0.2168	0	0.7099
MC	107	0.6387	0.3309	0.0424	1.0000
PS	107	0.9712	0.0596	0.7718	1.0000
DT	107	0.2792	0.3256	0	0.8302

Table 10
VIF values of the covariance test for 8 APM independent variables.

Variable	VIF	1/VIF
TBS	2.410	0.415
TM	2.370	0.421
DS	2.320	0.431
DT	2.140	0.467
PS	1.650	0.605
MC	1.590	0.628
PO	1.340	0.744
SM	1.150	0.866
Mean VIF	1.870	

Given that DEA-derived efficiency scores are bounded above zero, we employed a Tobit regression model (Equation (9):

$$EFF_i = \beta_0 + \beta_1 TM + \beta_2 SM + \beta_3 PO + \beta_4 TBS + \beta_5 DS + \beta_6 MC + \beta_7 PS + \beta_8 DT + \varepsilon_i \tag{9}$$

where β_0 is a constant, $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7$, and β_8 are the parameters to be estimated for the explanatory variable, and ε_i is the error term.

The Tobit regression analysis was performed via STATA 17 software, which yielded significant results for all the variables (Table 12). The key findings include the following.

1). Top management commitment (TM): This factor is negatively correlated with CRP operational efficiency (coefficient = −0.9432, $p < 0.01$), suggesting that increased authorization for project management teams may improve operational efficiency.

Table 12
Tobit regression analysis results.

EFF	Coefficient	std.err.	t	P>|t|	[95%conf.	interval]
TM	−0.9432***	0.0653	−14.44	0.000	−1.0728	−0.8136
SM	−0.0254	0.0498	−0.51	0.612	−0.1243	0.0735
PO	0.2266**	0.1036	2.19	0.031	0.0210	0.4322
TBS	0.1587*	0.0854	1.86	0.066	−0.0107	0.3281
DS	−0.0522	0.0909	−0.57	0.567	−0.2325	0.1282
MC	−0.1105**	0.0493	−2.24	0.027	−0.2084	−0.0126
PS	−0.8151***	0.2792	−2.92	0.004	−1.3691	−0.2610
DT	0.2026***	0.0582	3.48	0.001	0.0872	0.3180
_cons	1.5557***	0.2822	5.51	0.000	0.9957	2.1156
_se	−0.9432***	0.0653	−14.44	0.000	−1.0728	−0.8136

Note: * represents the 10% significance level, ** represents the 5% significance level, *** represents the 1% significance level.

2). Product owner involvement (PO): Positively correlated (coefficient = 0.2266, $p < 0.05$), indicating that aligning production with customer requirements can potentially increase sales and improve project outcomes.

3). Time, budget, and security constraints (TBS) are weakly positively correlated (coefficient = 0.1587, $p < 0.10$), suggesting that this factor does not have a strong direct effect on operational efficiency. This aligns with Pan and Pan (2020a) the findings of concerning the uncertainties associated with CRs.

4). Mission critical requirements implementation velocity (MC): Negatively correlated (coefficient = −0.1105, $p < 0.05$), supporting Russo (2021) the assertion that conventional plan-driven development may be insufficient in rapidly changing environments.

5). Project success (PS): Negatively correlated (coefficient = −0.8151, $p < 0.01$), indicating a need for improvement in traditional management techniques alongside technological advancements.

6). Developers' technical skills (DT): Positively correlated (coefficient = 0.2026, $p < 0.01$), suggesting that experienced project managers are more likely to achieve successful CRPs.

7). Scrum master leadership (SM) and developers' social skills (DS): These factors had less influence on CRP operational efficiency.

These findings highlight the complex interplay of factors affecting CRP operational efficiency and underscore the need for a nuanced approach to implementing APM and CR in the real estate sector. The results suggest that while technological advancements

Table 11
Correlation matrix between variables.

	eff	TM	SM	PO	TBS	DS	MC
eff	1						
TM	−0.921***	1					
SM	−0.012	−0.018	1				
PO	0.155	−0.125	−0.029	1			
TBS	0.411***	−0.373***	0.208**	0.314***	1		
DS	−0.005	0.019	0.141	0.413***	0.629***	1	
MC	0.115	−0.178*	0.154	0.132	−0.02	0.039	1
PS	−0.379***	0.358***	0.071	0.006	−0.074	0.029	−0.532***
DT	0.679***	−0.653***	0.019	−0.155	0.149	−0.281***	0.035
ROBOT_EFF	0.06	−0.042	0.017	−0.048	0.045	−0.016	0.026

	PS	*DT*	*ROBOT_EFF*
PS	1		
DT	−0.192**	1	
ROBOT EFF	−0.055	0.02	1

Note: * represents the 10% significance level, ** represents the 5% significance level, *** represents the 1% significance level.

such as CR offer potential benefits, their successful implementation requires careful consideration of management practices and organizational factors.

Notably, the weak correlation between *ROBOT_EFF* and other variables suggests that the impact of CR on operational efficiency may be indirect or moderated by other factors. This underscores the importance of considering both technological and managerial aspects when seeking to improve CRP efficiency. The negative correlation between *TM* and operational efficiency is particularly intriguing. This may indicate that in the context of CRPs, a more decentralized decision-making process, where professional managers have greater autonomy, could lead to improved efficiency. These findings challenge traditional hierarchical management structures and suggest that adaptability and quick decision-making at the operational level are crucial in the dynamic real estate development environment.

Furthermore, the positive correlation between *PO* and efficiency emphasizes the importance of customer-centric approaches in real estate development. By closely aligning project outcomes with market demands, CRPs can potentially achieve better operational efficiency and market success.

These insights provide valuable guidance for real estate developers and project managers looking to increase their operational efficiency through the integration of CR and APM principles. However, the complexity of the relationships observed also highlights the need for further research to fully understand the mechanisms through which these factors interact and influence CRP performance.

4.5. Analyzing efficiency improvement from a dialectical perspective

Despite the lack of a significant correlation between the work efficiency improvement of CR and its operational efficiency, the R&D of CR is currently limited to specific subprojects. The transformation of this comprehensive technology from a sector-specific advancement to a disruptive change is expected to be a lengthy process. Ma et al. (2022) highlighted the scarcity of construction robot varieties and variations in their proficiency and potential to replace human construction workers. Consequently, CR R&D is in its infancy and likely to remain so for a considerable period.

In this subsection, the typical CR constructible subprojects were categorized into three distinct construction stages, as shown in Table 13.

(1). The main structure stage;
(2). The interior trimming stage;
(3). The outdoor and basement decorative cover subproject stage.

Table 14
Correlation analysis of the CRP operational efficiency and the work efficiency improvement in the construction stage to which the CR applies.

	EFF	ROBOT_EFF	Stage 1	Stage 2	Stage 3
EFF	1				
ROBOT_EFF	0.0600	1			
stage1	0.0910	0.963***	1		
stage2	0.161*	0.211**	0.176*	1	
stage3	0.138	0.399***	0.241**	0.730***	1

Note: *t* statistics in parentheses, * represents the 10% significance level, ** represents the 5% significance level, and *** represents the 1% significance level.

Table 14 displays the correlation matrix between CR work efficiency and work efficiency improvement at each stage, with CRP operational efficiency serving as the explanatory variable. The results indicate that the implementation of Stage (2) has a favorable effect on the operating efficiency of the CRP through CR use. Our observations revealed that all CRPs employing CR had increased engagement with commercial residential customers. Project managers commonly use "customers face-to-face with the construction site," marketing to augment customer engagement. These project managers preferred Stage (2) for CR construction scenarios, primarily for ensuring customer safety. CR technology has been recognized for its environmental performance, efficiency, safety measures, and construction quality, making it a crucial subject in project manager—customer communications. From the contractor perspective, CR could enhance efficiency and reduce expenses. Contractors frequently preferred CR during Stages (1) and (3), recognizing its construction benefits. This observation is supported by the strong correlation between the CR and these three stages.

4.6. Robustness testing

To ensure the robustness of the results, we conducted a series of robustness tests via various approaches.

(1). *CR Usage Clustering*: We categorized the dataset into two groups on the basis of CR usage, incorporating a standard error for clustering.
(2). *Regional stratification*: The sample was stratified into three distinct categories on the basis of the CRP location, incorporating a standard error for clustering.
(3). *Construction Stage Efficiency*: We substituted the *ROBOT_EFF* variable with three work efficiency improvement variables

Table 13
Representation of 9 typical CRs and their corresponding application scenarios via CQQ codes.

Quota Code	Type	Stage 1	Stage 2	Stage 3
jzjqr001	Intelligent trailing robot feeder	A1-5B-2; A1-5B-3		
jzjqr002	Floor level-off construction robot	A1-5B-1; A1-5B-2; A1-5B-3; A1-5B-4; A1-5B-5	A1-12B-1; A1-12B-2; A1-12B-3; A1-12B-4; A1-12B-5	
jzjqr003	Ground screed construction robot		A1-12B-1; A1-12B-2; A1-12B-3; A1-12B-4; A1-12B-5	
jzjqr004	Interior Putty Cream spraying construction robot		A1-15B-1; A1-15B-2; A1-15B-3; A1-15B-4	
jzjqr005	Interior Putty sanding construction robot		A1-15B-1; A1-15B-2; A1-15B-3; A1-15B-4	
jzjqr006	Interior Paint Spraying construction robot		A1-15B-5; A1-15B-6	
jzjqr007	Exterior Paint Spraying construction robot			A1-15B-7; A1-15B-8
jzjqr008	Floor grinder construction robot			A1-15B-9
jzjqr009	Floor coating construction robot			A1-15B-9

corresponding to the construction stages outlined in Section 4.5.

(4). *Bootstrap Analysis*: We restricted the sample to the 30 projects that used CR and employed a bootstrap technique to compensate for variance.

(5). *Provincial interaction*: The 21 provinces in the sample were used as interaction variables to provide a more comprehensive understanding of the relationship between variables, capturing the interaction with the explanatory variable *EFF.*

(6). *Panel Data Perspective*: Although our sample and model are cross-sectional, we examined the 2023 data from a panel data perspective as a variant of approach (1).

Table 15 presents the comparison of regression results for these six cases, demonstrating the robustness of the variables TM (Top Management commitment), PO (Product Owner involvement), TBS (Time/Budget/Security constraints), PS (Project Success), and DT (Developers' Technical skills).

The key findings from the robustness tests include the following.

- The incorporation of CR in various construction phases yields positive enhancements in overall project efficiency.
- CR usage during the main structural phase shows a substantial increase in operational efficiency, with a correlation coefficient of 0.0438.

These results reinforce our main findings and provide additional insights into the relationship between CR usage and project efficiency across different contexts and analytical approaches.

5. Conclusions

5.1. Main insights

This study analyzed 107 CRP samples from 21 provinces in mainland China, including 30 projects using 9 types of CR technology. We propose a novel methodology that combines superefficiency SBM-DEA, the APM framework and a Tobit regression model to assess CRP operational efficiency, work efficiency and project management teams' capabilities. This approach provides a comprehensive assessment, attribution and explanation of regional and technical operational efficiency differences in CR use within CRPs. The key findings to respond to the RQ and subquestions include the following:

First, since most of the samples are in the lower-left quadrant of the operational efficiency evaluation matrix, the overall operational efficiency of CRPs in China is low. The operating efficiency of the CPR is relatively low in the central and western regions of China but relatively high in the eastern region. This implies that there is greater potential for enhancement in the realm of real estate projects within these provinces. On the basis of SBM-DEA theory, we posit that CRP projects exhibit a propensity for improvement in various aspects, including the IP, NSU, and BIN. For example, for Guizhou and Zhejiang, enhancing business negotiating efforts prior to finalizing the general contract, as well as minimizing fund expenditures, is recommended.

Second, the development of the CR has been undertaken on a significant scale under the direction of the government. Our analysis indicates that, on average, the implementation of 9 typical CRs resulted in a collective enhancement value of 1.0259 in terms of work efficiency. We determined that 3 of the 9 typical CRs are

Table 15
Six-dimensional comparisons are used to test the robustness characteristics of the results.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	EFF	EFF	EFF	EFF	EFF	EFF
TM	−0.9432***	−0.9432***	−0.9317***	−0.9019***	−0.9412***	−0.8979***
	(-23.0947)	(-14.9280)	(-17.1224)	(-5.0228)	(-13.6887)	(-11.2937)
SM	−0.0254	−0.0254				
	(-0.8792)	(-0.6279)				
PO	0.2266***	0.2266**	0.2166***	0.3369*	0.2709***	0.3509***
	(5.6266)	(2.5728)	(2.7611)	(1.7034)	(3.6679)	(3.2311)
TBS	0.1587***	0.1587***	0.1152***	0.1651	0.1197***	0.1780**
	(7.5578)	(4.2984)	(2.7651)	(1.0190)	(3.3442)	(2.3706)
DS	−0.0522	−0.0522				
	(-1.5553)	(-0.6393)				
MC	−0.1105***	−0.1105	−0.1144*	−0.0642	−0.1169	−0.0613
	(-25.8454)	(-1.4634)	(-1.7511)	(-0.8444)	(-1.5681)	(-1.0534)
PS	−0.8151***	−0.8151*	−0.8043	−0.8349*	−0.7525	−0.8645***
	(-13.9330)	(-1.6819)	(-1.4229)	(-1.9503)	(-1.4003)	(-3.2657)
DT	0.2026***	0.2026***	0.2211***	0.2823*	0.2264***	0.2877***
	(14.5074)	(4.6668)	(4.4787)	(1.7155)	(4.9610)	(3.9796)
ROBOT_EFF			−1.1429			0.5461
			(-0.8859)			(0.5074)
Stage1			0.3292	0.1911	0.0438***	0.0786
			(1.0959)	(0.9857)	(3.0001)	(0.3249)
Stage2			3.7609	23.5557	3.2815	28.8222*
			(0.5231)	(0.4265)	(0.6225)	(1.8935)
Stage3			0.2878	−0.3401	0.0701	−0.5518
			(0.6183)	(-0.1331)	(1.1002)	(-1.1112)
c.province_numeric#c.province_numeric					−0.0003***	
					(-5.1031)	
_cons	1.5557***	1.5557***	−1.7060	−22.0608	−1.8946	−27.5493*
	(32.8101)	(3.0279)	(-0.2368)	(-0.4188)	(-0.3321)	(-1.7814)
/						
var(e.eff)	0.0177***	0.0177***	0.0175***	0.0047***	0.0167***	
	(2.7924)	(16.9892)	(18.5401)	(4.1247)	(13.3674)	
N	107	107	107	30	107	30

Note: t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

situated within the critical path of the duration model. These three CRs have gained significant popularity among contractors because of their ability to reduce contractor costs and project durations immediately. Consequently, they become increasingly favored within the contractor community.

Third, we examined the influence of 8 dimensions of CRP management elements on operational efficiency. The measurement scale was developed on the basis of Russo (2021) research. The dimensionality reduction process yielded a favorable outcome of 8 consolidated dimensions above a trustworthy threshold of 0.9. TM, PO, TBS, PS, and DT had statistically significant impacts on operational efficiency and could withstand rigorous robustness checks. Without including the variable TM, the outcomes of this validation exhibited a substantial degree of consistency in terms of correlation with the measurements formulated by Russo (2021). This implies that while the APM framework initially emerged inside the software sector, it can also be applied to real estate project management.

Fourth, the use of Tobit regressions and robustness tests revealed that the overall improvement in work efficiency through CR is not significantly associated with operational efficiency. Our research further indicates that CRP project managers demonstrated a willingness to share their project status reports with customers and specifically highlight its progress. This practice is aimed at enhancing the range of discussion subjects available to engage with their customers. Our empirical findings indicate a robust positive association between product owner involvement and operational efficiency.

In summary, for future advancements in the CRP, mutually beneficial outcomes for both real estate developers and contractors may be attained. This can be achieved through two primary measures. First, reforming the existing real estate business model can be reformed, considering a transition from the presale system to a cash-and-delivery system in China. Second, the department may encourage the exploration of additional combinations of CR applicability to accommodate more diverse building formats.

5.2. Research implications

5.2.1. Theory implications

This study has several important theoretical implications for the fields of construction management and technology adoption:

(1). *Extension of APM Theory*: Our findings demonstrate the applicability of Agile Project Management principles beyond software development to real estate project management. This extends APM theory into nonsoftware domains (e.g., Klotschke et al. (2022)), suggesting its potential universality in project management across construction environments.

(2). *Refinement of Technology Adoption Models*: Our findings on the differential impacts of CR across construction stages contribute to a more nuanced understanding of technology adoption in construction. This builds on existing models (e.g., Law et al. (2022)) by highlighting the importance of considering project phase-specific factors in technology adoption decisions.

(3). *Collaborative stakeholder theory in construction innovation:* Our study contributes to stakeholder theory in construction management (e.g., Pan and Pan (2020a)) by demonstrating the potential for win–win scenarios in CR adoption. By analyzing both project manager and contractor perspectives, we reveal how seemingly divergent priorities (e.g., customer engagement for managers and efficiency gains for contractors) can be aligned through strategic CR implementation. This finding advances stakeholder theory by emphasizing the importance of identifying and leveraging complementary interests in technological innovation rather than viewing stakeholder benefits as a zero-sum game. This suggests that more inclusive, collaboration-focused efficiency models could enhance overall project success while meeting the specific needs of various stakeholders in the construction process.

(4). *Integration of Efficiency Measures*: By combining work efficiency and operational efficiency analyses, our study provides a more comprehensive framework for evaluating the impact of technological innovations in construction. This addresses a gap in the literature noted by Zhou et al. (2019) regarding the need for multidimensional efficiency assessments in construction projects.

5.2.2. Practical implications

Our empirical study on CRP work efficiency and operational efficiency yields several practical implications for the construction industry:

(1). *Policy and Investment Directions*: The demonstrated positive impact of CR on work efficiency provides empirical support for continued government and industry investment in CR development and adoption. Policymakers can use these findings to justify and target support for CR initiatives.

(2). *Efficiency-driven* business model innovation: On the basis of our efficiency calculations, we propose exploring new business models that align with efficiency improvements. This could include transitioning from presale systems to cash-and-delivery systems in the Chinese real estate market, which may better reflect and incentivize the efficiency gains achieved through CR implementation.

(3). *Customer-Centric Approaches*: The positive impact of product owner involvement underscores the importance of integrating customer feedback throughout the development process, suggesting a need for more collaborative project management approaches.

(4). *Management Structure Reconsideration:* The negative correlation between top management commitment and efficiency suggests that real estate firms should explore more decentralized decision-making structures to improve project outcomes.

5.3. Limitations

While our study provides insights, it has several limitations that point to directions for future research:

(1). *Longitudinal studies*: Our cross-sectional approach limits our ability to observe long-term trends in the impact of CR on CRP efficiency. Future studies could adopt a longitudinal design to track efficiency changes over time as CR technologies are implemented and refined.

(2). *Broader Geographic Scope*: While our study covers 21 Chinese provinces, future research could expand to other countries or regions to test the generalizability of our findings in different economic and regulatory contexts.

(3). *Mediating and Moderating Effects*: Further exploration of potential mediating or moderating effects among variables such as ROBOT_EFF and PO and between CR construction Stage 1 work efficiency and TBS could provide a more nuanced understanding of the factors influencing operational efficiency.

(4). *Structural Equation Modeling*: The extensive scope of our APM-based scales warrants further investigation via structural equation modeling to more robustly examine the relationships between management factors and operational efficiency.
(5). *Alternative Efficiency Measurement Techniques*: Future studies could employ alternative efficiency measurement techniques, such as stochastic frontier analysis, to complement and validate the findings from our DEA-based approach

In conclusion, this study provides a comprehensive assessment of the factors influencing CRP operational efficiency in the context of CR adoption and APM principles. By addressing the complex interplay between technological innovation and management practices, our findings contribute to both theory and practice in the fields of construction management and real estate development. As the industry continues to evolve, further research in this area will be crucial for optimizing project outcomes and driving sustainable growth in the sector.

Data availability

The data will be made available on request. The code of this study can be found in the GitHub repository (Link: https://github.com/lymgz/CR_eff_CRPs).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apmrv.2024.12.005.

Appendix

Appendix Table A
Nine frequently used CRs involved in this paper (*First Batch of Intelligent Construction (Construction Robotics) Quota sub-item (Trial)*, 2023).

Code	Type	Appearance
jzjqr001	Intelligent trailing robot feeder	
jzjqr002	Floor level-off construction robot	
jzjqr003	Ground Screed construction robot	
jzjqr004	Interior Putty Cream spraying construction robot	

(*continued on next page*)

Appendix Table A (*continued*)

Code	Type	Appearance
jzjqr005	Interior Putty sanding construction robot	
jzjqr006	Interior Paint Spraying construction robot	
jzjqr007	Exterior Paint Spraying construction robot	
jzjqr008	Floor grinder construction robot	
jzjqr009	Floor coating construction robot	

Appendix Table B
APM-based seven-point Likert scale for assessing a project management team's management capabilities.

Aggregate Dimensions	Code	Themes	Questions	Reference (Adapted from)
Top management commitment	TM_1	Goal-oriented	The top management of my organization demonstrates commitment and action with respect to our agile project management, including but not limited to product supply, delivery, subproject start, schedule, meeting management.	Kulkarni et al. (2006)
	TM_2	Efficiency & effectiveness	The top management of my organization periodically reviews the effectiveness of Agile project development to the whole company, including but not limited to: Monthly review of customer visit numbers, Monthly assessment of market changes, Monthly adjustments to sales strategy and pricing.	Kulkarni et al. (2006)
Scrum master leadership	SM_1	Organization knowledge	The Scrum Master (i.e., PM in this survey) directly always interacts knowledge with my team during the CRP development.	Anning Dorson Thomas (2018)
	SM_2	Problem solving skills	The Scrum Master (i.e., PM in this survey) anticipated workflow problems and avoided a crisis, including but not limited to: PM identification of CRP risks, PM supervises of contractors and control engineers.	Kayworth and Leidner (2002)
	SM_3	Facilitation skills	The Scrum Master (i.e., PM in this survey) require us systematically manages visa changes, including establishing a ledger, regular review, regular reporting to the investor, and implementation within the scope of the investor's authorization.	Kayworth and Leidner (2002)
Product Owner involvement	PO_1	Continuous interaction	The Product Owner satisfaction level with the project outcomes.	Serrador and Turner (2015)
	PO_2	Empowerment	The Product owner established a clear monthly sales plan and formulated a sales output plan.	Aaron J Shenhar and Dov Dvir (2007)
	PO_3	Empowerment	The Product owner established a clear monthly fascial planning, including but not limited to fiscal timelines in the schedule, bank loan and financing issues for the CRP.	Kermanshachi et al. (2021)
	PO_4	Continuous interaction	We had control over what they were supposed to delivery product, including but not limited to: We always gather the Product Owner's insights through virtual or face-to-face meetings.	Lee and Xia (2010)
	PO_5	Kanban	My team always makes good use of Business Intelligence (BI) systems and fully utilized in Management behaviors and processes.	Wael Zayat and Ozlem Senvar (2020)
	PO_6	Kanban	Our Business Intelligence (BI) system is fully utilized in CRP, including but not limited to data accuracy and timeliness.	Wael Zayat and Ozlem Senvar (2020)
Time/Budget/Security constraints	TBS_1	Spending Review	The CRP in meeting project monthly return cash flow goals.	Serrador and Turner (2015)
	TBS_2	Spending Review	The CRP achieved its sales performance monthly.	Fleming Quentin W (2022)
	TBS_3	Spending Review	The CRP in meeting project monthly refund on engineering deposit goals, including but not limited to payment on behalf water and power bills, quality, and safety deposit for the department.	Fleming Quentin W (2022)
	TBS_4	Compliance with standards	The CRP in meeting project time goals.	Serrador and Turner (2015)
	TBS_5	Compliance with standards	The PM fulfills of duties within the scope of the authorization.	Serrador and Turner (2015)
	TBS_6	Spending Review	Based on the project's monthly measurement of construction expenditures, the PM requires the QS to determine whether the current month's construction expenditures exceeded expectations.	Anning Dorson Thomas (2018)
Developers' social skills	DS_1	Collective ownership	My team coordinates activities or tasks to make things run smoothly.	Tesluk and Mathieu (1999)
	DS_2	Positive societal impact	I consider that our CRP has the potential to yield a positive societal impact.	Dotsenko et al. (2023)
	DS_3	Trust	I rely on my coworkers to complete tasks that I am unable to do alone.	Kiziloglu et al. (2023)
Mission critical requirements implementation Velocity	MC_1	Change of operations	In light of new business requirements that arose during project execution, the Scrum-developed CRP meets key project objectives and business needs, including but not limited to: Based on all housing products and their inventories in the sold buildings of the objective projects, the PM quantitatively assessed structural inventories or stock-outs by calculating the inventory-sales ratio (6-month opening inventory divided by sales for the same period).	Giovannetti et al. (2022)
	MC_2	System's flexibility	Considering the contractors claim that arose during project execution, the Scrum-developed CRP prevent and counterclaims of.	Giovannetti et al. (2022)
	MC_3	Operators' deployment timing	The PM require us according to the payment detail statement of the target project in the past 1 month, select the 3 most recent payments made by the project, and compare them with the description of the image progress in the payment information and the actual progress on the on-site.	Brunet Alain and César Franck (2021)
Project Success	PS_1	Business success	In light of new business requirements that arose during project execution, the Scrum-developed CRP overall is very successful, including but not limited to: Based on all housing products and their inventories in the sold buildings of the target project, the PM assessed the historical launch stock by calculating the new launch sell-through rate, which was used to assess the capability to manage the accumulation of new launch stock.	Giovannetti et al. (2022)
	PS_2	Delivery success	Considering new business requirements that arose during project execution, the project delivers all desirable features and functionality.	Giovannetti et al. (2022)
Developers' technical skills	DT_1	Technical expertise	My team members consider that our CRP has the potential to yield a positive quality and safety results.	Søvik and Forfang (2010)

(continued on next page)

Appendix Table B (*continued*)

Aggregate Dimensions	Code	Themes	Questions	Reference (Adapted from)
	DT_2	Technical expertise	My team members can always get the CRP subprojects started at the most reasonable time.	Søvik and Forfang (2010)
	DT_3	Programming skills	My team members are always able to make up for time lost due to unforeseen circumstances without compromising deliverables.	S. Gomez-Jaramillo, Moreno-Cadavid, & Zapata-Jaramillo, (2019); Søvik and Forfang (2010)

Appendix Table C
Average operational efficiency values and ranks of 107 research objectives.

Region	*Mean_eff*	Province	DMU	Year	*eff*	Rank
Central area	0.365	Henan	YX029	2023	0.165	67
		Henan	YX017	2023	0.594	23
		Henan	HN028	2023	0.176	64
		Anhui	AH038	2023	0.138	77
		Heilongjiang	DB005	2023	0.121	82
		Jilin	DB007	2023	1.253	5
		Henan	YX016	2023	1.026	17
		Henan	YX012	2023	0.112	84
		Shanxi	XX012	2023	1.064	14
		Henan	HN020	2023	0.195	59
		Henan	YX013	2023	0.135	78
		Anhui	AH010	2023	0.116	83
		Anhui	AH053	2023	1.666	1
		Anhui	AH037	2023	0.160	69
		Henan	HN017	2023	0.143	74
		Henan	YX020	2023	0.426	29
		Anhui	AH025	2023	0.000	104
		Henan	YX027	2023	0.302	38
		Henan	HN001	2023	0.000	107
		Henan	YX009	2023	0.063	98
		Shanxi	XX007	2023	0.226	53
		Henan	YX031	2023	0.058	99
		Henan	YX006	2023	0.218	54
		Shanxi	XX019	2023	0.726	20
		Henan	HN012	2023	0.043	101
Eastern area	0.396	Shanghai City	HS014	2023	1.266	4
		Hebei	BJ001	2023	0.362	33
		Liaoning	DB013	2023	0.261	47
		Jiangsu	HS037	2023	0.000	105
		Jiangsu	SB007	2023	0.160	70
		Shanghai City	HS019	2023	1.292	2
		Hebei	HB031	2023	0.108	87
		Shandong	SD021	2023	0.108	86
		Jiangsu	SB029	2023	1.150	7
		Jiangsu	HS046	2023	0.540	25
		Hebei	BJ003	2023	0.310	37
		Shandong	LD003	2023	0.055	100
		Shandong	LD004	2023	0.266	46
		Guangdong	GQ009	2023	0.205	57
		Jiangsu	JS013	2023	0.020	103
		Jiangsu	JS014	2023	0.142	75
		Shandong	LD012	2023	0.196	58
		Hebei	HB052	2023	0.000	106
		Zhejiang	ZJ013	2023	0.190	60
		Guangdong	GQ003	2023	0.269	44
		Shandong	LD006	2023	0.207	56
		Zhejiang	ZJ006	2023	0.267	45
		Jiangsu	HS021	2023	1.070	13
		Shandong	LD002	2023	1.073	12
		Beijing City	BJ008	2023	0.468	27
		Shandong	SD060	2023	0.494	26
		Zhejiang	ZJ003	2023	0.165	66
		Jiangsu	HS030	2023	0.275	42
		Jiangsu	HS029	2023	0.030	102
		Jiangsu	HS027	2023	0.347	35
		Jiangsu	HS025	2023	0.180	63
		Jiangsu	SB023	2023	0.277	41
		Shandong	SD064	2023	0.069	94
		Hebei	HB030	2023	1.109	9
		Shanghai City	HS015	2023	0.933	19
		Liaoning	DB021	2023	0.165	68
		Jiangsu	SB031	2023	0.425	30

Appendix Table C (*continued*)

Region	*Mean_eff*	Province	DMU	Year	*eff*	Rank
		Hebei	HB051	2023	0.079	93
		Jiangsu	JS001	2023	0.134	79
		Hebei	HB024	2023	0.633	22
		Jiangsu	HS004	2023	0.289	40
		Jiangsu	SB026	2023	1.093	11
		Liaoning	DB003	2023	0.357	34
Western area	0.379	Shaanxi	SX015	2023	0.127	81
		Shaanxi	SX010	2023	0.153	73
		Shaanxi	SX023	2023	1.141	8
		Shaanxi	SX003	2023	0.066	96
		Guizhou	GZ021	2023	1.190	6
		Gansu	XB008	2023	1.024	18
		Gansu	XB029	2023	0.166	65
		Shaanxi	SX012	2023	0.209	55
		Xinjiang Uygur	XB021	2023	0.067	95
		Chongqing City	CQ001	2023	0.133	80
		Shaanxi	SX004	2023	0.459	28
		Shaanxi	SX019	2023	0.274	43
		Shaanxi	SX009	2023	0.156	71
		Shaanxi	SX001	2023	1.050	15
		Shaanxi	SX002	2023	0.065	97
		Shaanxi	SX016	2023	0.228	52
		Yunnan	YN001	2023	0.187	61
		Shaanxi	SX021	2023	0.155	72
		Shaanxi	SX014	2023	0.094	90
		Shaanxi	SX013	2023	0.321	36
		Yunnan	YN006	2023	0.246	49
		Chongqing City	CQ002	2023	0.180	62
		Guizhou	GZ018	2023	1.035	16
		Guizhou	GZ015	2023	1.289	3
		Xinjiang Uygur	XB019	2023	0.254	48
		Chongqing City	CQ014	2023	0.111	85
		Qinghai	XB026	2023	0.637	21
		Shaanxi	SX006	2023	0.106	88
		Shaanxi	SX024	2023	0.585	24
		Nei Mongol	BJ013	2023	0.101	89
		Guizhou	GZ017	2023	0.139	76
		Shaanxi	SX008	2023	1.100	10
		Nei Mongol	BJ018	2023	0.413	31
		Guizhou	GZ011	2023	0.090	91
		Shaanxi	SX007	2023	0.231	50
		Shaanxi	SX017	2023	0.231	51
		Shaanxi	SX018	2023	0.082	92
		Yunnan	YN004	2023	0.296	39
		Shaanxi	SX005	2023	0.388	32

Note: *eff* represents the operational efficiency of the CRP.

Appendix Table D
The slack values of 107 research objectives.

Province	DMU	Rank	*NE_Slack*	*LA_Slack*	*IP_Slack*	*DDU_Slack*	*ACWP_Slack*	*NSU_Slack*	*BIN_Slack*
Henan	YX029	67	9.692	0.980	0.000	66.729	0.150	1.115	432.365
Henan	YX017	23	0.000	3.061	0.000	1.707	47.788	0.000	214.898
Henan	HN028	64	10.019	2.486	0.000	29.407	55.295	0.000	1635.260
Anhui	AH038	77	18.880	30.724	0.000	40.824	78.909	0.000	2971.706
Heilongjiang	DB005	82	15.290	10.974	0.000	16.199	0.000	20.979	1991.974
Jilin	DB007	5	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Henan	YX016	17	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Henan	YX012	84	18.390	2.823	3.039	0.000	0.000	0.000	5289.823
Shanxi	XX012	14	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Henan	HN020	59	9.716	3.217	0.000	23.848	37.500	0.000	2272.621
Henan	YX013	78	19.898	0.000	0.000	14.616	0.000	0.000	2217.983
Anhui	AH010	83	15.068	12.606	0.000	25.778	2.821	0.000	3135.851
Anhui	AH053	1	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Anhui	AH037	69	5.893	2.084	0.000	23.817	0.000	36.457	2398.326
Henan	HN017	74	8.164	3.817	0.000	20.412	0.000	0.000	840.578
Henan	YX020	29	0.000	0.000	0.000	16.577	43.944	0.000	424.425
Anhui	AH025	104	5.903	7.775	0.000	65.719	0.000	218.847	67.043
Henan	YX027	38	0.000	3.415	0.000	2.827	38.132	0.000	981.158
Henan	HN001	107	5.103	2.047	0.000	33.757	1.933	117.618	1175.629
Henan	YX009	98	8.709	1.324	0.000	29.237	2.224	0.000	1233.430
Shanxi	XX007	53	11.429	1.465	0.000	15.629	8.743	0.000	1332.308
Henan	YX031	99	13.411	1.957	0.000	31.617	0.000	0.000	1338.377
Henan	YX006	54	28.086	0.260	0.000	64.208	18.629	0.000	2485.877
Shanxi	XX019	20	1.734	1.215	0.000	3.585	29.417	0.000	0.000
Henan	HN012	101	50.387	3.121	0.000	7.967	48.005	284.096	2983.924
Shanghai City	HS014	4	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hebei	BJ001	33	3.519	5.384	0.000	27.093	19.141	0.000	386.401
Liaoning	DB013	47	8.473	13.623	0.000	0.000	0.000	0.000	1912.473
Jiangsu	HS037	105	0.000	7.736	0.000	42.375	0.000	402.795	57.624
Jiangsu	SB007	70	18.439	1.473	0.000	17.713	11.473	0.000	165.965
Shanghai City	HS019	2	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hebei	HB031	87	0.000	33.462	62.372	28.000	60.931	14.800	3005.199
Shandong	SD021	86	19.289	17.611	0.000	1.223	0.000	179.266	5612.135
Jiangsu	SB029	7	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Jiangsu	HS046	25	8.243	0.561	0.000	0.000	0.000	0.000	1424.049
Hebei	BJ003	37	13.184	11.711	0.000	0.000	0.000	0.000	1488.230
Shandong	LD003	100	0.000	0.000	51.665	21.826	0.000	126.037	1918.083
Shandong	LD004	46	0.000	3.168	0.000	40.712	19.867	0.000	710.250
Guangdong	GQ009	57	1.231	12.493	0.000	126.212	11.461	0.000	2033.071
Jiangsu	JS013	103	0.000	0.222	27.855	13.513	0.000	350.606	1468.352
Jiangsu	JS014	75	12.874	0.822	0.000	20.532	36.776	0.000	1091.634
Shandong	LD012	58	4.193	0.000	0.000	9.073	0.000	84.610	2933.262
Hebei	HB052	106	0.000	16.015	0.000	15.334	0.000	644.247	221.592
Zhejiang	ZJ013	60	39.000	8.500	612.417	0.000	10.825	211.800	2176.301
Guangdong	GQ003	44	0.000	7.414	0.000	41.972	159.526	0.000	352.945
Shandong	LD006	56	2.935	2.703	0.000	17.509	0.000	0.000	1021.951
Zhejiang	ZJ006	45	16.960	4.328	0.000	6.679	36.809	0.000	1925.047
Jiangsu	HS021	13	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Shandong	LD002	12	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Beijing City	BJ008	27	11.754	9.232	130.282	0.000	67.356	0.000	1325.944
Shandong	SD060	26	6.403	0.000	0.000	11.990	67.656	0.000	0.000
Zhejiang	ZJ003	66	11.486	0.000	0.000	11.846	81.275	0.000	1853.518
Jiangsu	HS030	42	3.583	0.000	0.000	0.000	0.000	0.000	1950.541
Jiangsu	HS029	102	0.000	0.000	10.800	15.978	0.000	202.905	859.600
Jiangsu	HS027	35	25.589	0.552	0.000	12.020	7.907	0.000	1913.126
Jiangsu	HS025	63	15.760	2.790	0.000	16.242	0.000	9.644	1766.706
Jiangsu	SB023	41	0.000	0.489	0.000	0.292	27.228	0.000	1110.019
Shandong	SD064	94	9.301	4.836	0.000	64.754	17.443	12.959	633.169
Hebei	HB030	9	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Shanghai City	HS015	19	1.219	0.000	0.000	0.000	0.000	35.893	0.000
Liaoning	DB021	68	20.990	20.440	0.000	1.946	0.000	284.632	4855.243
Jiangsu	SB031	30	8.253	5.904	0.000	8.148	37.876	0.000	419.073
Hebei	HB051	93	30.270	31.056	0.000	31.675	40.230	67.831	2909.781
Jiangsu	JS001	79	72.786	209.622	0.000	38.423	129.446	0.000	16003.728
Hebei	HB024	22	0.000	3.331	0.000	8.862	0.000	0.000	160.038
Jiangsu	HS004	40	27.461	3.733	0.000	14.738	0.000	0.000	1964.622
Jiangsu	SB026	11	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Liaoning	DB003	34	5.082	15.335	0.000	0.000	0.000	0.000	1450.266
Shaanxi	SX015	81	9.527	3.125	0.000	44.156	0.000	0.000	1698.348
Shaanxi	SX010	73	4.620	1.442	0.000	6.342	102.683	0.000	3110.032
Shaanxi	SX023	8	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Shaanxi	SX003	96	5.129	1.769	0.000	42.464	136.934	0.000	2518.187
Guizhou	GZ021	6	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Gansu	XB008	18	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Appendix Table D (*continued*)

Province	DMU	Rank	*NE_Slack*	*LA_Slack*	*IP_Slack*	*DDU_Slack*	*ACWP_Slack*	*NSU_Slack*	*BIN_Slack*
Gansu	XB029	65	15.196	3.069	0.000	15.512	2.695	0.000	723.796
Shaanxi	SX012	55	12.183	2.123	0.000	9.334	0.000	0.000	2457.446
Xinjiang Uygur	XB021	95	9.754	18.679	0.000	5.884	79.056	255.599	4388.774
Chongqing City	CQ001	80	23.802	16.651	2.800	53.506	0.000	197.828	2813.558
Shaanxi	SX004	28	0.000	10.071	0.000	26.008	0.000	0.000	1045.001
Shaanxi	SX019	43	49.568	14.429	0.000	13.958	172.733	0.000	5524.615
Shaanxi	SX009	71	15.962	11.472	0.000	41.660	9.390	0.000	376.181
Shaanxi	SX001	15	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Shaanxi	SX002	97	13.821	4.595	0.000	40.946	192.099	0.000	3171.951
Shaanxi	SX016	52	16.996	3.438	0.000	3.724	39.173	0.000	2563.581
Yunnan	YN001	61	8.382	4.621	0.000	3.956	0.000	70.874	1239.080
Shaanxi	SX021	72	46.800	5.590	335.893	0.000	141.705	306.920	4595.808
Shaanxi	SX014	90	10.007	4.861	0.000	64.847	0.000	0.000	856.070
Shaanxi	SX013	36	8.404	6.095	0.000	2.506	10.303	0.000	1065.378
Yunnan	YN006	49	13.736	2.089	0.000	5.421	0.578	0.000	1728.709
Chongqing City	CQ002	62	5.668	0.000	0.000	13.154	27.839	0.000	2061.474
Guizhou	GZ018	16	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Guizhou	GZ015	3	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Xinjiang Uygur	XB019	48	8.625	5.941	0.000	15.311	37.903	0.000	1568.444
Chongqing City	CQ014	85	9.257	0.870	0.000	24.215	4.827	0.000	272.069
Qinghai	XB026	21	15.312	2.402	0.000	15.755	0.000	0.000	0.000
Shaanxi	SX006	88	6.774	3.987	0.000	31.097	0.000	0.000	3475.349
Shaanxi	SX024	24	28.436	7.711	23.710	0.000	0.000	0.000	1827.538
Nei Mongol	BJ013	89	13.262	21.562	0.000	38.399	0.000	0.000	906.792
Guizhou	GZ017	76	5.855	2.774	0.000	0.000	0.000	0.000	3869.754
Shaanxi	SX008	10	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Nei Mongol	BJ018	31	3.660	21.656	0.000	8.016	11.225	0.000	421.494
Guizhou	GZ011	91	34.570	14.652	1541.173	0.000	0.000	0.000	2622.266
Shaanxi	SX007	50	2.297	4.782	0.000	49.874	0.000	0.000	1131.904
Shaanxi	SX017	51	9.589	8.751	0.000	6.758	12.036	0.000	1346.034
Shaanxi	SX018	92	10.422	6.209	0.000	14.113	11.769	0.000	826.180
Yunnan	YN004	39	3.635	3.152	0.000	17.237	18.244	0.000	695.748
Shaanxi	SX005	32	6.423	3.748	0.000	18.529	0.000	0.000	780.724

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Dr. Nuzul's research focuses on various areas within the field of civil engineering, including project management, construction management, construction technology, construction contract management, construction cost estimation, industrialized building system, and quality function deployment. With a strong publication record, Dr. Nuzul Azam Haron has authored over 40 articles that have been published in reputable academic journals. Some of the notable journals he has contributed to include the IOP Conference Series: Earth and Environmental Science, Journal of Science and Technology, and the American Journal of Applied Sciences. His research contributions have helped advance knowledge and understanding in the field of civil engineering, particularly in the areas of project management, construction management, and related disciplines.

Dr. Nabilah's research interests primarily revolve around seismic hazard analysis, finite element analysis, and structural analysis and testing. Bakar N.A. has made significant contributions to the academic community, with a portfolio of over 30 articles published in esteemed academic journals. His work has been featured in prominent publications such as the Journal of Building Engineering, the European Journal of Environmental and Civil Engineering, and other notable journals. Through his research, Dr. Bakar N.A. has advanced knowledge in the fields of seismic hazard analysis, finite element analysis, and structural analysis and testing. His contributions have enriched the understanding of these subjects and contributed to the broader field of civil engineering.

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