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A dynamic hybrid model (system dynamics -network data envelopment analysis) for predictive evaluation of sustainable procurement performance in construction industry

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Abstract Sustainable Procurement Management (SPM) plays an important role in improving the environmental and economic performance of construction projects; however, conventional efficiency assessment approaches, particularly Data Envelopment Analysis (DEA), are primarily retrospective and provide limited support for evaluating the future effects of alternative management policies. This study therefore develops an integrated System Dynamics (SD)–Network Data Envelopment Analysis (NDEA) framework to simulate the future performance of SPM and evaluate the efficiency of alternative policy scenarios in the construction industry of an emerging economy. First, a causal-loop SD model was developed to capture the dynamic relationships among key SPM factors and to forecast relevant inputs and outputs under alternative management scenarios. The simulation results were subsequently incorporated into a two-stage series NDEA model to evaluate efficiency across the construction and operation phases and to identify inefficiencies transmitted between consecutive stages. The proposed framework was empirically applied to data from ten major construction projects in Tehran, Iran. The results showed that the mean efficiency was 0.78 in the construction phase and 0.65 in the operation phase, indicating a 16.7% efficiency gap between the two stages. Scenario analysis further demonstrated that proactive investment in sustainable supplier development could substantially improve long-term performance, with the projected efficiency increasing to 0.88 over a five-year horizon, corresponding to an improvement of approximately 23% relative to the baseline scenario. These findings demonstrate that integrating SD simulation with multi-stage NDEA can complement conventional retrospective efficiency assessment by linking dynamic policy simulation with network-based efficiency evaluation. The proposed framework provides construction managers and policymakers with a forward-looking decision-support tool for comparing policy alternatives, improving resource allocation, and supporting more sustainable procurement practices in construction projects.

Keywords: System Dynamics (SD), Data Envelopment Analysis (DEA), Sustainable Procurement Management, Construction Project.

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1 Introduction

The 21st century's rapid population growth has caused a global environmental crisis [1]. The construction industry is a primary contributor, consuming 40% of natural resources and generating up to 65% of all waste [2-4]. Furthermore, the sector accounts for nearly 50% of global greenhouse gas emissions. With the urban population projected to reach 6.5 billion by 2050, the demand for construction is unprecedented [5,6]. While the UN Sustainable City and Society Program emphasizes global housing needs, growth must be managed sustainably to mitigate environmental damage, prompting a re-evaluation of traditional methods [1]. This shift toward sustainable construction is essential for reducing energy consumption and recycling materials [7,8].

Sustainable procurement management has emerged as a cornerstone of organizational strategy to balance economic efficiency, environmental protection, and social responsibility [9, 10]. However, evaluating its performance in the complex construction sector remains challenging. While conceptual aspects are well-explored, a gap exists in predicting long-term performance. Traditional methods like conventional Data Envelopment Analysis (DEA) evaluate past efficiency but fail to capture dynamic interdependencies or provide a framework for future decision-making. This research addresses this gap by developing a hybrid model combining System Dynamics (SD) simulation with DEA. This approach leverages SD's causal modeling and DEA's performance measurement to assess procurement scenarios accurately.

1.1 Importance and necessity of the study

The importance of this study arises from the complex, dynamic, and multidimensional nature of Sustainable Procurement Management (SPM) in the construction industry. Unlike conventional procurement practices, which primarily emphasize cost, quality, and delivery time, sustainable procurement requires a simultaneous balance among economic, environmental, and social objectives. These objectives may not only conflict with one another, but the consequences of procurement decisions may also emerge with time delays and propagate through feedback relationships across subsequent project stages. Therefore, SPM performance cannot be adequately evaluated solely on the basis of cross-sectional indicators or historical data. This necessity is particularly pronounced in construction industries operating in developing and emerging economies, including Iran. Financial constraints, economic fluctuations, limited access to sustainable technologies and materials, inadequate information infrastructure, limited supplier capabilities, stakeholder coordination problems, and weaknesses in policy mechanisms may cause the effects of sustainable procurement policies to differ substantially between the short and long terms. Under such conditions, decision-makers require an analytical tool that can not only measure current performance but also simulate and compare the potential consequences of alternative policies before their implementation.

From a managerial perspective, a major challenge is that increasing resources or investment in a specific area does not necessarily result in an immediate improvement in efficiency. For example, investment in sustainable supplier development may increase procurement costs in the short term but may improve overall project performance in the long term through waste reduction, improved material quality, reduced rework, and increased productivity. Conversely, some policies may produce favorable short-term outcomes but fail to maintain their effectiveness over a longer horizon. Consequently, effective decision-making requires an

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approach capable of evaluating the temporal behavior and cumulative consequences of policies alongside their relative efficiency.

Conventional DEA provides an effective mechanism for evaluating the relative efficiency of decision-making units using multiple inputs and outputs and is therefore potentially suitable for SPM performance assessment. However, traditional DEA is largely dependent on observed data and historical performance and cannot, by itself, simulate future changes resulting from policy interventions. Furthermore, when a process consists of multiple sequential stages, black-box DEA cannot adequately identify where inefficiency originates or how it is transferred from one stage to another.

System Dynamics (SD), in contrast, provides the capability to represent causal relationships, feedback loops, time delays, and changes in system variables over time. These characteristics make SD particularly suitable for examining alternative policy scenarios and forecasting their long-term consequences. However, SD alone does not provide a standardized measure of the relative efficiency of alternative scenarios. Therefore, using either of these approaches independently is insufficient to capture all dimensions of the problem addressed in this study.

Accordingly, the central necessity of the present research lies in establishing a link between "forecasting system behavior" and "measuring efficiency". Integrating SD with network data envelopment analysis (NDEA) makes it possible to first simulate the dynamic and long-term effects of alternative policies and then evaluate the resulting scenarios in terms of relative efficiency and stage-specific performance. Such an integrated framework can determine not only how a policy affects system variables but also whether these changes ultimately translate into improved efficiency.

A further necessity arises from the multi-stage structure of construction projects. Sustainable procurement performance cannot necessarily be treated as a single undifferentiated process because procurement-related outcomes generated during the construction phase may affect subsequent operation performance. The use of NDEA therefore enables the separate evaluation of sequential stages and the identification of locations where inefficiencies originate or are transferred. This information cannot be fully obtained through conventional DEA.

From a scientific perspective, a substantial proportion of previous studies has focused either on identifying and ranking sustainable procurement barriers or on evaluating performance using predominantly static approaches. In contrast, studies that simultaneously incorporate temporal dynamics, policy scenarios, and multi-stage efficiency assessment within an integrated framework remain limited. This gap is particularly relevant in the Iranian construction context, where economic, institutional, and managerial characteristics may influence the effectiveness of sustainable procurement policies.

Therefore, the present study is necessary from three complementary perspectives: First, from a theoretical perspective, to bridge the gap between dynamic policy modeling and efficiency assessment; second, from a methodological perspective, to develop an integrated SD–NDEA framework for forward-looking and multi-stage analysis; and third, from a practical perspective, to provide project managers and policymakers with a quantitative tool for comparing alternative policy scenarios and improving resource allocation in support of sustainable construction.

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2 Theoretical background
2.1 Sustainable procurement management in construction

Sustainable Procurement Management (SPM) has received increasing attention in both academic research and managerial practice because of growing concerns regarding environmental degradation, resource depletion, and social responsibility [11-14]. The concept extends conventional procurement, which traditionally emphasizes cost, quality, and delivery, by incorporating environmental and social considerations into purchasing and supplier-management decisions. In the construction industry, sustainable procurement can therefore be defined as the strategic management of procurement activities to simultaneously achieve economic, environmental, and social objectives throughout the project life cycle [15].

The importance of SPM in construction is associated with the substantial influence of procurement decisions on material consumption, waste generation, project cost, quality, environmental impacts, and supplier performance. Sustainable supplier selection, responsible sourcing, environmentally preferable materials, and long-term supplier development can contribute to resource efficiency and improved project sustainability. Nevertheless, conventional procurement criteria remain dominant in many construction tenders, where price and previous performance are often prioritized over sustainability-related capabilities [16-17].

The adoption of SPM has also been supported by the increasing emphasis on the Sustainable Development Goals (SDGs) and the transition toward more responsible production and consumption patterns. However, the implementation of sustainable procurement remains considerably more challenging in developing and emerging economies than in developed countries [18]. Differences in institutional structures, financial capacity, regulatory environments, supplier capabilities, and organizational culture can significantly affect the effectiveness of sustainable procurement practices. In construction, these challenges are further intensified by the fragmented nature of project supply chains, the large number of stakeholders, short-term contractual relationships, and strong pressure to control cost and schedule. Consequently, sustainable procurement should not be viewed merely as a supplier-selection problem; rather, it represents a dynamic management process in which economic, environmental, organizational, and institutional factors interact over time.

2.2. Barriers to sustainable procurement

Previous research has identified a wide range of barriers that constrain the adoption and effective implementation of sustainable procurement. These barriers can be broadly classified into four interrelated categories: financial and economic, organizational and cultural, knowledge and technical, and policy and governance barriers.

Financial and economic barriers include high initial investment requirements, limited financial resources, uncertainty regarding the return on sustainable investments, and short-term decision-making [19, 20]. Although sustainable procurement may generate long-term economic and environmental benefits, organizations may hesitate to make such investments when immediate financial returns are uncertain.

Organizational and cultural barriers include resistance to change, weak sustainability-oriented organizational cultures, inadequate leadership, strategic misalignment, and insufficient resources [21-24]. These barriers are particularly important in construction because procurement decisions involve multiple actors with different objectives and responsibilities.

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Knowledge and technical barriers are associated with insufficient sustainability knowledge, limited access to reliable project information, inadequate technical capabilities, and a lack of qualified personnel [25]. Such limitations can prevent organizations from accurately evaluating sustainable alternatives and suppliers. Policy and governance barriers include weak regulatory mechanisms, inadequate incentives, limited transparency, inconsistent policy implementation, and poor alignment between national sustainability objectives and operational procurement practices [26]. These factors may be particularly influential in developing countries, where institutional mechanisms supporting sustainable procurement may still be evolving.

Although these studies provide valuable evidence regarding the determinants of sustainable procurement, most focus on identifying or ranking barriers rather than examining how these barriers interact dynamically or how alternative interventions may influence performance over time. This distinction is important because the effects of procurement interventions may accumulate gradually and may not be observable through cross-sectional analysis.

2.3. Sustainable procurement performance assessment

Beyond identifying barriers, an important research stream has focused on evaluating sustainable procurement performance and determining the extent to which procurement practices contribute to organizational and project-level outcomes. Existing studies have employed various approaches, including surveys, regression analysis, factor analysis, multi-criteria decision-making (MCDM), and fuzzy methods [27-29].

For example, Riadi and Machfudiyanto (2023) examined critical success factors associated with sustainable procurement in Indonesia [28], whereas Osuizugbo and Adenuga (2024) identified factors such as satisfaction and value for money as important determinants in the Nigerian construction context [30]. Other studies have applied methods such as ISM, AHP, PCA, fuzzy ANP, and factor analysis to establish relationships or priorities among sustainability-related criteria. Although these methods are useful for identifying important factors and supporting prioritization, they generally provide a relatively static representation of procurement performance. In particular, they do not fully capture the temporal evolution of procurement systems, feedback effects, or the cumulative consequences of management interventions. Consequently, a high-priority factor identified through a static analysis does not necessarily indicate that investment in that factor will produce the greatest long-term improvement in system performance.

This limitation highlights the need to distinguish between factor importance and dynamic policy effectiveness**.** The former identifies which factors are important under observed conditions, whereas the latter requires an understanding of how changes in one variable propagate through the system over time.

2.4. Dynamic modeling and system dynamics

The dynamic nature of sustainable procurement has motivated the use of simulation-based approaches, particularly SD. SD provides a framework for representing complex systems through causal relationships, feedback loops, stocks and flows, and time delays. This capability is particularly relevant to sustainable procurement because decisions regarding supplier

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development, financial investment, environmental performance, resource consumption, and project outcomes may influence one another over time.

Unlike purely statistical or cross-sectional methods, SD enables researchers to examine the evolution of a system under alternative intervention scenarios. Therefore, it can be used to investigate questions such as how increased investment in sustainable suppliers may influence future procurement performance, how regulatory changes may propagate through the supply chain, or whether an intervention that produces short-term costs may generate long-term benefits. Despite these advantages, SD primarily provides information about system behavior rather than a standardized measure of relative efficiency among alternative scenarios. Two scenarios may both demonstrate improvement over time, but SD alone does not necessarily indicate which scenario converts its available resources into desirable outcomes more efficiently. This limitation creates an opportunity to integrate SD with an efficiency-assessment approach.

2.5. DEA and network DEA in performance assessment

DEA is a nonparametric technique widely used to evaluate the relative efficiency of decision-making units (DMUs) based on multiple inputs and outputs. Its ability to accommodate multiple performance dimensions without requiring a predefined functional relationship makes it suitable for evaluating complex organizational and project-level systems. However, conventional DEA generally treats each DMU as a black box. This assumption can be restrictive when the system contains multiple interconnected stages through which inputs are transformed into intermediate products and final outputs. In such circumstances, overall efficiency may conceal substantial differences in the efficiency of individual stages. NDEA extends conventional DEA by explicitly incorporating the internal structure of DMUs and the relationships among their constituent processes [31]. In a series network, for example, the output of one stage can become an intermediate input for a subsequent stage. This structure enables researchers to identify not only overall efficiency but also stage-specific efficiency and the transmission of inefficiencies across interconnected processes. The NDEA perspective is particularly relevant to construction projects because procurement-related decisions and outcomes can influence different stages of the project life cycle. For instance, procurement decisions made during the construction phase may affect the quality, resource efficiency, and operational performance of the subsequent phase. Therefore, a multi-stage efficiency framework can provide more detailed diagnostic information than a conventional black-box DEA model.

Nevertheless, NDEA is primarily an efficiency-assessment methodology and, when applied to observed data, does not inherently forecast how efficiency may evolve under alternative future policies. This limitation complements the limitation identified for SD. While SD provides a mechanism for forecasting system behavior but does not directly measure relative efficiency, NDEA measures relative efficiency but does not inherently generate future policy scenarios. The combination of these two approaches therefore provides a theoretically consistent basis for addressing both dimensions of the problem.

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2.6. Problem-solving approaches and research gap

The reviewed literature demonstrates that sustainable procurement research has developed along several complementary directions. The first stream focuses on identifying barriers and critical success factors. The second emphasizes supplier selection and prioritization using MCDM and fuzzy approaches. The third evaluates procurement or sustainability performance using statistical and efficiency-based methods. The fourth uses simulation approaches to investigate dynamic system behavior and policy interventions. Despite these advances, the literature reveals four important gaps.

First, the application gap: Many studies identify barriers or critical factors but provide limited mechanisms for translating these findings into operational policies and measurable performance improvements.

Second, the temporal gap: Most existing assessment approaches are static or retrospective and therefore provide limited insight into the long-term consequences of procurement interventions.

Third, the integration gap: Relatively limited research has integrated dynamic simulation with efficiency assessment. In particular, the combined use of SD and NDEA for sustainable procurement performance assessment remains insufficiently explored.

Fourth, the multi-stage and contextual gap: Conventional performance assessment may treat procurement systems as black boxes, while relatively limited research examines how procurement-related performance evolves across sequential project stages. Moreover, empirical evidence from the Iranian construction industry remains limited, despite the importance of institutional, financial, and managerial conditions in shaping sustainable procurement outcomes.

Table 1 summarizes representative studies in sustainable and green procurement and positions the present study relative to previous research.

Table 1 Classification of representative studies on sustainable and green procurement in construction

Study	Main focus	Method	Main contribution	Remaining limitation	References
Simion et al. (2019)	Green procurement barriers	Cluster analysis	Identified major procurement-related barriers	Limited dynamic and predictive analysis	[32]
Opoku et al. (2019)	Environmental sustainability barriers	Thematic analysis	Identified sustainability challenges in construction	Limited quantitative performance assessment	[33]
Zaidi et al. (2019)	Sustainable procurement resistance	ISM	Examined structural relationships among resistance factors	No dynamic policy simulation	[34]
Ghadge et al. (2019)	Procurement performance	Regression	Examined determinants of procurement performance	Limited multi-stage and predictive analysis	[35]
Alqadami et al. (2020)	Green procurement challenges	Survey	Identified implementation challenges	No dynamic performance evaluation	[36]
Ershadi et al. (2021)	Sustainable procurement	Interviews	Explored organizational and managerial factors	Limited quantitative decision support	[24]

Gounder et al. (2021)	Sustainable materials	RII, EFA	Prioritized major barriers	No integrated dynamic-performance framework	[37]
Ogunsanya et al. (2022)	Sustainable procurement barriers	EFA	Identified and prioritized implementation barriers	No future policy evaluation	[12]
Oyewobi & Jimoh (2022)	Sustainable procurement barriers	EFA	Examined organizational and procurement challenges	Static assessment	[38]
Mojumder et al. (2022)	Green procurement barriers	ANOVA, FBWM	Evaluated and prioritized mitigation strategies	No dynamic performance modeling	[39]
Riadi & Machfudiyanto (2023)	Sustainable procurement CSFs	Empirical analysis	Identified critical success factors	Limited predictive capability	[28]
Agyekum et al. (2023)	Sustainable procurement implementation	PCA	Examined major implementation factors	No dynamic simulation	[26]
Al Hazza et al. (2023)	Sustainable procurement barriers	AHP	Prioritized sustainability-related barriers	No multi-stage efficiency assessment	[40]
Pourvaziri et al. (2024)	Sustainable procurement factors	ISM/Fuzzy methods	Examined relationships among influential factors	Limited future-oriented analysis	[29]
Sajid et al. (2024)	Circular/sustainable procurement	PRISMA and qualitative analysis	Synthesized circular procurement barriers	No quantitative efficiency evaluation	[]
Kikwasi & Baruti (2024)	Sustainable procurement barriers	Qualitative analysis	Identified implementation challenges	No dynamic or predictive framework	[42]
Fathy (2025)	Sustainable/green implementation	Fuzzy ANP	Prioritized influential factors	No integrated simulation-efficiency model	[14]
Mogaji et al. (2025)17	Sustainable construction/procurement	Empirical analysis	Examined sustainability-related determinants	Limited dynamic and multi-stage analysis	[17]
Present study	Forward-looking SPM performance	SD–NDEA	Integrates dynamic simulation with multi-stage efficiency assessment and policy scenario analysis	Addresses the identified methodological and contextual gaps	

The evidence summarized in Table 1 indicates that previous studies have generated valuable knowledge concerning the determinants, barriers, and implementation mechanisms of sustainable procurement. Nevertheless, the majority of existing approaches remain focused on what the important factors are rather than how alternative interventions involving these factors will influence system performance over time. Furthermore, the literature provides limited evidence on the simultaneous evaluation of future policy outcomes and multi-stage efficiency. To address these limitations, the present study develops a hybrid SD–NDEA framework. SD is used to represent causal relationships and forecast system behavior under alternative policy

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scenarios, while NDEA is subsequently employed to evaluate the relative efficiency of the simulated scenarios across sequential project stages. This integration transforms the analysis from a predominantly descriptive assessment of barriers into a forward-looking decision-support framework capable of linking policy interventions, dynamic system behavior, and multi-stage efficiency outcomes**.**

The proposed framework is empirically examined using construction projects in Tehran, thereby providing evidence from a context that has received comparatively limited attention in the sustainable procurement literature. In this way, the study seeks to contribute not only a methodological framework but also context-specific evidence that can assist construction managers and policymakers in designing and prioritizing sustainable procurement interventions.

3 Methodology

This study employs a mixed-methods research design, combining qualitative and quantitative approaches to achieve its objectives. The research is descriptive and applied in nature, aiming to develop and validate a hybrid model for predicting and evaluating the performance of sustainable procurement management in urban construction projects. The methodology is structured in two distinct phases: A qualitative phase to identify key factors and a quantitative phase for modeling and performance analysis.

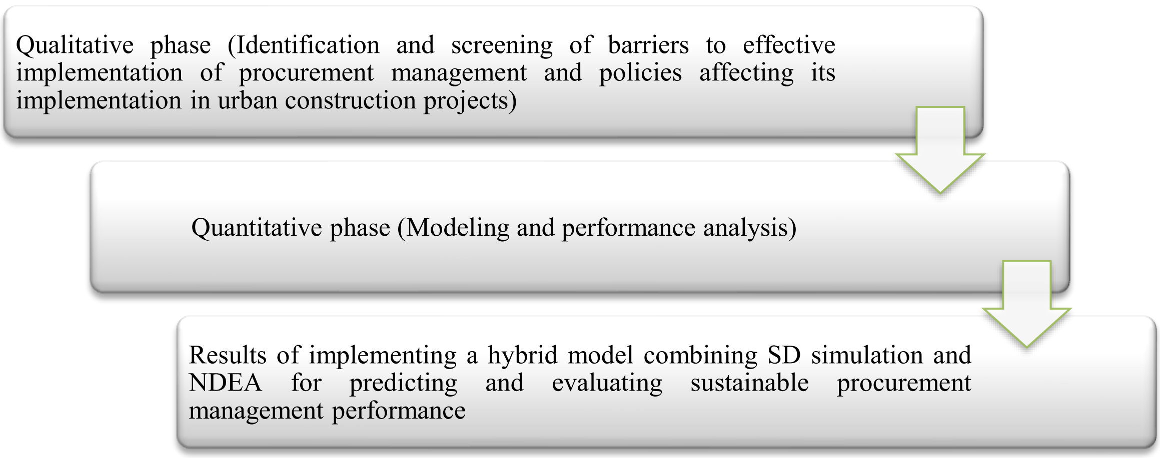

Fig. 1 Research implementation process

3.1 Phase I: Qualitative analysis

The first phase identified and screened critical barriers and policies influencing sustainable procurement implementation in urban construction.

- Meta-synthesis: A systematic meta-synthesis of global literature was conducted to compile an exhaustive list of initial factors and policies.
- Delphi method: A two-stage Delphi process was employed to validate these factors. A purposive panel of experts—comprising university professors, project management

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researchers, and urban specialists—refined the list through structured questionnaires until consensus was reached.

- Data validation: To ensure robustness, the Content Validity Ratio (CVR) was used to assess content validity, while Cronbach's alpha confirmed the reliability of the expert feedback. The validated factors are summarized in Table 2.

Table 2 Barriers to implementing sustainable procurement management and policies affecting it

Type	Primary criterion	Indices	Symbol
Policies	Environmental	Choosing sustainable suppliers	I_1
		Using sustainable building materials	I_2
		Reducing energy consumption	I_3
		Life Cycle Analysis (LCA)	I_4
		Environmental Risk Management	I_5
		Reducing water consumption	I_6
		Developing sustainable transportation systems	I_7
		Attention to biodiversity	I_8
		Establishing environmental management systems	I_9
		Considering climate impacts	I_{10}
		Resource management with a sustainable approach	I_{11}
		Using modern construction methods	I_{12}
		New technologies	I_{13}
		Performance evaluation and monitoring	I_{14}
	Social	Developing training programs for suppliers	I_{15}
		Attention to the needs of the local community	I_{16}
	Economic	Sustainable cost-benefit analysis	I_{17}
		Developing sustainable cost reduction strategies	I_{18}
		Supply chain management	I_{19}
		Developing sustainable purchasing policies	I_{20}
		Attention to the quality of products and services	I_{21}
		Using information technologies in procurement management	I_{22}
Barriers		Lack of awareness and education	D_1
		Financial constraints	D_2
		Inadequate infrastructure	D_3
		Insufficient laws and regulations	D_4
		Lack of coordination among stakeholders	D_5
		Lack of access to new technologies	D_6
		Economic and political impacts	D_7
		Lack of transparency in the supply chain	D_8

3.2 Phase II: Quantitative analysis

This phase developed a hybrid framework integrating dynamic simulation with multi-stage performance evaluation.

- SD model development: A SD simulation model was constructed using Vensim software. This model captures the feedback loops and causal relationships among the factors identified in Phase I, allowing for a longitudinal understanding of system behavior over time.

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- NDEA performance analysis: To evaluate the efficiency of construction projects as DMUs, an advanced NDEA model was employed. Unlike standard DEA, NDEA accounts for internal process structures and subunit interconnections, offering a more nuanced efficiency assessment [31].
- Model Integration: The predictive outputs from the SD model—representing future inputs and outputs—were integrated into the NDEA framework. This synergy transforms the evaluation from a static retrospective to a forward-looking decision-support system, enabling the assessment of future procurement performance under various scenarios.

3.3 System dynamics (SD) method

SD, developed by Forrester (1961), is a methodology for analyzing the nonlinear behavior of complex systems through feedback loops, making it ideal for project management and urban studies [43].

3.3.1 SD model implementation

Following Goodarzi et al. (2025), the SD modeling process involved [44]:

1. Problem conceptualization: Defining the system and developing a conceptual model based on Phase I expert input.
2. Formal modeling: Converting concepts into stock-and-flow diagrams and mathematical equations using Vensim.
3. Simulation and analysis: Observing system behavior over time across various scenarios.
4. Model validation: Rigorous testing of structural and behavioral validity against historical data. Sternman's tests—including adequacy of scope, parameter estimation, and sensitivity analysis—ensured model robustness [45, 46].

The model utilizes reinforcing (positive) and balancing (negative) feedback loops. Eight identified Barriers (D1-D8) introduce negative relationships, where an increase in barriers stabilizes or inhibits system growth through balancing loops.

3.4 Network data envelopment analysis (NDEA) method
3.4.1 NDEA implementation and structure

The NDEA implementation followed a four-step optimization process [31]: (1) Identifying DMU variables using SD-forecasted data; (2) Network modeling of internal project structures; (3) Mathematical programming to derive efficiency scores; and (4) Solving via advanced optimization to pinpoint inefficiencies. Unlike black-box DEA, NDEA identifies internal stage inefficiencies. This study adopts a multi-stage series (chain) system where the output of the consecution phase (Stage 1) acts as the intermediate input (Z) for the operation phase (Stage 2). To handle stochastic uncertainties, fuzzy NDEA is integrated to ensure robust membership functions. As shown in Figure 2, we consider a parallel system consisting of k subunits, where each subunit operates independently without intermediate output connections. For a $DMU_j; j = 1, \dots, n$, subunit $P(p = 1, \dots, k)$ consumes the same inputs xp_{ij} $(i = 1, \dots, m)$, which come from outside the decision-making units, to produce outputs $yp_{rj}(r \in O_p)$, where the set

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Op includes the outputs used for subunit p and $Op \subset \{1, 2, \ldots., s\}$. This means a subunit can differ from the others, making the subunits heterogeneous. It is worth noting that the parallel structure is one of the two fundamental structures in network analysis, characterized by subunits in the system connected in parallel and operating independently. Thus, if active links between subunits are considered, it becomes a series network system, which will be examined in later models in this research.

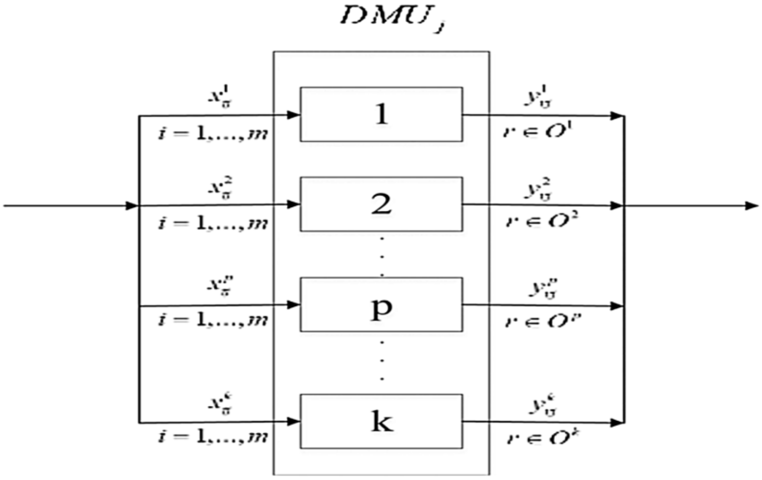

Figure. 2 Parallel model with identical inputs and heterogeneous outputs [31]

For the parallel decision-making unit shown in Figure 2, let the input and output vectors of randomly $\tilde{x}_j = (\tilde{x}_{1j}, \ldots, \tilde{x}_{mj})\tilde{y}_j = (\tilde{y}_{1j}, \ldots, \tilde{y}_{sj})$DMUj be denoted by $x_j=(x_{1j}, \ldots, x_{mj})$ and $y_j=(y_{1j}, \ldots, y_{sj})$, respectively. The subset *Op* identifies the outputs associated with subunit *p*. Based on these definitions, the initial stochastic fractional NDEA formulation is presented as Model (1).

$$
\begin{aligned}
& Max\ E = \frac{\sum_{r\in o_p} u_r \tilde{y}_{ro}^{p}}{\sum_{i=1}^{m} v_i \tilde{x}_{io}} \qquad (1) \\
& s.t. \\
& \left(\frac{\sum_{r\in o_p} u_r \tilde{y}_{rj}^{p}}{\sum_{i=1}^{m} v_i \tilde{x}_{ij}} \le \beta_0\right) \ge 1 - \alpha_j \\
& v_i;\ u_r \ge 0 \\
& i = 1, \ldots, m; j = 1, \ldots, n;\ o_p = 1, \ldots, p
\end{aligned}
$$

Model (1) represents the initial stochastic fractional formulation of the parallel NDEA system. Its objective function maximizes the efficiency score *E* of the evaluated DMU by taking the ratio of the weighted aggregate outputs to the weighted aggregate inputs.

The constraints impose the corresponding weighted output–input relationship for every reference DMU j and require it to satisfy a chance constraint with probability at least $1-\alpha_j$. Here, u_r and v_i are nonnegative output and input weights, respectively, β_0 is the benchmark efficiency level, and α_j controls the probability level of the stochastic constraint. Because the input/output observations are treated as random quantities, Model (1) simultaneously contains fractional terms and uncertain parameters. Consequently, it cannot be solved directly as a conventional deterministic linear programming model.

The main limitation of Model (1) is therefore twofold: (i) The efficiency objective is fractional because it is defined as a ratio of weighted outputs to weighted inputs; and (ii) The constraints are stochastic because the input/output terms are treated as random quantities and are imposed through chance constraints. To obtain a deterministic and tractable formulation, the linearization is performed in successive stages. First, the chance constraint is standardized by isolating the random expression and representing it through its mean and standard deviation. The resulting probability statement is then converted into a deterministic inequality using the inverse cumulative distribution function of the standard normal distribution, denoted by $\varphi^{-1}(\cdot)$. Second, the fractional objective is reformulated by introducing the auxiliary efficiency variable λ and imposing the corresponding inequality constraint. Finally, the remaining bilinear term $M\lambda$ is replaced by the auxiliary continuous variable Δ. The transformations are presented in Equations (2)– (11), leading to the deterministic linearized primal formulation in Model (12).

$$(\sum_{r\in o_p} u_r\tilde{y}^p_{rj} - \beta_j \sum_{i=1}^{m} v_i\tilde{x}_{ij} \leq 0) \geq 1-\alpha_j$$

A key step in transforming the stochastic chance constraint is to characterize the probability distribution of the random expression appearing in the constraint. Accordingly, the expression in parentheses is standardized using its expected value and standard deviation, as shown in Equation (2).

$$\frac{(\sum_{r\in o_p} u_r\tilde{y}^p_{rj}-\beta_j\sum_{i=1}^m v_i\tilde{x}_{ij})-(\sum_{r\in o_p} u_r y^p_{rj}-\beta_j\sum_{i=1}^m v_i x_{ij})}{\delta(\sum_{r\in o_p} u_r\tilde{y}^p_{rj}-\beta_j\sum_{i=1}^m v_i\tilde{x}_{ij})} \leq \frac{-(\sum_{r\in o_p} u_r y^p_{rj}-\beta_j\sum_{i=1}^m v_i x_{ij})}{\delta(\sum_{r\in o_p} u_r\tilde{y}^p_{rj}-\beta_j\sum_{i=1}^m v_i\tilde{x}_{ij})} \quad (2)$$

$$\frac{(\sum_{r\in o_p} u_r\tilde{y}^p_{rj}-\beta_j\sum_{i=1}^m v_i\tilde{x}_{ij})-(\sum_{r\in o_p} u_r y^p_{rj}-\beta_j\sum_{i=1}^m v_i x_{ij})}{\delta(\sum_{r\in o_p} u_r\tilde{y}^p_{rj}-\beta_j\sum_{i=1}^m v_i\tilde{x}_{ij})},$$

The resulting standardized random variable $\tilde{\zeta}_J$ follows a standard normal distribution, N(0,1), and is denoted by Z. Accordingly, Equation (3) is obtained.

$$\tilde{\zeta}_J \leq \frac{-(\sum_{r\in o_p} u_r y^p_{rj}-\beta_j\sum_{i=1}^m v_i x_{ij})}{\delta(\sum_{r\in o_p} u_r\tilde{y}^p_{rj}-\beta_j\sum_{i=1}^m v_i\tilde{x}_{ij})} \quad (3)$$

Using the cumulative distribution function of the standard normal distribution, the probability associated with the chance constraint can be expressed as Equation (4).

$$\phi\left(\frac{-\left(\sum_{r\in o_p} u_r y^p_{rj}-\beta_j\sum_{i=1}^m v_i x_{ij}\right)}{\delta\left(\sum_{r\in o_p} u_r\tilde{y}^p_{rj}-\beta_j\sum_{i=1}^m v_i\tilde{x}_{ij}\right)}\right) \geq (1-\alpha_j) \quad (4)$$

Since the cumulative distribution function of the standard normal distribution is strictly increasing and therefore invertible, Equation (4) can be transformed using its inverse function, as shown in Equation (5).

$$\left(\frac{-\left(\sum_{r\in o_p} u_r y^p_{rj}-\beta_j\sum_{i=1}^m v_i x_{ij}\right)}{\delta\left(\sum_{r\in o_p} u_r\tilde{y}^p_{rj}-\beta_j\sum_{i=1}^m v_i\tilde{x}_{ij}\right)}\right) \geq \phi^{-1}(1-\alpha_j) \quad (5)$$

At this stage, the random terms in the numerator have been standardized $\delta\left(\sum_{r\in o_p} u_r\tilde{y}^p_{rj} - \beta_j\sum_{i=1}^m v_i\tilde{x}_{ij}\right)\mu_j$, whereas the denominator still contains random and uncertain terms. Therefore, the denominator expression is represented by the corresponding continuous auxiliary variable. Using the properties of the normal distribution and the preceding transformations, the deterministic equivalent is obtained in Equation (6).

$$\left(\sum_{r\in o_p} u_r y^p_{rj} - \beta_j\sum_{i=1}^m v_i x_{ij}\right) - \phi^{-1}(\alpha_j)\mu_j \leq 0 \quad (6)$$

Therefore, the stochastic chance constraint in Model (1) is replaced by its deterministic equivalent in Equation (6), yielding Model (7). This model preserves the probabilistic requirement while removing the random term from the constraint.

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$$Max\ E = \frac{\sum_{r\in o_p} u_r \tilde{y}_{ro}^p}{\sum_{i=1}^m v_i \tilde{x}_{io}} \geq \beta_0 \tag{7}$$
$$s.t.$$
$$\left(\sum_{r\in o_p} u_r y_{rj}^p - \beta_j \sum_{i=1}^m v_i x_{ij}\right) - \phi^{-1}(\alpha_j)\mu_j \leq 0$$
$$v_i;\ u_r;\ \mu_j \geq 0$$
$$i = 1, \dots, m; j = 1, \dots, n;\ o_p = 1, \dots, p$$

Based on model (7), the stochastic constraint has been replaced by its deterministic equivalent; however, the objective function remains fractional. To remove the fractional objective, the efficiency ratio E is represented by the auxiliary variable λ. Because the original problem is a maximization problem, λ is maximized subject to the corresponding inequality that bounds the fractional efficiency ratio. Thus, Model (7) is reformulated as Model (8).

$$Max\ \lambda \tag{8}$$
$$s.t.$$
$$\left(\frac{\sum_{r\in o_p} u_r \tilde{y}_{ro}^p}{\sum_{i=1}^m v_i \tilde{x}_{io}} \geq \beta_0\right) \leq \lambda$$
$$\left(\sum_{r\in o_p} u_r y_{rj}^p - \beta_j \sum_{i=1}^m v_i x_{ij}\right) - \phi^{-1}(\alpha_j)\mu_j \leq 0$$
$$v_i;\ u_r;\ \mu_j \geq 0$$
$$i = 1, \dots, m; j = 1, \dots, n;\ o_p = 1, \dots, p$$

After this transformation of the objective function, the first constraint again contains a fractional expression and an uncertain term. Therefore, the same standardization procedure used for the stochastic constraint in model (1) is applied to this constraint, and the resulting transformations are summarized in Equation (9).

$$\left(\frac{\sum_{r\in o_p} u_r \tilde{y}_{ro}^p}{\sum_{i=1}^m v_i \tilde{x}_{io}} \geq \beta_0\right) \leq \lambda \tag{9}$$
$$\left(\sum_{r\in o_p} u_r \tilde{y}_{ro}^p \geq \beta_0 \sum_{i=1}^m v_i \tilde{x}_{io}\right) \leq \lambda$$
$$(\beta_0 \sum_{i=1}^m v_i \tilde{x}_{io} - \sum_{r\in o_p} u_r \tilde{y}_{ro}^p \leq 0) \leq \lambda$$
$$\frac{\beta_0 \sum_{i=1}^m v_i \tilde{x}_{io} - \sum_{r\in o_p} u_r \tilde{y}_{ro}^p - (\beta_0 \sum_{i=1}^m v_i x_{io} - \sum_{r\in o_p} u_r y_{ro}^p)}{\sigma(\beta_0 \sum_{i=1}^m v_i \tilde{x}_{io} - \sum_{r\in o_p} u_r \tilde{y}_{ro}^p)} \leq \frac{-(\beta_0 \sum_{i=1}^m v_i x_{io} - \sum_{r\in o_p} u_r y_{ro}^p)}{\sigma(\beta_0 \sum_{i=1}^m v_i \tilde{x}_{io} - \sum_{r\in o_p} u_r \tilde{y}_{ro}^p)}$$
$$\phi\left(\frac{-\left(\beta_0 \sum_{i=1}^m v_i x_{io} - \sum_{r\in o_p} u_r y_{ro}^p\right)}{\sigma(\beta_0 \sum_{i=1}^m v_i \tilde{x}_{io} - \sum_{r\in o_p} u_r \tilde{y}_{ro}^p)}\right) \leq \lambda$$
$$\frac{-\left(\beta_0 \sum_{i=1}^m v_i x_{io} - \sum_{r\in o_p} u_r y_{ro}^p\right)}{\sigma(\beta_0 \sum_{i=1}^m v_i \tilde{x}_{io} - \sum_{r\in o_p} u_r \tilde{y}_{ro}^p)} \geq \phi^{-1}(\lambda)$$

Using the resulting expression, Equation (10) is obtained. At this stage $\sigma(\beta_0 \sum_{i=1}^m v_i \tilde{x}_{io} - \sum_{r\in o_p} u_r \tilde{y}_{ro}^p) = M$, the uncertain quantities have been converted into their deterministic equivalents; however, the term Mλ remains bilinear because it is the product of two decision variables.

$$\left(\sum_{r\in o_p} u_r y_{ro}^p - \beta_0 \sum_{i=1}^m v_i x_{io} - \phi^{-1} M\lambda\right) \le 0 \quad (10)$$

In Equation (10), the uncertain quantities have been converted into deterministic terms $\phi^{-1}M\lambda$. Nevertheless, the product Mλ makes the formulation nonlinear. To restore linearity, the auxiliary continuous variable Δ is introduced to represent Mλ. Substitution of this auxiliary variable gives Equation (11).

$$\left(\sum_{r\in o_p} u_r y_{ro}^p - \beta_0 \sum_{i=1}^m v_i x_{io} - \Delta\phi^{-1}\right) \le 0 \quad (11)$$

Accordingly, the deterministic and linearized network model with heterogeneous random outputs is obtained as model (12). This is the final primal deterministic formulation resulting from the preceding transformations.

$$Max\ \lambda \quad (12)$$

$$s.t.$$

$$\left(\sum_{r\in o_p} u_r y_{ro}^p - \beta_0 \sum_{i=1}^m v_i x_{io} - \Delta\phi^{-1}\right) \le 0$$

$$\left(\sum_{r\in o_p} u_r y_{rj}^p - \beta_j \sum_{i=1}^m v_i x_{ij}\right) - \phi^{-1}(\alpha_j)\mu_j \le 0$$

$$v_i;\ u_r;\ \mu_j;\ \Delta \ge 0$$

$$i = 1, \dots, m;\ j = 1, \dots, n;\ o_p = 1, \dots, p$$

The corresponding deterministic dual formulation of the network model with heterogeneous random outputs is presented as model (13).

$$Min\ \sum_{o_n=1}^p \alpha_p \Delta\phi^{-1} + \sum_{i=1}^{n_i} \phi^{-1}(\alpha_j)\mu_j\beta_j \quad (13)$$

$$s.t.$$

$$\sum\nolimits_{j=1}^n \beta_j x_{ij} \le \beta_o x_{io}$$

$$\sum\nolimits_{j=1}^n \alpha_{op} Y_{op}^p \ge Y_{op}$$

$$\beta_j;\ \alpha_p;\ \mu_j;\ \Delta \ge 0$$

$$i = 1, \dots, m;\ j = 1, \dots, n;\ o_p = 1, \dots, p$$

In Equation (14), the products μjβj and αpΔ are bilinear terms. To obtain a linear dual formulation $\mu_j\beta_j\alpha_p\Delta$, these products are replaced by the auxiliary variables φj and ωp, respectively, as defined in Equation (14).

$$\mu_j\beta_j = \varphi_j; \qquad \alpha_p\Delta = \omega_p \quad (14)$$

After introducing these auxiliary variables, the final linear deterministic dual model is obtained as Model (15).

$$Min\ \sum_{o_n=1}^p \omega_p\phi^{-1} + \sum_{i=1}^{n_i} \phi^{-1}(\alpha_j)\varphi_j \quad (15)$$

$$s.t.$$

$$\sum\nolimits_{j=1}^n \beta_j x_{ij} \le \beta_o x_{io}$$

$$\sum\nolimits_{j=1}^n \alpha_{op} Y_{op}^p \ge Y_{op}$$

$$\beta_j;\ \alpha_p;\ \varphi_j;\ \omega_p \ge 0$$

$$i = 1, \dots, m;\ j = 1, \dots, n;\ o_p = 1, \dots, p.$$

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4 Result and Findings
4.1 Model Structure and Variables

The study's SD model, which aims to examine urban construction procurement management, incorporates key feedback loops to understand system functionality. The model's loops include both positive (reinforcing) and negative (balancing) feedback loops. In this model, all identified factors are considered to have a positive influence on procurement management in urban construction projects, so all relationships within the loops are considered positive. The model's variables are classified into primary and secondary categories, which are further defined as state, flow, or auxiliary variables (see Table 3). These variables include a wide range of policies and barriers across environmental, social, and economic dimensions.

Table 3 Problem variables

Variable	Primary variables	Secondary variables	Symbol	Variable mode
Policies	Environmental	Choosing sustainable suppliers	I_1	Auxilliary
		Using sustainable building materials	I_2	Auxilliary
		Reducing energy consumption	I_3	Auxilliary
		Life Cycle Analysis (LCA)	I_4	Auxilliary
		Environmental Risk Management	I_5	Auxilliary
		Reducing water consumption	I_6	Mode
		Developing sustainable transportation systems	I_7	Mode
		Attention to biodiversity	I_8	Auxilliary
		Establishing environmental management systems	I_9	Mode
		Considering climate impacts	I_{10}	Auxilliary
		Resource management with a sustainable approach	I_{11}	Auxilliary
		Using modern construction methods	I_{12}	Auxilliary
		New technologies	I_{13}	Current
		Performance evaluation and monitoring	I_{14}	Auxilliary
	Social	Developing training programs for suppliers	I_{15}	Auxilliary
		Attention to the needs of the local community	I_{16}	Auxilliary
	Economic	Sustainable cost-benefit analysis	I_{17}	Mode
		Developing sustainable cost reduction strategies	I_{18}	Current
		Supply chain management	I_{19}	Auxilliary
		Developing sustainable purchasing policies	I_{20}	Auxilliary
		Attention to the quality of products and services	I_{21}	Auxilliary

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	Using information technologies in procurement management	I_{22}	Mode
Barriers	Lack of awareness and education	D_1	Auxilliary
	Financial constraints	D_2	Auxilliary
	Inadequate infrastructure	D_3	Mode
	Insufficient laws and regulations	D_4	Current
	Lack of coordination among stakeholders	D_5	Auxilliary
	Lack of access to new technologies	D_6	Auxilliary
	Economic and political impacts	D_7	Auxilliary
	Lack of transparency in the supply chain	D_8	Mode

The circular model of sustainable urban construction procurement management (Figure 3) is the SD Causal-Loop Diagram that serves as the predictive engine within a larger hybrid SD-NDEA framework. Its circular nature is defined by a dynamic network of feedback loops, linking 22 Policies (representing positive interventions across environmental, social, and economic sustainability) and 8 Barriers (representing inhibiting factors like financial constraints and lack of awareness) to the overall SPM performance. This diagram formalizes the complex, non-linear, and time-dependent relationships between these factors, with Policies driving reinforcing (positive) loops that promote performance growth, and Barriers driving balancing (negative) loops that stabilize or inhibit performance, allowing for the simulation of future system behavior and the identification of long-term policy impacts. The circular relationships and the overall framework are visualized in Figure 3.

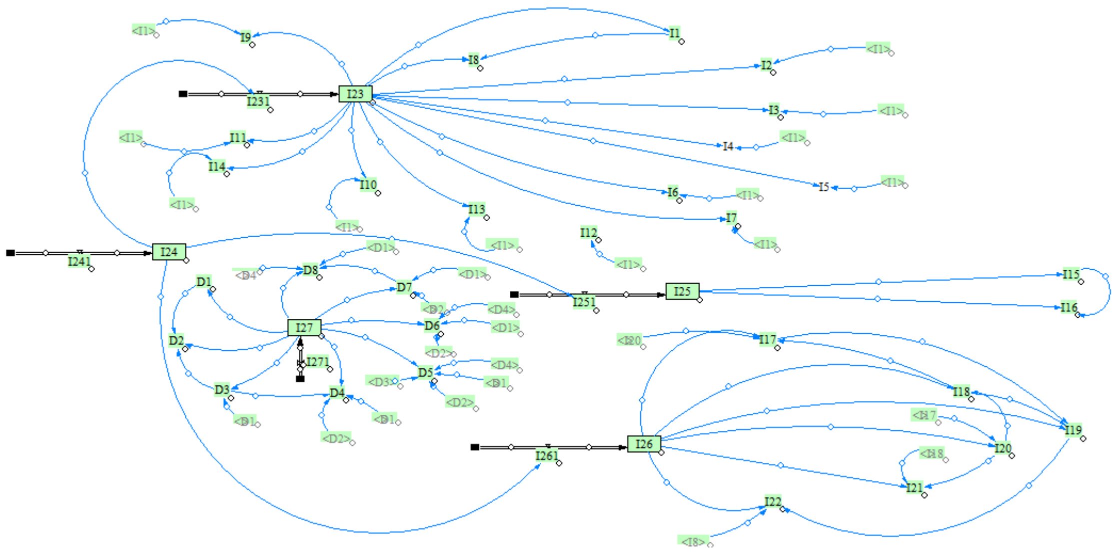

Fig. 3 Circular model of sustainable urban construction procurement management

The model consists of two main types of interconnected variables that drive the circularity of the system:

Policies (I1-I22): These represent the drivers or interventions in SPM. The 22 policies are typically categorized across the three pillars of sustainability—environmental (e.g., Life Cycle Analysis, waste reduction), social (e.g., stakeholder communication, training programs), and economic (e.g., cost-benefit analysis, supply chain collaboration). An arrow originating from a Policy variable represents a direct, often positive relationship leading toward improved SPM Performance.

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Barriers (D1-D8): These represent the inhibitors or resistance within the system. Examples often include "Lack of awareness," "Financial constraints," or "Insufficient laws." An arrow originating from a Barrier typically represents a direct, negative relationship leading to a degradation of SPM Performance.

4.2 Model validation and simulation

The SD model's logical behavior was confirmed through simulation. A simulation of revenue from procurement management over 100 months shows a continuous increase, indicating that the model behaves logically in the presence of both effective factors and barriers (see Figure 4).

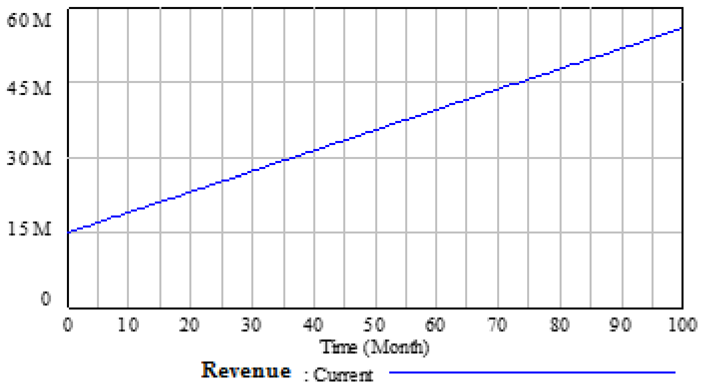

Fig. 4 Simulation of income from procurement management in urban projects

Model validation, a crucial step, was performed using two key tests:

1. Limit test: This test examines the model's behavior under extreme conditions. The simulation demonstrates that a lack of improvement in procurement management and failure to overcome barriers leads to a significant decrease in customer order deliveries and revenue. Conversely, an increase in customer orders directly increases revenue, confirming the model's logical response to policy changes (see Figure 5).

Fig. 5 Limit test of the number of customer order deliveries concerning income

2. Behavior reproducibility test: This test compares the model's simulated behavior to real-world data to ensure its accuracy. The simulation showed that as appropriate procurement intensifies over time, the non-procurement rate increases, which indicates a logical behavior consistent with real-world scenarios (see Figure 6).

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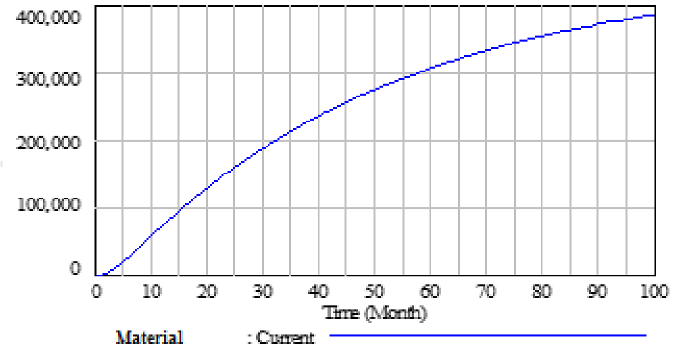

Fig. 6 Rate of change in attention to community needs over time

4.3 Proposed scenarios

Three scenarios were developed based on their potential impact on economic consequences or income, with the goal of identifying policies that best enhance model performance. The results of these simulations, presented below, can be used by experts and policymakers to evaluate different strategies.

- Scenario 1: Strengthening economic factors
    - This scenario focuses on enhancing factors like sustainable cost-benefit analysis, sustainable cost reduction strategies, and the use of information technologies in procurement management.
    - The simulation shows that strengthening these factors reduces the impact of barriers and positions income at a more favorable state (see Figure 7). While the change was not significant from 2011-2019, an exponential growth was observed from 2019 onward, demonstrating that effective management policies can overcome barriers and lead to higher income.

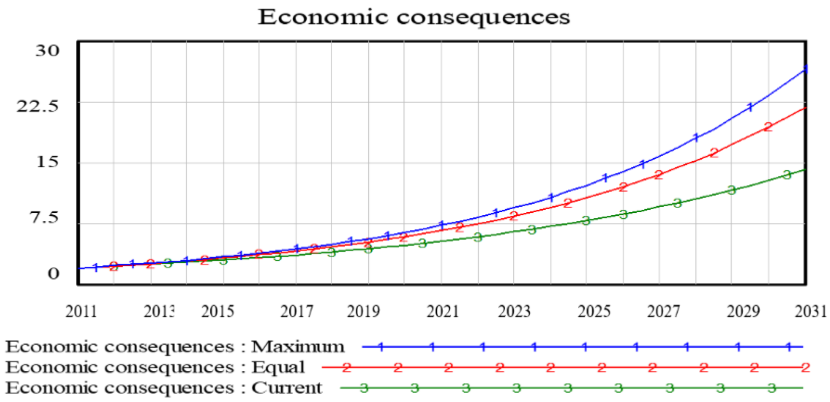

Fig. 7 Simulation of the first scenario

- Scenario 2: Strengthening Social Factors
    - This scenario simulates the effects of strengthening social factors, such as developing supplier training programs and addressing the needs of local communities.

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- The results indicate that strengthening these factors also leads to higher income, with a particularly noticeable upward trend from 2027 until the end of the simulation period (see Figure 8).

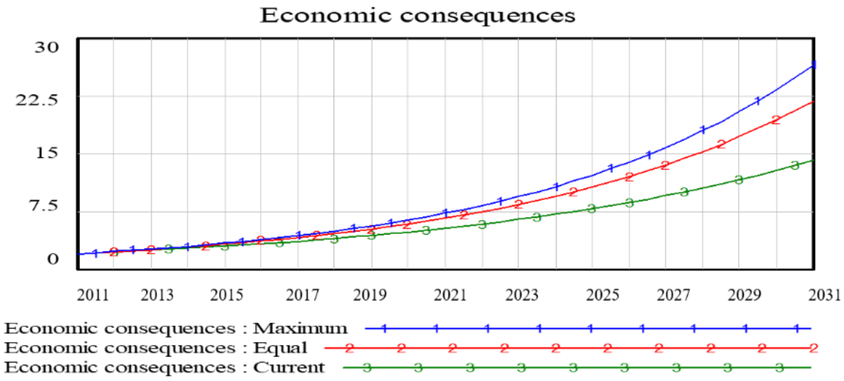

Fig. 8 Simulation of the second scenario

- Scenario 3: Strengthening environmental factors
  - This scenario focuses on enhancing environmental factors like using sustainable materials, reducing energy consumption, and implementing environmental risk management.
  - Similar to Scenario 2, the simulation shows a narrow gap between the equal and maximum states until 2027, followed by a noticeable increasing trend for the rest of the period (see Figure 9).

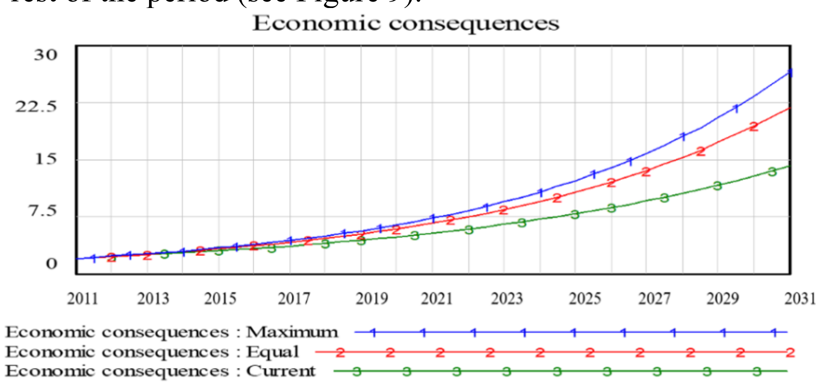

Fig. 9 Simulation of the third scenario

4.4. Construction project performance results
4.4.1. NDEA performance analysis

The performance of 10 urban construction projects in Tehran was calculated using the NDEA model, based on a classification of various inputs and outputs (see Table 4). The model evaluates efficiency in two stages: the construction phase and the operation phase, and also provides an overall performance score for each project (see Table 5).

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Table 4 Classification of inputs and outputs for calculating the performance score

Type	Primary criterion	Indies	Symbol	Factor type	
				Input	Output
Policies	Environmental	Choosing sustainable suppliers	I_1	*	
		Using sustainable building materials	I_2	*	
		Reducing energy consumption	I_3	*	
		Life Cycle Analysis (LCA)	I_4	*	
		Environmental Risk Management	I_5	*	
		Reducing water consumption	I_6	*	
		Developing sustainable transportation systems	I_7	*	
		Attention to biodiversity	I_8	*	
		Establishing environmental management systems	I_9	*	
		Considering climate impacts	I_{10}	*	
		Resource management with a sustainable approach	I_{11}	*	
		Using modern construction methods	I_{12}	*	
		New technologies	I_{13}	*	
		Performance evaluation and monitoring	I_{14}	*	
	Social	Developing training programs for suppliers	I_{15}	*	
		Attention to the needs of the local community	I_{16}	*	
	Economic	Sustainable cost-benefit analysis	I_{17}		*
		Developing sustainable cost reduction strategies	I_{18}		*
		Supply chain management	I_{19}		*
		Developing sustainable purchasing policies	I_{20}	*	
		Attention to the quality of products and services	I_{21}		*
		Using information technologies in procurement management	I_{22}	*	
	Barriers	Lack of awareness and education	D_1	*	
		Financial constraints	D_2	*	
		Inadequate infrastructure	D_3	*	
		Insufficient laws and regulations	D_4	*	
		Lack of coordination among stakeholders	D_5	*	
		Lack of access to new technologies	D_6	*	
		Economic and political impacts	D_7	*	
		Lack of transparency in the supply chain	D_8	*	

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Table 5 Performance value

		Proposed model			Available model	
Project	**Consecution phase**	**Operation phase**	**Overall performance**	**Consecution phase**	**Operation phase**	**Overall performance**
1	1	1	1	1	1	1
2	9484.0	9802.0	9643.0	9434.0	9669.0	9551.0
3	1	1	1	1	1	1
4	9063.0	1	9531.0	9025.0	1	9513.0
5	1	8223.0	9112.0	1	8147.0	9073.0
6	1	1	1	1	1	1
7	0984.0	1	9492.0	894.0	1	9470.0
8	8983.0	1	9492.0	9479.0	9157.0	9318.0
9	8594.0	1	9297.0	83.0	1	9150.0
10	9831.0	1	9915.0	9775.0	1	9887.0

- Efficient Projects: Projects 1, 3, and 6 were found to be efficient in both the construction and operation phases, resulting in an overall efficiency score of 1.
- Inefficient Projects: Project 2 was the only one found to be inefficient in both stages. Projects 2, 4, 5, 7, 8, 9, and 10 showed varying levels of inefficiency in one or both stages.

4.4.2. Numerical analysis comparing the proposed model and the available model

Based on data from 10 projects, the performance of the proposed model was evaluated in comparison to the existing model in three main indicators: Execution phase, Operation phase, and Overall performance. The average of the indicators for each model was calculated as follows:

Table 6 Numerical analysis comparing the proposed model and the available model

Index	Proposed model	Available model	Improvement rate (%)
Consecution phase	0.9578	0.9493	+0.9%
Operation phase	0.9803	0.9697	+1.1%
Overall performance	0.9648	0.9591	+0.6%

The comparative analysis of ten large-scale construction projects revealed that the proposed model achieved average performance scores of 0.9578, 0.9803, and 0.9648 for the consecution phase, operation phase, and overall performance, respectively. In contrast, the existing model recorded corresponding values of 0.9493, 0.9697, and 0.9591. These findings demonstrate that the proposed model consistently outperforms the existing approach by approximately 0.9% to 1.1% across the key performance dimensions. The greatest improvement was observed during the operation phase, highlighting the superior capability of the proposed model in capturing dynamic project performance and supporting more effective managerial decision-making.

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5 Discussion

The central finding is the successful validation of the SD-NDEA hybrid model, which transforms static SPM evaluation into a dynamic predictive framework. Model reliability was confirmed through the Limit Test (correlating procurement failures with revenue decrease) and the Behavior Reproducibility Test. Quantitative analysis of ten Tehran-based projects established a baseline efficiency of 0.78, indicating a systemic 22% efficiency deficit in sustainable resource utilization.

The NDEA component identified 'Supplier Selection and Contract Management' as the primary operational bottleneck, providing a precise target for restructuring. Furthermore, SD-based simulations revealed that implementing a 'Green Technology Investment Index' policy could reverse efficiency declines, generating an 11.5% improvement in long-term SPM performance. This quantitative foresight confirms that targeted financial investment in green technology is the primary leverage point for policymakers in this emerging market.

5.1 Contributions and novelty of the study

The main novelty of this study does not lie in the independent use of SD or NDEA, as both approaches have been extensively applied in previous research. Rather, the primary contribution of the present study lies in the systematic integration of these two approaches to support forward-looking SPM efficiency assessment, policy scenario analysis, and multi-stage inefficiency diagnosis in construction projects. The proposed framework establishes a methodological link between dynamic system behavior, policy experimentation, and network-based efficiency evaluation.

First, the study establishes a dynamic-to-efficiency analytical linkage. Studies based on System Dynamics primarily focus on representing causal relationships, feedback loops, time delays, accumulations, and the evolution of system variables over time, whereas DEA-based approaches generally evaluate the relative efficiency of decision-making units based on observed inputs and outputs. These two analytical perspectives are often applied independently. The present study connects them by using the outputs generated by the SD simulation as inputs to the NDEA model. Consequently, efficiency can be assessed not only under existing conditions but also in relation to the projected outcomes of alternative management scenarios.

Second, the study extends conventional retrospective efficiency assessment toward prospective scenario-based evaluation. Conventional DEA primarily evaluates the efficiency of existing decision-making units using observed data and therefore has limited capability to assess the potential consequences of policies that have not yet been implemented. In the proposed framework, SD simulation enables alternative management policies to be examined before their actual implementation, while NDEA evaluates the efficiency implications of the resulting simulated outcomes. This combination enables decision-makers to compare alternative policies based on their expected long-term efficiency consequences rather than relying exclusively on historical performance.

Third, the study incorporates the multi-stage nature of SPM into the efficiency assessment. Sustainable procurement performance in construction projects cannot always be adequately represented as a single black-box process because decisions and outcomes in one project phase may affect subsequent phases. The two-stage series NDEA framework adopted in this study explicitly considers the sequential relationship between the construction and operation phases.

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This structure enables the analysis to distinguish between phase-specific efficiency and overall system efficiency and to identify inefficiencies that may emerge or be transferred between consecutive phases. Accordingly, the proposed framework provides more detailed diagnostic information than a conventional single-stage DEA model, in which internal efficiency differences may remain concealed within an aggregate efficiency score.

Fourth, the study provides a quantitative mechanism for assessing the long-term efficiency consequences of management interventions. The proposed framework is not limited to ranking existing alternatives. Instead, it enables alternative interventions to be simulated over time and their resulting efficiency trajectories to be evaluated. For example, the findings indicate that increasing investment in sustainable supplier development can improve the future performance of the system. The framework therefore establishes an analytical connection among management intervention, dynamic system response, and resulting efficiency, providing a quantitative basis for prioritizing corrective actions and long-term improvement strategies.

Fifth, the study provides an empirically grounded framework adapted to the Iranian construction context. The institutional, managerial, financial, and supply-chain conditions of emerging construction markets may differ substantially from those of developed economies. Consequently, analytical frameworks developed in other contexts may require contextual adaptation before they can be effectively applied to the Iranian construction industry. By using empirical information from major construction projects in Tehran, this study demonstrates the applicability of the integrated SD–NDEA framework to a complex construction environment in an emerging economy. This contextual contribution does not imply that the reported efficiency values are universally generalizable; rather, it demonstrates how the proposed methodology can be adapted to a specific institutional and industrial context.

Sixth, the study connects efficiency assessment with policy prioritization and managerial decision-making. The proposed framework does not merely provide an overall efficiency score. It enables decision-makers to compare alternative scenarios, examine changes in the efficiency of different stages, and identify interventions with greater potential for improving long-term SPM performance. This capability can support more targeted resource allocation and the selection of management interventions based on their expected system-wide consequences.

Overall, the central contribution of this study is the development of a forward-looking and integrated SD–NDEA framework that connects dynamic system behavior, management policy experimentation, and multi-stage efficiency assessment. Within this framework, SD provides the capability to represent causal relationships, feedback mechanisms, and the temporal effects of management interventions, whereas NDEA provides a structured mechanism for evaluating the relative efficiency of the resulting scenarios and diagnosing inefficiencies across sequential stages. The proposed framework therefore complements conventional SD and DEA approaches by enabling the simultaneous examination of how the system evolves over time and how efficiently the resulting system configurations perform.

From a theoretical perspective, the study contributes by connecting dynamic simulation and network-based efficiency assessment, thereby linking two analytical perspectives that are commonly treated separately. From a methodological perspective, it provides a structured procedure for transforming simulated policy scenarios into comparable decision-making units within an NDEA framework. From a practical perspective, the framework provides construction managers and policymakers with quantitative support for comparing sustainable procurement policies, diagnosing stage-specific inefficiencies, prioritizing corrective interventions, and improving long-term resource-allocation decisions.

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6 Conclusion

This study developed a forward-looking framework for evaluating SPM performance in construction projects, an area that remains methodologically and practically underdeveloped in developing countries, particularly in urban construction contexts. The findings demonstrate that static performance assessment alone cannot adequately capture the long-term consequences of sustainable procurement policies. By integrating SD simulation with NDEA, the proposed framework enables the simultaneous examination of future system behavior, comparison of alternative policy scenarios, and identification of inefficiencies across sequential project stages. The empirical application to construction projects in Tehran further demonstrated that the framework can provide not only efficiency estimates but also diagnostic information for targeting corrective actions.

Theoretical implications. The principal theoretical implication of this study is the development of an integrated perspective for examining sustainable procurement performance by shifting efficiency assessment from a static and retrospective task toward a dynamic and forward-looking process. Rather than evaluating performance solely on the basis of observed conditions, the proposed framework links policy interventions, temporal system behavior, and the efficiency of sequential project stages. In this respect, the study strengthens the conceptual connection between the System Dynamics and network-efficiency literatures and demonstrates the potential of their integration for analyzing complex, multi-stage sustainable procurement systems.

Practical implications. From a managerial perspective, the findings indicate that sustainable procurement policies should not be evaluated solely according to their initial costs or current performance. Scenario-based simulation enables project managers to examine the potential consequences of alternative interventions before implementation. Furthermore, the NDEA component provides stage-specific diagnostic information, allowing decision-makers to identify the sources of inefficiency and direct resources toward areas with greater improvement potential. The proposed framework can therefore support sustainable supplier development, procurement-process improvement, supply-chain coordination, and the design of targeted support policies.

Managerial and policy recommendations. Based on the findings, construction organizations and policymakers are encouraged to evaluate sustainable procurement interventions over a sufficiently long planning horizon rather than focusing exclusively on short-term outcomes. Priority should be given to developing sustainable supplier-support programs, providing appropriate economic incentives for sustainable procurement, strengthening supplier-performance evaluation systems, and improving information sharing among supply-chain stakeholders. In addition, scenario-based assessment before committing substantial resources to a policy intervention can reduce decision-making risks and facilitate more targeted resource allocation.

Limitations. This study has several limitations. First, the empirical validation was based on selected construction projects in Tehran; therefore, the generalizability of the findings to other cities, regions, or project types should be considered with caution. Second, the SD simulation results depend on model assumptions, input-data quality, and the policy scenarios defined in the study. Third, NDEA results are sensitive to the selection of inputs, outputs, and stage structures. Changes in these specifications may therefore affect the resulting efficiency estimates. In addition, certain institutional, economic, and behavioral factors that are difficult to quantify may not have been fully represented in the model.

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Future research. Future studies can validate the proposed framework using larger datasets and more diverse construction projects across different cities and countries. The framework can also be extended by incorporating additional economic, environmental, and social indicators together with supply-chain risk and resilience measures. The use of continuously updated real-world data and comparison of SD–NDEA results with alternative forecasting and efficiency-assessment techniques could further strengthen the robustness and generalizability of the framework. Moreover, integrating machine-learning techniques with System Dynamics simulation represents a promising direction for developing more advanced decision-support tools for sustainable procurement management.

Overall, the principal value of the proposed framework lies in moving performance assessment from retrospective measurement toward forward-looking analysis and from simple efficiency ranking toward diagnostic and decision-support capabilities**.** Accordingly, SD–NDEA can serve as a complementary analytical tool for designing, evaluating, and prioritizing sustainable procurement policies in complex and dynamic construction environments.

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