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Reconciling Productivity Growth and Carbon Emission Reduction: A System Dynamics Study on Pathway for High-quality Development of the Construction Industry

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Abstract

This study aims to identify an optimal pathway for achieving high-quality development of the construction industry (HQDCI) by examining how total factor productivity (TFP) improvement and carbon emission (CE) reduction can be advanced synergistically. A system dynamics model integrating TFP and CE was developed, using which the long-term evolution of China's HQDCI was simulated under baseline, single-factor, and multi-factor scenarios. The results demonstrated that: (1) maintaining the current development mode would prevent the construction industry from achieving significant TFP growth and reaching the carbon peak before 2030; (2) pursuing either greenization or intelligentization alone cannot simultaneously deliver both TFP growth and CE reduction; and (3) the optimal pathway for HQDCI is to prioritize rapid greenization alongside steady intelligentization. This study advances the understanding of the intrinsic mechanisms and long-term evolutionary dynamics of HQDCI when subject to dual TFP and CE constraints and provides a systematic strategy for enhancing productivity while reducing emission.

Keywords: Construction industry; High-quality development; Total factor productivity; Carbon emission; System dynamics.

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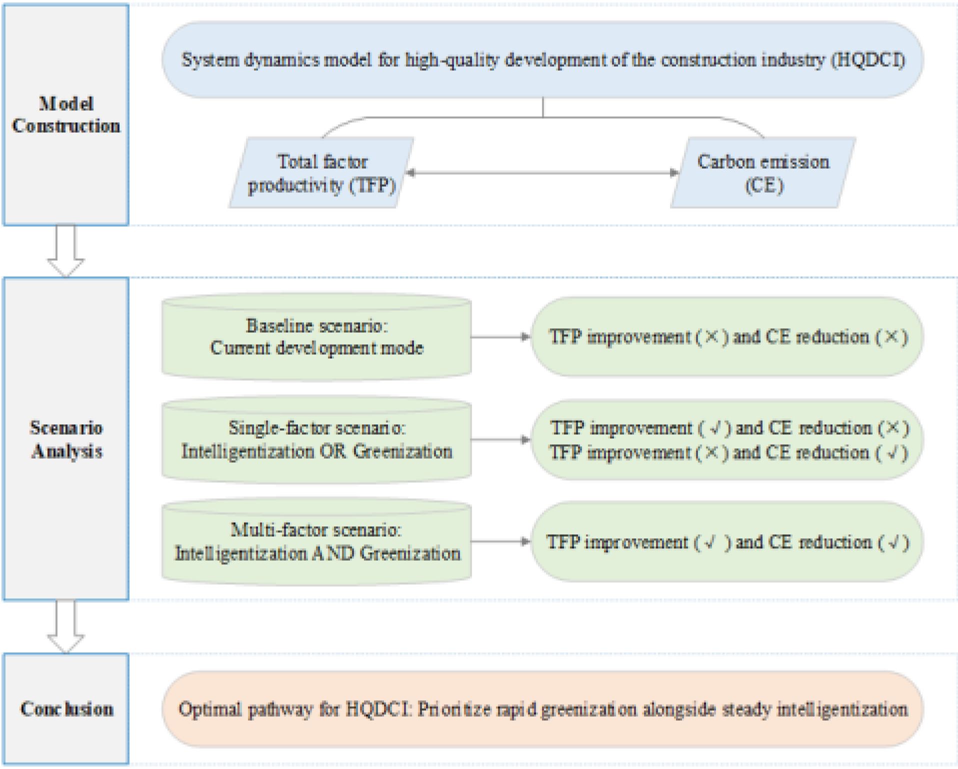
Graphical abstract



1. Introduction

China's economy is transitioning from a phase of high-speed growth to one focused on high-quality development. As a pillar industry of the national economy, the high-quality development of the construction industry (HQDCI) plays a crucial role in supporting this overarching transition. However, the construction industry currently faces multiple challenges, including low production efficiency (Wang *et al.*, 2025), slow adoption of advanced technologies (Liu *et al.*, 2022), a constrained labor supply (You, 2024). Meanwhile, against the backdrop of the escalating urgency and complexity of the global climate crisis (Lei & Xu, 2025), the issue of high carbon emissions in the construction industry remains prominent (Zhang *et al.*, 2024a). These issues significantly hinder the industry's transformation toward a sustainable, high-quality development mode. Therefore, identifying effective pathways for HQDCI is crucial for advancing China's overall economic development quality.

HQDCI represents an integrated mode emphasizing green growth, efficiency, innovation, and sustainability (Song *et al.*, 2022). Achieving this objective requires not only improving productivity but also ensuring that development occurs within environmental constraints. In the construction industry, productivity growth and carbon emission reduction have increasingly become two closely intertwined challenges during the transition toward high-quality development. On the one hand, improving productivity is essential for strengthening industrial competitiveness and sustaining long-term growth. On the other hand, as one of China's major sources of energy consumption and emissions, the construction industry faces growing pressure to contribute to national carbon-peaking and carbon-neutrality goals. Therefore, reconciling productivity growth with low-carbon development has become a critical issue in advancing HQDCI.

To address this challenge, this study focused on productivity growth and low-carbon development. Total factor productivity (TFP), widely viewed as the central indicator of high-quality development, reflects improvements in production efficiency, technological progress, and resource allocation efficiency (Gong & Zhang, 2023). Meanwhile, promoting green and low-carbon development, with substantial carbon emission (CE) reduction as a fundamental constraint, is an essential requirement for achieving high-quality development in the construction industry (Hao *et al.*, 2022). Accordingly, TFP and CE are selected as representative indicators of productivity and low-carbon development, respectively. Therefore, identifying pathways for their coordinated improvement is essential for advancing HQDCI.

However, in the context of high-quality development, existing research tends to examine TFP and CE separately. One strand of literature treats TFP as the primary measure of HQDCI, analyzing it across enterprise, industrial, and regional levels (Liu *et al.*, 2021; Sun *et al.*, 2023; Zhou *et al.*, 2024). Another strand focuses on CE as a critical constraint within the high-quality development framework (Hu *et al.*, 2025; Li *et al.*, 2025; Zhang *et al.*, 2023; Zhu *et al.*, 2025). Although these studies offer valuable insights, they do not systematically investigate the intrinsic relationship and potential conflicts between productivity growth and emission reduction—where, for instance, TFP gains may coincide with rising CE. Accordingly, systematic research that jointly analyzes TFP and CE is needed to identify viable pathways for HQDCI.

Scholars have employed various approaches (e.g., analytic hierarchy process, geographically and temporally weighted regression) to explore pathways for the HQDCI (Li & Ma, 2024; Wang & Cheng, 2024; Zhang & Zhang, 2024). However, these studies rely on static analytical frameworks and fail to adequately incorporate interactions, nonlinear relationships, and dynamic feedback among the factors influencing HQDCI. As a result, the intrinsic mechanisms and long-term evolutionary dynamics of HQDCI remain poorly understood, hindering the identification of its optimal pathway. HQDCI is inherently a dynamic, multi-factor, and continuously evolving process. That is, uncovering its optimal pathway requires analytical methods capable of capturing multi-factor interactions, nonlinearity, and dynamic feedback within complex systems.

System dynamics combined with scenario analysis may be an appropriate method for identifying the optimal pathway for HQDCI. Scenario analysis is a method for assessing and optimizing the long-term effects of interventions by comparing how a system evolves under different future conditions (Zhan *et al.*, 2024). System dynamics serves as a well-suited tool for this purpose (Zhang *et al.*, 2021), as it enables the analysis of complex system structures and factor interactions, handles nonlinear relationships, and supports the dynamic simulation and prediction of system evolution (Ding *et al.*, 2016).

To sum up, this study aims to identify the optimal pathway for HQDCI by developing a system dynamics model integrating TFP and CE and conducting scenario analysis. Through this approach, this study is expected to reveal the underlying mechanisms and long-term evolutionary patterns of HQDCI under the dual constraints of TFP and CE. Furthermore, the identified optimal pathway for HQDCI will offer valuable insights to support long-term industry planning and policy formulation.

2. Methodology

2.1. *Model construction*

2.1.1. System boundaries

This study examined the HQDCI in China, using TFP and CE as its core indicators. The analysis covers mainland China spatially and extends from 2010 to 2035 temporally. Owing to data availability, 2010–2022 was designated as the investigation period and 2023–2035 as the experimental period, with a simulation time step of one year.

To systematically analyze the dynamic evolution of HQDCI, a system dynamics model comprising five subsystems was developed. First, following the Solow model (Solow, 1957), investment, labor, and output subsystems were established to capture the effects of capital input, human input, and economic growth, respectively. Second, given the recognized role of technological progress in driving TFP improvement (Xu & Deng, 2022), a dedicated technology subsystem was included. Third, in response to China's dual-carbon targets and the energy-intensive nature of construction, an environmental subsystem was integrated to incorporate CE constraints into the evaluation framework.

2.1.2. Causal loop diagram

Constructing a causal loop diagram requires identifying key variables and their causal relationships within the system. This study began with a systematic review of HQDCI-related literature to extract critical factors and their linkages across subsystems. To enhance the model's validity, the group model building (GMB) method was then employed to verify and refine these elements.

GMB is a participatory modeling technique that leverages stakeholder expertise to identify factors and feedback mechanisms in complex systems (Li *et al.*, 2023). Following the approach of Xu *et al.* (2023), an eight-member expert panel was assembled for this study. The members were selected based on the following criteria: (a) at least 10 years of work experience in fields relevant to the construction industry (such as corporate management, government regulation, and industry research); (b) the unit covers the main links of the construction industry value chain (enterprises, governments, industry associations, academic institutions); and (c) practical experience in participating in industry policy consultation or strategic planning. The composition of the panel is summarized in **Table 1**.

Table 1. Basic information of discussion group members

Experts	Position	Gender	Work experience (year)
1	Senior manager in construction enterprises	Male	22
2	Senior manager in construction enterprises	Male	19
3	Government regulators	Male	31
4	Government regulators	Female	12
5	Experts from industry associations	Male	16
6	Experts from industry associations	Male	17
7	University professor	Male	26
8	University professor	Female	18

All experts participated in their individual capacities, and no single organization or project affiliation dominated the consultation process. To ensure the independence and impartiality of the expert input, the recruitment strategy deliberately sought diversity across institutional backgrounds—including academic researchers, industry practitioners, and policy-related professionals—rather than relying on a single source or stakeholder group. This multi-source approach minimized the risk that the judgement of any one participant would be influenced by financial or institutional incentives tied to specific policy outcomes or technology preferences.

To ensure transparency in variable selection, explicit inclusion and exclusion criteria were established prior to the group discussion. Variables were considered for inclusion if they met following criteria: (a) repeatedly identified as a core influencing factor in the literature on HQDCI; (b) supported by accessible statistical data; and (c) theoretically linked to either TFP or CE. Variables were excluded if they: (a) could not be quantified or lacked reliable data; (b) exhibited high overlap with already included variables; or (c) fell outside the system boundary of this study.

Informed by the expert panel, key variables and their causal links were identified through a structured four-step process:

Step 1: Introduction and task briefing

An offline kick-off meeting was held, in which the facilitator (the author) presented the research aims, introduced the system dynamics methodology, outlined the workshop procedure, and described the expected model outputs. The workshop lasted 2.5 hours in total, with the following time allocation: 60 minutes for variables screening and confirmation, 60 minutes for causal relationships identification, and 30 minutes for consensus confirmation.

Step 2: Screening and confirming subsystem variables

Participants were divided into two heterogeneous groups. Each group independently discussed and refined a preliminary list of factors drawn from the literature, focusing on the identification of key determinants influencing the HQDCI. The groups subsequently presented their selections. The facilitator then guided a plenary discussion to evaluate the representativeness and independence of the proposed variables, merging those with high overlap or strong correlation. This process yielded a finalized set of variables across five subsystems, as presented in **Table 2**.

Table 2. Subsystem factors

Subsystem	Factors	References
Investment	Real estate development investment	(Kong *et al.*, 2016; Okunevičiūtė Neverauskienė *et al.*, 2025)
	Fixed-asset investment of construction enterprises	(Shi *et al.*, 2023; Wang *et al.*, 2022a)
	Current-asset investment of construction enterprises	(Al-Kasasbeh *et al.*, 2021; Jin *et al.*, 2021)
Labor	Number of migrant workers	(Cao *et al.*, 2022; Ye *et al.*, 2019)
	Number of employees in the construction industry	(Assaad & El-adaway, 2021; Ma *et al.*, 2022)
	Education level per capita among employees in the construction industry	(Bambi & Pea-Assounga, 2025; Meng & Wen, 2024)
	Labor productivity in the construction industry	(Lu *et al.*, 2021; Zhang & Zhang, 2024)
Output	Building construction area	(Wu *et al.*, 2023; Zhang *et al.*, 2024b)
	Completed floor area of buildings	(Berardi, 2017; Wu *et al.*, 2019)
	Demolition floor area of buildings	(Sizirici *et al.*, 2021; Zhao *et al.*, 2023)
	Stock of building area	(Berardi, 2017; Wu *et al.*, 2019)
	Total output value of the construction industry	(Wang *et al.*, 2020a; Zhang & Zhang, 2024)
	Total profit of construction enterprises	(Rajala *et al.*, 2022; Yadav *et al.*, 2022)
	Per capita profit in the construction industry	(Meiryani *et al.*, 2020; Xiang *et al.*, 2024)
Technology	Robot substitution rate	(Ma *et al.*, 2022; Yang *et al.*, 2019)
	Own machinery and equipment at the end of the year	(Zhang *et al.*, 2024c; Zhu *et al.*, 2022a)
	R&D investment	(Bambi & Pea-Assounga, 2025; Lei *et al.*, 2025)
	TFP	(Wang *et al.*, 2020b; Zhu *et al.*, 2022a)
Environment	Energy consumption	(Du *et al.*, 2019; Wu *et al.*, 2019)
	Building materials consumption	(Chen *et al.*, 2022; Zhang *et al.*, 2024b)
	Energy consumption from the building operation	(Du *et al.*, 2019; Zhang *et al.*, 2024b)
	Carbon emissions from building demolition	(Zhao *et al.*, 2023; Zhu *et al.*, 2022b)
	Carbon emissions from the construction industry	(Du *et al.*, 2019; Wang *et al.*, 2022b)
	Carbon emissions per unit of output value in the construction industry	(Du *et al.*, 2019; Gan *et al.*, 2022)

Step 3: Identifying causal relationships

Each group analyzed the causal links among the agreed-upon variables, guided by several core questions: "What factors influence TFP?" and "What factors influence CE?" The groups identified both positive and negative causal relationships between variables, and further discussed whether these connections form reinforcing loops or balancing loops, and how these feedback shape the dynamic evolution of HQDCI. The two groups subsequently presented their diagrams to each other, engaging in focused debate where their interpretations differed. Throughout this process, the facilitator documented the independent views of both groups and facilitated a plenary discussion after each group's presentation. For causal relationships where disagreements persisted, the following resolution procedure was applied: (a) members holding differing views were invited to present their justifications; (b) the facilitator guided all members to discuss based on literature evidence and industry experience; and (c) if disagreement remained, the causal relationship was included on the basis of majority agreement. Through several rounds of discussion, a consensus was reached on the main feedback loops in the system.

Step 4: Finalizing the causal loop diagram

Using the consensus feedback structure, the author constructed a causal loop diagram in Vensim and circulated it to all participants for feedback. After incorporating suggestions and refinements, the diagram was reviewed and unanimously approved by the expert panel. The final version is presented in **Figure 1**.

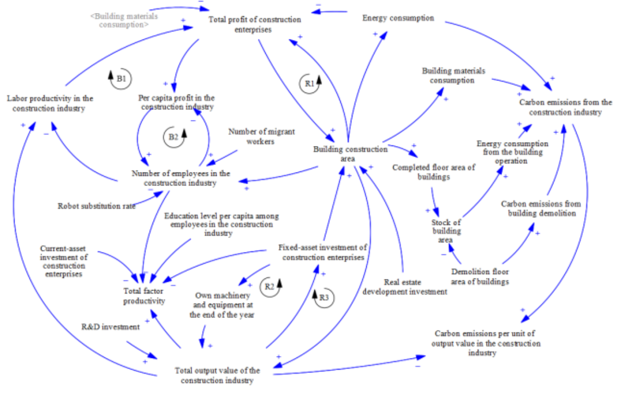


Figure 1. Causal loop diagram.

The causal loop diagram identifies five major feedback loops, consisting of three reinforcing loops (R1–R3) and two balancing loops (B1–B2), which together shape the interactions within the HQDCI.

R1: Total profit serves as a key source of funding for corporate expansion (Yadav *et al.*, 2022). Higher profits strengthen a firm's ability to expand operations, increasing the building construction area (Rajala *et al.*, 2022). This expansion generates economies of scale, which further raise total profit (Wu *et al.*, 2023).

R2: Increased fixed-asset investment drives technological upgrading (Lu *et al.*, 2021), reflected in improved production capacity of machinery and equipment (Shehadeh *et al.*, 2021). This raises the industry's total output value, which signals market vitality and stimulates further fixed-asset investment (Wang *et al.*, 2020a).

R3: Sustained economic growth and market demand boost fixed-asset investment, expanding construction scale and increasing total output value (Hung *et al.*, 2019). The rise in output value in turn encourages additional fixed-asset investment (Wang *et al.*, 2020a).

B1: Labor productivity (total output value per employee) influences total profit (Xu *et al.*, 2022). Higher productivity raises profit and per-capita profit, attracting more employees (Serrasqueiro *et al.*, 2023). However, with output held constant, a larger workforce reduces labor productivity.

B2: Per-capita profit (total profit divided by employee count) is negatively related to industry employment. A decline in per-capita profit weakens firms' expansion capacity, reducing demand for new labor and thus lowering employment (Xiang *et al.*, 2024).

TFP is shaped by three primary dimensions: capital input, labor input, and economic output. Capital input includes both current and fixed asset investment of construction enterprises. Labor input consists of the number of employees and their average education level within the industry. Economic output is represented by the total output value of construction.

CE is driven by four main sources: consumption of building materials, energy use during construction (Zhang *et al.*, 2024b), operational energy consumption of buildings (Wu *et al.*, 2019), and emission generated from building demolition (Du *et al.*, 2019).

2.1.3. Main equations and stock flow diagram

Based on the causal loop diagram, a stock flow diagram was constructed as shown in **Figure 2**.

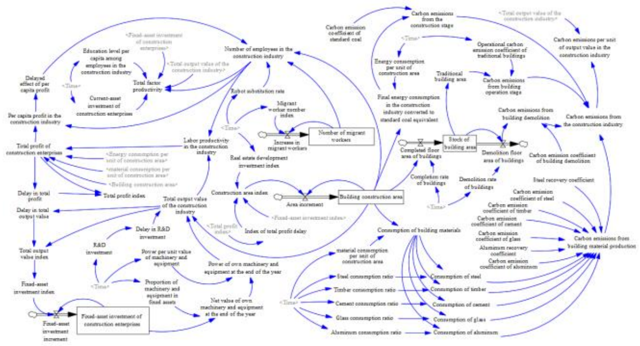


Figure 2. Stock flow diagram.

Equations were established to define relationships among variables, thereby quantifying interactions between system factors. For variables lacking explicit functional relationships, linear multiple regression equations were developed using SPSSPRO software to construct functional relationships (Qayoom & H.W. Hadikusumo, 2019). Parameters and equations for main variables are presented in **Table 3.**

2.2. *Model test*

2.2.1. Structure test

Structure test has been used to assess the consistency of the model structure with the actual situation (Tu *et al.*, 2023). In this study, the model was validated by reviewing the relevant literature, and test result confirmed its structure was logical and consistent with the actual situation. Thus, the model passed the structure test.

2.2.2. Boundary-adequacy test

Boundary-adequacy test aims to ensure that the model includes all key variables relevant to the study objectives (Zhang *et al.*, 2021). In this study, the model highlights the main variables and has a clear system boundary. Therefore, the model passed the boundary-adequacy test.

Table 3. Parameters and equations for main variables.

Variable	Equation	Unit	R^2
Fixed-asset investment of construction enterprises	Fixed-asset investment of construction enterprises=INTEG (Fixed-asset investment increment,12847.8)	10^8CNY	-
Fixed-asset investment index	Fixed-asset investment index=0.53+0.465*Total output value index	-	0.614
Number of migrant workers	Number of migrant workers=INTEG (Increase in migrant workers,24223)	10^4person	-
Labor productivity in the construction industry	Labor productivity in the construction industry=Total output value of the construction industry/Number of employees in the construction industry	10^8CNY/10^4person	-
Total output value of the construction industry	Total output value of the construction industry=EXP (-1.202-0.212*LN(Power of own machinery and equipment at the end of the year)+0.264*LN(Delay in R&D investment)+1.041*LN(Building construction area))	10^8CNY	0.990
Total profit of construction enterprises	Total profit of construction enterprises=EXP(3.342+0.007* Labor productivity in the construction industry +0.423*LN(Building construction area)-0.015*Energy consumption per unit of construction area*10000-0.794* material consumption per unit of construction area)	10^8CNY	0.968
Net value of own machinery and equipment at the end of the year	Net value of own machinery and equipment at the end of the year=Fixed-asset investment of construction enterprises* Proportion of machinery and equipment in fixed assets	10^8CNY	-
TFP	TFP=LN(Total output value of the construction industry)-0.661*LN(Fixed-asset investment of construction enterprises)-0.359*LN(Current-asset investment of construction enterprises)-0.454*LN(Number of employees in the construction industry*Education level per capita among employees in the construction industry/10000)	-	0.989
Carbon emissions from the construction industry	Carbon emissions from the construction industry=Carbon emissions from building material production+Carbon emissions from the construction stage+Carbon emissions from building operation stage+Carbon emissions from building demolition	10^4t	-

2.2.3. Historicity test

Historicity test assesses model validity by comparing simulation results with historical data through relative error. The relative error is calculated according to Equation (1).

$$D=\frac{X_t^{'}-X_t}{X_t}\times 100\% \tag{1}$$

In the equation, $X_t{'}$ denotes the simulated value of the model at time *t*, X_t represents the historical actual value at time *t*, and *D* indicates the deviation level.

The relative error range of the primary variables in this study fell within ±10%, indicating that the simulated values of each variable were largely consistent with historical data (Zhu *et al.*, 2024). Therefore, the model passed the historicity test. **Table 4** reports the historicity test results for representative variables.

2.3. *Scenario design*

This study designed three scenario types: the baseline scenario, single-factor scenario, and multi-factor scenario.

2.3.1. Baseline scenario

In the baseline scenario, the HQDCI system continues under its current development mode, with all parameters held at their present levels. This setup simulates a business-as-usual evolutionary path. The results serve as a reference for evaluating the effects of various interventions in subsequent single-factor and multi-factor scenarios.

2.3.2. Single-factor scenario

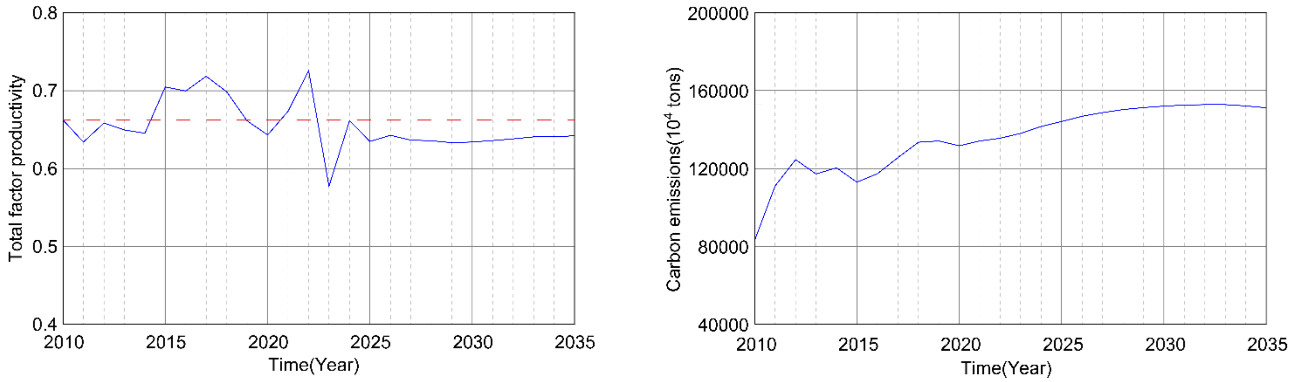
Currently, the construction industry faces challenges such as technological lag and resource dependence (Liu *et al.*, 2022; Wang *et al.*, 2025). To assess how policy priorities could address these issues, this study designs a set of single-factor scenarios along two dimensions: intelligentization and greenization.

To tackle technological lag, an intelligentization-focused scenario was established: the robot substitution rate growth scenario (A1). As China's construction industry faces structural labor shortages and an urgent need to upgrade, robot substitution has taken center stage as the most representative direction of intelligentization in policy and practice.

Table 4 Historicity test results for variables

Year	Fixed-asset investment of construction enterprises (10^8 CNY)			Number of employees in the construction industry (10^4 people)			Total profit of construction enterprises (10^8 CNY)			Building construction area (10^4 square meters)		
	HV	SV	ER	HV	SV	ER	HV	SV	ER	HV	SV	ER
2010	12847.77	12847.80	0.00%	4708.29	4477.07	-4.91%	3409.07	3716.18	9.01%	708024	708024	0.00%
2011	14059.60	14417.00	2.54%	4996.20	4854.70	-2.83%	4168.20	4172.47	0.10%	851828	860612	1.03%
2012	15476.93	15629.30	0.98%	4629.11	5072.72	9.58%	4776.14	4899.12	2.57%	986428	1004200	1.80%
2013	16894.72	16905.70	0.06%	5026.53	5321.63	5.87%	6079.25	5994.55	-1.39%	1132003	1137910	0.52%
2014	17940.31	17796.50	-0.80%	5563.45	5592.09	0.51%	6407.13	6519.30	1.75%	1249826	1236340	-1.08%
2015	18823.20	18646.60	-0.94%	5578.49	5697.52	2.13%	6451.23	6984.61	8.27%	1239718	1284370	3.60%
2016	18979.84	19711.50	3.85%	5743.97	5837.42	1.63%	6986.05	7198.24	3.04%	1264216	1342490	6.19%
2017	19974.40	20385.40	2.06%	6148.46	5929.32	-3.56%	7491.78	7448.50	-0.58%	1318374	1397610	6.01%
2018	21627.60	21219.60	-1.89%	5946.87	6006.83	1.01%	7974.82	7649.48	-4.08%	1371995	1462670	6.61%
2019	20799.80	21701.00	4.33%	6216.15	6089.23	-2.04%	8279.55	7885.07	-4.76%	1441505	1535740	6.54%
2020	21171.09	21865.00	3.28%	6241.40	6071.47	-2.72%	8447.74	8593.80	1.73%	1494754	1580270	5.72%
2021	21941.76	21956.70	0.07%	6193.93	6285.95	1.49%	8470.81	8578.20	1.27%	1575464	1602070	1.69%
2022	23062.26	22781.20	-1.22%	6274.49	6290.30	0.25%	8381.46	9101.32	8.59%	1556364	1639300	5.33%

Note: HV = Historical value; SV = Simulation value; ER = Error.



(a) Total factor productivity
(b) Carbon emissions

Figure 3. Baseline scenario simulation results.

To reduce resource dependency, three greenization-oriented scenarios were formulated: material consumption per unit of construction area reduction (B1), energy consumption per unit of construction area reduction (B2), and operational carbon emission coefficient reduction for traditional buildings (B3). These scenarios focused on measures such as reducing energy and material consumption, covering the main aspects of the greenization transformation of the construction industry.

Each scenario includes three development paces: steady, relatively fast, and rapid. For the intelligentization scenario (A1), the parameter settings are anchored on the documented robot–labor substitution rate in manufacturing as a reference benchmark, given the absence of construction-specific historical data and quantitative policy targets. The average substitution effect in manufacturing is approximately 2.6% (Cheng *et al.,* 2018). Considering the higher technical and economic barriers in construction—such as complex site conditions and fragmented project-based operations—the initial penetration rate is expected to be lower. However, once key technical adaptations are achieved, catch-up growth could accelerate and eventually surpass the manufacturing benchmark. Based on this benchmark and the construction sector's distinct characteristics, the annual growth rates were set at 1% (steady, representing slow initial diffusion), 2% (relatively fast, approaching the manufacturing average), and 3% (rapid, reflecting accelerated catch-up beyond the benchmark).

For the greenization scenarios (B1–B3), the rates were calibrated using historical data from China's construction industry (2010–2022). The annual decrease in material consumption per unit floor area averaged 1.4% and accelerated to 2% after 2013 under green policy incentives; energy consumption per unit floor area declined at a stable rate of approximately 1.5% per year after 2015; and the operational carbon emission coefficient of conventional buildings fell by 2% per year after peaking in 2013. Based on these trends, we set the annual reduction rates at –1% (a conservative baseline), –1.5% (consistent with the sustained energy-efficiency improvement rate), and –2% (matching the historically highest reduction rate, representing a rapid, technology-driven scenario).

2.3.3. Multi-factor scenario

As HQDCI is often shaped by multiple concurrent factors, multi-factor scenarios were designed to capture the reinforcing or balancing effects that emerge from their interactions (Hao *et al.*, 2019). Specifically, the three development paces in the intelligentization dimension (steady, relatively fast, rapid) were combined with the three parallel paces in the greenization dimension, resulting in nine multi-factor scenarios (see **Table 5**).

Table 5. Multi-factor scenario design.

Dimension		Greenization		
		Steady	**Relatively fast**	**Rapid**
Intelligentization	Steady	case1	case2	case3
	Relatively fast	case4	case5	case6
	Rapid	case7	case8	case9

2.4. *Data sources*

This study draws on data from the period 2010–2022, primarily sourced from comprehensive and industry-specific statistical yearbooks published by the National Bureau of Statistics of China. Macro-economic and social-level indicators were obtained from the China Statistical Yearbook. Industry-specific data—covering investment, output, labor, and other dimensions of construction—were extracted systematically from the China Construction Industry Statistical Yearbook. Labor-quality indicators came from the China Labor Statistical Yearbook, while energy-consumption figures were drawn from the China Energy Statistical Yearbook. Data on research and development activities within the construction industry, used to analyze technological innovation inputs, were sourced from the China Science and Technology Statistical Yearbook. The various conversion factors used to calculate carbon emissions are primarily based on the Standard for the Calculation of Carbon Emissions from Buildings, the China Energy Statistical Yearbook and relevant domestic and international industry research. Regarding the handling of missing data, this study employed a grey-model to make supplementary estimates.

3. Results

3.1. *Baseline scenario analysis*

Figure 3 presents the simulation results of the HQDCI system dynamics model under the baseline scenario. As shown in Fig. 3(a), TFP from 2023 to 2035 settles below its 2010 level throughout the simulation period. Fig. 3(b) indicates that CE from the construction industry peaks in 2032. These outcomes imply that, under business-as-usual conditions, the industry fails to achieve meaningful TFP growth and does not reach carbon peak before 2030.

3.2. *Single-factor scenario analysis*

The simulation results of the single-factor scenarios are presented in **Table 6**.

3.2.1. Robot substitution rate growth scenario (A1)

In scenario A1, as the pace of robot substitution accelerates from steady to rapid, the growth rate of TFP rises from 8.14% to 27.99%. However, CE from the construction industry also increases, with its growth rate climbing from 0.49% to 1.83%. Moreover, the carbon peak under all three patterns occurs after 2030. These results indicate that while robot substitution effectively enhances TFP, pursuing it in isolation intensifies the challenge of reducing CE.

3.2.2. Material consumption reduction per unit of construction area scenario (B1)

In scenario B1, the implementation pace intensifies from steady to rapid, the TFP growth rate rises from 0.17% to 0.32%, while the CE reduction rate expands from 4.2% to 7.95%. The CE peak also shifts earlier, moving from 2031 under the steady pattern to 2029 under the rapid pattern. These outcomes indicate that a faster reduction in material consumption per unit of construction area leads to stronger improvements in TFP, deeper cuts in CE, and an earlier attainment of the emission peak.

Table 6. Simulation results of the single-factor scenarios.

Scenario	Development pace	TFP	CE	Peak time of CE
A1	Steady	8.14%	0.49%	2032
	Relatively fast	17.36%	1.09%	2033
	Rapid	27.99%	1.83%	2033
B1	Steady	0.17%	-4.20%	2031
	Relatively fast	0.25%	-6.13%	2030
	Rapid	0.32%	-7.95%	2029
B2	Steady	0.36%	0.35%	2032
	Relatively fast	0.52%	0.51%	2032
	Rapid	0.67%	0.67%	2033
B3	Steady	/	-7.34%	2029
	Relatively fast	/	-10.96%	2028
	Rapid	/	-13.84%	2027

3.2.3. Energy consumption reduction per unit of construction area scenario (B2)

In scenario B2, as the intensity of energy-saving efforts is raised from a steady to a rapid pace, TFP shows a gradual increase, with its growth rate rising from 0.36% to 0.67%. In contrast, CE does not decline but instead grows at rates ranging from 0.35% to 0.67% across the patterns, and the CE peak occurs after 2030 in all cases. These results indicate that merely reducing energy consumption per unit of construction area can support TFP improvement but does not contribute to—and may even hinder—the achievement of CE reduction targets.

3.2.4. Operational carbon emission coefficient reduction of traditional buildings scenario (B3)

Based on the causal relationship shown in Fig. 1 and Fig. 2, the operational carbon emission coefficient of traditional buildings does not directly affect TFP. Thus, scenario B3 focuses exclusively on its impact on construction CE. As presented in **Table 6**, the CE reduction rates under the steady, relatively fast, and rapid growth patterns are 7.34%, 10.96%, and 13.84%, respectively. These results indicate that a faster reduction in the operational carbon emission coefficient leads to a greater decline in CE. Furthermore, the carbon peak occurs before 2030 in all cases, with the earliest peak (2027) achieved under the rapid pattern. These findings suggest that lowering the operational carbon emission coefficient of traditional buildings is the most effective single measure for reducing emission in the construction industry.

3.3. *Multi-factor scenario analysis*

As shown in **Table 7**, TFP in all multi-factor scenarios exceeds the baseline level. When the pace of intelligentization is held constant, TFP rises as greenization accelerates—evident in the sequences case1 < case2 < case3 (steady intelligentization), case4 < case5 < case6 (relatively fast intelligentization), and case7 < case8 < case9 (rapid intelligentization). Conversely, with a fixed pace of greenization, TFP increases as intelligentization accelerates, as seen in case1 < case4 < case7 (steady greenization), case2 < case5 < case8 (relatively fast greenization), and case3 < case6 < case9 (rapid greenization).

Table 7. Simulation results of the multi-factor scenarios.

Case	TFP	CE	Peak time of CE	PEV (10^4 t)	CPE
Case1	8.57%	-10.83%	2028	142167	-6.96%
Case2	8.76%	-16.05%	2026	138682	-9.24%
Case3	8.94%	-20.99%	2026	136034	-10.97%
Case4	17.68%	-10.30%	2028	142407	-6.80%
Case5	17.83%	-15.55%	2027	138790	-9.17%
Case6	17.96%	-20.52%	2026	136134	-10.91%
Case7	28.2%	-9.64%	2028	142666	-6.63%
Case8	28.29%	-14.93%	2027	138964	-9.05%
Case9	28.37%	-19.94%	2026	136238	-10.84%

Note: PEV refers to peak emission volume; CPE refers to change in peak emissions relative to the baseline. The baseline scenario peaks in 2032, with a carbon emission volume of 152800 × 10^4 t.

The highest TFP improvement (28.37% above baseline) occurs in case9, where both intelligentization and greenization develop rapidly. This indicates that simultaneously advancing the two dimensions at a rapid pace is the most effective way to enhance TFP.

As shown in **Table 7**, CE in all multi-factor scenarios is lower than in the baseline scenario. When the pace of intelligentization is held constant, CE declines as greenization accelerates: under steady intelligentization, CE decreases from case1 to case3; under relatively fast intelligentization, CE decreases from case4 to case6; and under rapid intelligentization, CE decreases from case7 to case9. This pattern confirms that faster greenization consistently enhances emission reduction when intelligentization remains unchanged, with the most pronounced effect occurring under rapid greenization. In such scenarios (see **Table 7**), CE peaks as early as 2026—six years ahead of the baseline—aligning with the carbon peak timing projected under deep-reduction pathways (Tan *et al.*, 2018).

When the pace of greenization is held constant, accelerating intelligentization weakens the carbon reduction outcome: under steady greenization, CE rises from case1 to case4 to case7; under relatively fast greenization, CE rises from case2 to case5 to case8; and under rapid greenization, CE rises from case3 to case6 to case9.

Notably, case3—which combines steady intelligentization with rapid greenization—delivers the strongest emission reduction. Here, CE falls by 20.99 % relative to the baseline, with the carbon peak occurring six years earlier, and the peak emission reduction being the largest, at 10.97% (see **Table 7**). Notably, the baseline scenario is projected to peak in 2032 at 152800 × 10^4 t, meaning case3 achieves an absolute peak reduction of approximately 16766 × 10^4 t. Meanwhile, it still maintains a positive improvement in TFP, indicating that substantial emission reduction can be achieved without sacrificing productivity growth. In contrast, although more aggressive intelligentization pathways generate larger TFP gains, their emission-reduction performance is comparatively weaker. Within the background of HQDCI, carbon reduction represents a binding constraint associated with China's carbon peaking and carbon neutrality commitments. Therefore, among the scenarios that achieve positive TFP growth, greater weight is assigned to the pathway that delivers the largest emission reductions and the earliest carbon peak. Therefore, case3 represents the optimal pathway for HQDCI, as it achieves the best trade-off between productivity enhancement and emission reduction through rapid greenization supported by steady, well-paced intelligentization.

3.4. *Sensitivity analysis*

To verify the robustness of the conclusions to key parameter specifications, a sensitivity analysis was conducted by perturbing the annual growth and reduction rates by ±0.05%. This perturbation magnitude reflects the typical year-to-year fluctuation observed in greenization indicators and, for intelligentization, constitutes a conservative deviation that preserves the relative positioning of the three diffusion paces against the manufacturing benchmark.

For the single-factor scenarios, the intelligentization rates (A1) were adjusted downward to 0.95% (steady), 1.95% (relatively fast), 2.95% (rapid) and upward to 1.05% (steady), 2.05% (relatively fast), 3.05% (rapid); the greenization rates (B1–B3) were adjusted downward to –0.95% (steady), –1.45% (relatively fast), –1.95% (rapid) and upward to –1.05% (steady), –1.55% (relatively fast), –2.05% (rapid). The simulation results are reported in **Table 8**. As shown, all scenarios retain their baseline response patterns: faster intelligentization continues to raise both TFP and CE, while faster greenization consistently deepens emission reductions and advances the peak year, with no sign reversal or structural change observed.

Table 8. Sensitivity analysis results of the single-factor scenarios.

Scenario	Development pace	Downward			Upward		
		TFP	CE	PT	TFP	CE	PT
A1	Steady	7.71%	0.46%	2032	8.57%	0.52%	2032
	Relatively fast	16.87%	1.06%	2033	17.85%	1.12%	2033
	Rapid	27.42%	1.79%	2033	28.57%	1.88%	2033
B1	Steady	0.16%	-4%	2031	0.18%	-4.4%	2031
	Relatively fast	0.24%	-5.94%	2030	0.25%	-6.32%	2030
	Rapid	0.31%	-7.78%	2029	0.33%	-8.13%	2029
B2	Steady	0.34%	0.33%	2032	0.38%	0.36%	2032
	Relatively fast	0.51%	0.49%	2032	0.54%	0.53%	2032
	Rapid	0.66%	0.65%	2033	0.69%	0.69%	2033
B3	Steady	/	-6.99%	2029	/	-7.68%	2029
	Relatively fast	/	-10.36%	2028	/	-11.01%	2028
	Rapid	/	-13.53%	2027	/	-14.14%	2027

Note: PT refers to peak time of CE.

For the multi-factor scenarios, sensitivity was assessed under two conditions. First, the greenization rates were held constant at their baseline values while the intelligentization rates were perturbed downward to 0.95% (steady), 1.95% (relatively fast), and 2.95% (rapid), and upward to 1.05% (steady), 2.05% (relatively fast), and

3.05% (rapid). **Table 9** reports the results for this condition. Across all perturbations of intelligentization, Case3 (rapid greenization with steady intelligentization) consistently achieves the lowest CE and the earliest peak, with the CE reduction ranging from 20.97% to 21.01% and the peak emission decline relative to baseline from 10.97% to 10.98%. Second, the intelligentization rates were held constant while the greenization rates were perturbed downward to –0.95% (steady), –1.45% (relatively fast), and –1.95% (rapid), and upward to –1.05% (steady), –1.55% (relatively fast), and –2.05% (rapid). **Table 9** reports the results for this condition. Under both downward and upward perturbations of greenization, Case3 again remains the optimal pathway, with the CE reduction ranging from 20.51% to 21.47% and the peak emission decline from 10.80% to 11.14%. In neither condition does an alternative parameter combination overturn the superiority of Case3.

Taken together, the single-factor and multi-factor sensitivity analyses demonstrate that rapid greenization combined with steady intelligentization (Case3) remains the optimal pathway under all reasonable parameter perturbations, confirming that the core conclusion is robust to parameter specification and is not an incidental result of a particular set of assumed rates.

Table 9. Sensitivity analysis results of the multi-factor scenarios (Greenization pace fixed).

Case	Intelligentization pace downward					Intelligentization pace upward				
	TFP (%)	CE (%)	PT	PEV (10^4 t)	CPE (%)	TFP (%)	CE (%)	PT	PEV (10^4 t)	CPE (%)
Case1	8.15%	-10.85%	2028	142155	-6.97%	9.00%	-10.80%	2028	142178	-6.95%
Case2	8.34%	-16.07%	2026	138677	-9.24%	9.19%	-16.03%	2026	138687	-9.24%
Case3	8.52%	-21.01%	2026	136029	-10.98%	9.36%	-20.97%	2026	136039	-10.97%
Case4	17.20%	-10.33%	2028	142394	-6.81%	18.17%	-10.27%	2028	142419	-6.79%
Case5	17.34%	-15.58%	2027	138782	-9.17%	18.31%	-15.52%	2027	138799	-9.16%
Case6	17.48%	-20.55%	2026	136129	-10.91%	18.44%	-20.5%	2026	136139	-10.90%
Case7	27.63%	-9.67%	2028	142653	-6.64%	28.77%	-9.6%	2028	142680	-6.62%
Case8	27.73%	-14.96%	2027	138955	-9.06%	28.86%	-14.89%	2027	138973	-9.05%
Case9	27.81%	-19.97%	2026	136233	-10.84%	28.94%	-19.91%	2026	136244	-10.84%

Note: PT refers to peak time of CE; PEV refers to peak emission volume; CPE refers to change in peak emissions relative to the baseline.

Table 10. Sensitivity analysis results of the multi-factor scenarios (Intelligentization pace fixed).

Case	Greenization pace downward					Greenization pace upward				
	TFP (%)	CE (%)	PT	PEV (10^4 t)	CPE (%)	TFP (%)	CE (%)	PT	PEV (10^4 t)	CPE (%)
Case1	8.55%	-10.29%	2028	142569	-6.70%	8.59%	-11.36%	2028	141766	-7.22%
Case2	8.74%	-15.54%	2027	138957	-9.06%	8.78%	-16.56%	2026	138416	-9.41%
Case3	8.92%	-20.51%	2026	136297	-10.8%	8.96%	-21.47%	2026	135771	-11.14%
Case4	17.67%	-9.76%	2028	142809	-6.54%	17.70%	-10.84%	2028	142005	-7.06%
Case5	17.81%	-15.04%	2027	139121	-8.95%	17.84%	-16.06%	2026	138517	-9.35%
Case6	17.95%	-20.04%	2026	136397	-10.73%	17.97%	-21.01%	2026	135871	-11.08%
Case7	28.19%	-9.09%	2028	143069	-6.37%	28.21%	-10.18%	2028	142264	-6.90%
Case8	28.28%	-14.41%	2027	139295	-8.84%	28.30%	-15.44%	2027	138634	-9.27%
Case9	28.36%	-19.45%	2026	136502	-10.67%	28.38%	-20.43%	2026	135975	-11.01%

Note: PT refers to peak time of CE; PEV refers to peak emission volume; CPE refers to change in peak emissions relative to the baseline

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4. Discussion

4.1. *Theoretical implications*

This study yields several theoretical implications.

First, by integrating TFP and CE into a unified analytical framework, it offers a more systemic perspective for understanding the mechanisms of HQDCI. Previous research has tended to focus on only one objective—either TFP improvement (Li *et al.*, 2024; Wang & Wu, 2022) or CE reduction (Li *et al.*, 2025; Zhang *et al.*, 2023; Zhu *et al.*, 2025)—without adequately examining the potential synergies and trade-offs between the two. As a result, the intrinsic dynamics of HQDCI have remained unclear, hindering the identification of viable development pathways. To address this gap, the present study developed a system model capable of jointly analyzing TFP and CE and conducted scenario-based simulations. The results reveal that single-minded pursuit of TFP growth can impede CE reduction, while focusing exclusively on CE cuts does not guarantee significant TFP gains, indicating a mutually constraining relationship between the two objectives during HQDCI. By establishing a coupled analytical framework, this research provides a basis for a more integrated understanding of HQDCI mechanisms.

From a scenario-specific viewpoint, prioritizing TFP alone may adversely affect CE targets. For instance, in scenario A1, raising the robot substitution rate improves TFP through process optimization and accelerated production (Li *et al.*, 2022), yet it also increases CE owing to efficiency-induced rebound effects (Wang & Wei, 2020). Thus, TFP growth can coincide with higher emissions. This finding echoes the broader environmental economics literature, which suggests that improvements in economic performance do not automatically translate into environmental benefits and are often shaped by technological pathways and policy interventions (Acemoglu *et al.,* 2012; Stern 2004). Conversely, measures aimed solely at CE reduction—such as lowering material use (scenario B1) or reducing operational carbon coefficients (scenario B3)—often fail to stimulate industry-wide technological progress and therefore have limited impact on TFP (Zhang *et al.*, 2024b). This suggests that narrowly targeting emission reduction may not simultaneously drive substantial productivity improvement.

Second, by accounting for interactions among factors and employing dynamic analytical tools, this study clarifies the evolutionary dynamics of HQDCI. Much of the existing literature relies on static frameworks to examine HQDCI pathways (Li & Ma, 2024; Zhang & Zhang, 2024), with limited attention to how factors interact over time. Consequently, prior work has been unable to capture the dynamic, multi-factor feedback that shapes system behavior or to reliably assess the long-term effects of different interventions. To address this, the present study designed multiple scenarios along the intelligentization and greenization dimensions, building on the interactions and feedback mechanisms identified in the HQDCI system. These scenarios were simulated using a system dynamics model to trace the system's evolution under varying conditions. The results show that TFP increases most under simultaneous rapid intelligentization and greenization (case9), whereas the strongest CE reduction occurs when greenization advances rapidly alongside steady intelligentization (case3). Through this dynamic, scenario-based approach, the research reveals how multi-factor interactions drive the long-term evolution of HQDCI.

Specifically, the largest improvement in TFP observed in case9 may be mainly attributed to accelerated advancement of intelligentization (Xu & Song, 2025), while greenization supports productivity through resource efficiency. However, the scaling effect of rapid intelligentization also raises resource and energy consumption (Lei & Kocoglu, 2025; Yang & Li, 2017), partly offsetting the emission-reduction benefits of greenization. This finding aligns with the directed technical change perspective, which emphasizes that the environmental consequences of technological progress depend on the direction of innovation. Technological advancement focused primarily on productivity enhancement does not necessarily lead to lower emissions unless it is accompanied by sufficient green-oriented innovation (Acemoglu *et al.*, 2012). Similarly, Aghion *et al.* (2016) argues that sustainable green growth depends not only on the pace of technological progress but also on whether innovation is directed toward environmentally sustainable development. By contrast, case3 achieves optimal CE reduction by emphasizing green building materials and lower construction energy use (Li *et al.*, 2021). Here, moderate intelligentization bolsters efficiency without inducing large-scale resource expansion, allowing greenization to deliver sustained emission cuts.

These multi-factor simulations illustrate that accelerating only one dimension can enhance one objective while undermining another, due to the feedback and trade-offs embedded in the system. Hence, identifying robust HQDCI pathways requires a systemic, multi-objective perspective that explicitly accounts for factor interactions and dynamic mechanisms.

4.2. *Practical implications*

This study reveals that if China's construction industry continues its current development mode, achieving high-quality development will remain out of reach. Moreover, a development mode emphasizing only greenization or intelligentization cannot simultaneously fulfill the dual objectives of substantial TFP growth and CE reduction. The optimal pathway for HQDCI is to prioritize rapid greenization alongside steady intelligentization.

The scenario analysis suggests that a balanced pathway combining rapid greenization with moderate intelligentization provides the most favorable trade-off between productivity improvement and emission reduction. Policy efforts should place greater emphasis on accelerating greenization, as it contributes directly to emission reduction while supporting long-term high-quality development. To accelerate greenization, this industry should promote green materials, enhance material recycling, adopt refined management, and optimize construction techniques—measures that reduce emission from material production and construction phases. However, the deployment of green materials and energy-efficient technologies often involves substantial upfront investment costs. Therefore, appropriate policy support, such as financial incentives, subsidies, or carbon-pricing mechanisms, may be necessary to facilitate their large-scale adoption. Governments and the sector should also strengthen operational-phase efficiency by raising building energy standards, retrofitting existing stock, and promoting low-carbon awareness.

At the same time, intelligentization should be advanced in a gradual and targeted manner. While rapid intelligentization can substantially improve productivity, the simulation results indicate that excessive expansion of intelligentization production capacity may partially offset emission-reduction benefits through increased resource and energy demand. Therefore, intelligentization technologies should be deployed strategically to improve construction accuracy, reduce material waste, and optimize energy management, thereby supporting both productivity growth and environmental performance. Policy guidance should ensure that the promotion of intelligentization technologies is coordinated with resource and environmental carrying capacity, avoiding unchecked capacity expansion that could undermine the emission reduction gains achieved through greenization. Moreover, the advancement of intelligent construction requires parallel improvements in digital infrastructure and workforce capabilities. Given the substantial regional disparities in economic development and technological readiness, policy measures should be tailored to local conditions rather than adopting a uniform implementation approach.

4.3. *Limitations and future work*

While this study offers important insights, several limitations should be acknowledged. First, this study simulated a limited number of scenarios, and future research could extend the scenario design to include a broader range of policy variables and development pathways. Second, this study relied primarily on industry-level macro data, and future research could incorporate firm-level panel data to better reflect micro-level variations across enterprises. Third, this study's nationally aggregated findings may not fully capture regional variations due to China's geographical and economic disparities, and future research could draw on regional data to build differentiated modes for more localized guidance. In addition, several extensions could further enhance the analytical framework. Future research could adopt standard multi-criteria decision-making techniques to evaluate alternative development pathways under different policy preferences. Incorporating economic cost variables and implementation constraints into the model would also enable quantitative cost - benefit assessment of intelligentization and greenization measures. Finally, extending the current sector-level framework to include cross-sectoral interactions and broader macroeconomic feedback mechanisms would allow for a more comprehensive evaluation of the economy-wide impacts of the construction industry's transition toward intelligentization and greenization.

5. Conclusions

To explore the optimal pathway for HQDCI under the dual constraints of TFP growth and CE reduction, this study developed a system dynamics model that integrates TFP and CE. Scenario simulation results indicated that continuing the current development mode would prevent China's construction industry from achieving significant TFP growth and reaching the carbon peak target before 2030. Moreover, a development mode focusing solely on either greenization or intelligentization is insufficient to simultaneously advance both objectives. The optimal pathway for HQDCI is to prioritize rapid greenization alongside steady intelligentization.

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