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Enhancing Organizational and Technological Structures in Construction via a Mixed Framework Validated Through Delphi and NSGA-II

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ABSTRACT

The construction industry faces persistent challenges in coordination, scheduling, and cost control, particularly in environments with low digital maturity. This study proposes an integrated digital-organizational framework linking organizational, technological, and financial subsystems through digital transformation and data-driven optimization. A mixed analytical approach—combining survey diagnostics, Delphi-based expert validation, and NSGA-II multi-objective optimization—was applied to enhance project structures. Four key performance indicators were analyzed: Digital Readiness Score (DRS), Return on Investment (ROI), Cost Growth (CG), and Coordination Delay Index (CDI). Validation across twelve simulated projects and one real case study at TEPLOSTROY (Russia) demonstrated measurable gains: 17% cost reduction, 24% shorter duration, and 40% productivity improvement. Deviations between simulated and field results ranged from 3.9% to 7.4%, confirming predictive reliability. The framework provides a replicable, data-driven basis for improving efficiency, coordination, and decision-making in digitally enabled construction environments.

1. INTRODUCTION

The construction industry continues to face persistent inefficiencies, including fragmented coordination, schedule delays, and cost overruns, particularly in contexts with limited digital maturity. Although Building Information Modeling (BIM) and related digital tools have improved visualization and data management, their adoption across the Architecture, Engineering, and Construction (AEC) field remains inconsistent and often disconnected from managerial and financial processes. Recent empirical findings indicate that the use of BIM can significantly enhance cost and schedule accuracy in construction projects [1].

Existing frameworks primarily focus on the technological aspects of digitalization but rarely integrate expert consensus and quantitative performance optimization into a unified structure. As a result, many approaches lack the analytical capacity to translate digital transformation strategies into measurable outcomes related to cost, time, coordination, and readiness. Moreover, advanced performance analytics approaches, such as support vector machine models, have begun to deliver measurable improvements in time and cost metrics [2].

To address this gap, the present study develops and validates an integrated digital–organizational framework that combines survey diagnostics, Delphi-based expert validation, and NSGA-II multi-objective optimization. This mixed framework links organizational, technological, and financial subsystems to enhance coordination, efficiency, and investment performance in construction projects. Ultimately, it offers a data-driven and replicable pathway toward sustainable digital transformation in the construction sector.

2. LITERATURE REVIEW

2.1 BIM maturity and digital readiness gaps

Recent studies in the AEC sector emphasize performance-based digital transformation, linking BIM Level 3 maturity (aligned with ISO 19650) to up to 50% faster delivery and measurable productivity gains [3]. Similar benefits are also evident in healthcare, where BIM enhances coordination and compliance [4], reflecting a global shift toward lifecycle-driven collaboration [5].

Yet, despite advances such as AI-assisted clash detection [6] and cloud BIM [7], most frameworks still inadequately assess organizational readiness. Many remain conceptual or overly technical, lacking attention to agility, workforce capability, and financial planning [8], and rarely provide empirical validation [9].

Recent studies, therefore, call for holistic, quantifiable readiness indices incorporating leadership commitment, investment capacity, and measurable ROI [10] to support context-sensitive digital transformation strategies across varied organizations.

2.2 Expert-based approaches and the role of the Delphi method

To address the limitations of traditional diagnostic models, recent studies have increasingly applied expert-based methods—particularly the Delphi technique—to examine the multifaceted challenges of construction digitalization [11]. Through iterative expert consensus, the method refines priorities and produces actionable strategies.

Notable applications include identifying generative-AI use cases linked to real project performance [12] and shaping national BIM strategies, investment assessments, and regional maturity benchmarks [13].

This shift reflects a move from static checklists toward adaptive frameworks integrating expert judgment with quantitative performance data, enabling robust and context-specific digital transformation models.

2.3 Contribution of this study

This study contributes to the growing body of digital transformation research by introducing a multidimensional digital-organizational framework that unites technological, organizational, and methodological dimensions, highlighting novel practices and solutions supported by BIM and Revit applications in recent AEC studies [14]:

(1) BIM Maturity Assessment, to evaluate organizational capability levels in line with international standards and industry best practices.
(2) Algorithmic Performance Modeling, which applies multi-objective optimization to interlink digital readiness, cost efficiency, coordination improvement, and ROI.
(3) Delphi-Based Expert Validation, ensuring methodological rigor and practical applicability through iterative expert consensus.

By embedding predictive simulation and real-world implementation within the same research cycle, the framework closes the gap between digital ambition and operational execution. In doing so, it provides a structured, scalable, and evidence-based pathway for digital transformation in construction, reinforcing earlier models of BIM maturity [15] and BIM-integrated optimization frameworks [16].

3. OBJECTIVES OF THE STUDY

The overarching objective of this research is to develop and validate a comprehensive digital–organizational transformation framework for construction projects, emphasizing improvements in coordination, performance, and cost efficiency through BIM-enabled processes and multi-objective optimization.

The study pursues the following specific objectives:

(1) Assess digital readiness in construction organizations using novel quantitative equations that capture human resource capability, technological infrastructure, and process integration.
(2) Identify and validate critical Key Performance Indicators (KPIs)-namely Digital Readiness Score (DRS), Return on Investment (ROI), Cost Growth (CG), and Coordination Delay Index (CDI)-through Delphi-based expert consensus.
(3) Design and implement a computational optimization model (NSGA-II) to achieve balanced improvements across multiple performance metrics in a Pareto-optimal manner.
(4) Evaluate predictive accuracy and practical robustness by comparing simulation outcomes with real-world project applications.

4. METHODOLOGY

4.1 Research design

This study employs a longitudinal mixed-methods design, integrating quantitative modeling with qualitative expert validation. The research framework was structured across three interconnected phases: (i) an exploratory survey to identify readiness and coordination gaps, (ii) a Delphi-based expert consensus to refine and validate transformation factors, and (iii) application and validation [10].

4.2 Exploratory survey

An exploratory survey was conducted with 94 participants representing contractors, consultants, site engineers, and public officials. It assessed readiness across organizational, technological, and financial domains for BIM and digital transformation.

The analysis employed a combination of quantitative and qualitative techniques: Likert-scale items measured readiness, while open-ended responses identified obstacles and enablers. Root Cause, Pareto, and Fishbone analyses, along with RI%, ensured methodological depth and triangulation.

Of 47 challenges identified, 36 were analyzed and consolidated into 25 key obstacles—organizational (9), technological (10), and financial (6)—representing 80% of cumulative impact and validating the Pareto Principle.

Findings emphasized stronger governance, digital interoperability, and capacity-building as essential for improved coordination and performance. These variables formed the input for the Delphi consensus process.

4.3 Delphi study

4.3.1 Expert panel composition

The Delphi process engaged 18 experts from Iraq and Russia, representing diverse roles across the construction sector (Table 1). This composition ensured inclusion of strategic, managerial, and operational perspectives, enhancing methodological balance and contextual validity.

Table 1. Delphi experts by country and stakeholder category

Country	No. of Experts	Stakeholder Group
Russia	3	General Contractors
Iraq, Russia	3	Engineering Consultants
Iraq, Russia	4	Resident Engineers
Iraq	2	Public Executives
Russia	2	Specialized Subcontractors
Iraq, Russia	2	Private Beneficiaries
Iraq	2	Public Beneficiaries

The panel's diversity strengthened the process by integrating qualitative insights with quantitative analysis, improving the reliability of factor validation and refinement of transformation indicators.

Evaluation occurred over two iterative rounds using the Relative Importance Index (RII), Kendall's W, and the Kruskal–Wallis test, combined with expert feedback to ensure robust empirical validation of key transformation factors.

4.3.2 Delphi process flow - Round I

In the first Delphi round, experts evaluated the preliminary factors derived from the exploratory survey through quantitative ratings and qualitative feedback. The aim was to refine and consolidate findings across organizational, technological, and financial domains.

The analysis produced revised factors reflecting both consensus and domain relevance, which served as the foundation for Round II. However, the achieved consensus was insufficient for practical implementation, prompting a second round to strengthen alignment and ensure methodological validity.

4.3.3 Delphi process flow - Round II

The second round of the Delphi process was structured to validate and refine the consolidated factors emerging from the first round. Experts re-assessed the proposed variables using the same hybrid approach, combining quantitative agreement metrics with qualitative commentary to enhance precision.

This iterative evaluation yielded a final set of 16 validated sub-variables. These were systematically categorized under four principal KPIs, which formed the analytical core of the subsequent simulation and optimization phases:

- Digital Readiness Score (DRS);
- Return on Investment (ROI);
- Cost Growth (CG);
- Coordination Delay Index (CDI).

The convergence of expert opinion in this round signaled a sufficient level of consensus for empirical modeling and multi-dimensional optimization.

4.4 Application and validation

The framework was validated through three stages to assess its reliability and practical value:

(1) Historical Simulations: Twelve previously completed projects (2003–2019) were digitally simulated to establish empirical benchmarks for cost, schedule, and coordination.
(2) Comparative Modeling: A 29-story residential project was modeled under two configurations: one using a traditional structure and the other applying the proposed digital-organizational model. This comparison helped evaluate the expected performance improvements.
(3) Field Implementation: The same residential project was subsequently executed (2022–2025) using the proposed framework, allowing direct comparison between simulation forecasts and real-world outcomes.

Detailed numerical outcomes from these stages are presented in Section 5.

4.5 Digital readiness and performance assessment model

Prior to framework implementation, the company's digital readiness was evaluated using a matrix model developed by the researcher, focusing on four factors: employee training, digital infrastructure, BIM adoption, and staff digital skills.

Based on the assessment, two strategic actions were implemented:

(1) targeted training to strengthen BIM and digital competencies.
(2) recruitment of BIM and digital transformation experts to address skill gaps.

These actions enhanced readiness and ensured smoother framework adoption.

4.6 Mathematical modeling formulations

To evaluate digital transformation impacts and support decision-making, a set of mathematical models was formulated to quantify performance and assess cost–benefit relationships:

4.6.1 Total transformation value (TV_t)

Estimates the maximum benefit achievable from human resources under ideal digital integration:

$$TV_t = Lc \times (S \times 3) + Mc \times (S \times 4.5) + Hc \times (S \times 6) \tag{1}$$

where,

- *Lc, Mc, Hc*: Number of employees with low, medium, and high digital competence;
- *S*: Unit investment per competence level;
- Multipliers (*3, 4.5, 6*): Estimated productivity and onboarding costs.

4.6.2 Partial transformation value (TV_p)

Represents the realistically achievable portion of TV during the early implementation stage:

$$TV_p = TV_t \times 50\% \tag{2}$$

This accounts for learning curves, resistance to change, and training absorption rates.

4.6.3 ROI

Estimates of net economic gain relative to total investment:

$$ROI = \frac{Benefit - Investment}{Investment} \tag{3}$$

where,

- *Benefit*: Represented by (TVp);
- *Investment*: Total expenditure of software, training, and implementation;
- Positive ROI indicates value creation, while negative ROI reflects inefficiency.

4.6.4 CG over time

Models cost escalation due to delays or inefficiencies:

$$C_i + 1 = C_i \times (1 + r) \tag{4}$$

where,

- C_i: Project cost at time step (i);
- *r*: Escalation rate (empirical or assumed);

This model predicts how delays or inefficiencies compound costs over time.

4.6.5 DRS

Measures the organization's overall capacity for digital adoption:

$$DRS = f(x_1, x_2, x_3, x_4) \tag{5}$$

where,

- x_1: Proportion of digitally skilled staff;
- x_2: Average training program duration;
- x_3: Investment in digital infrastructure;
- x_4: Degree of BIM integration.

The four DRS variables (x_1–x_4) represent aggregated dimensions synthesized from 28 validated factors identified through survey and Delphi analyses. Each variable group interrelates human, technological, organizational, and financial indicators, enabling the model to convert complex readiness data into a measurable composite index that accurately reflects an organization's overall capacity for digital transformation.

4.7 NSGA-II multi-objective optimization

To balance multiple project objectives, the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) was employed due to its efficiency in handling nonlinear and conflicting goals in construction management. Unlike traditional optimization methods such as GA or MOPSO, NSGA-II employs non-dominated sorting and crowding-distance mechanisms that resolve trade-offs while maintaining diversity on the Pareto front, making it ideal for complex, multi-dimensional decision environments [17].

The model integrates four KPIs—DRS, ROI, CG, and CDI—into a unified matrix of sixteen sub-variables (d_1–d_4, r_1–r_4, c_1–c_4, i_1–i_4), as expressed in Eq. (6):

$$\begin{bmatrix} DRS \\ ROI \\ CG \\ CDI \end{bmatrix} = \begin{bmatrix} d1 & r1 & c1 & i1 \\ d2 & r2 & c2 & i2 \\ d3 & r3 & c3 & i3 \\ d4 & r4 & c4 & i4 \end{bmatrix} \tag{6}$$

Figure 1 illustrates how these sub-variables feed into the four KPIs.

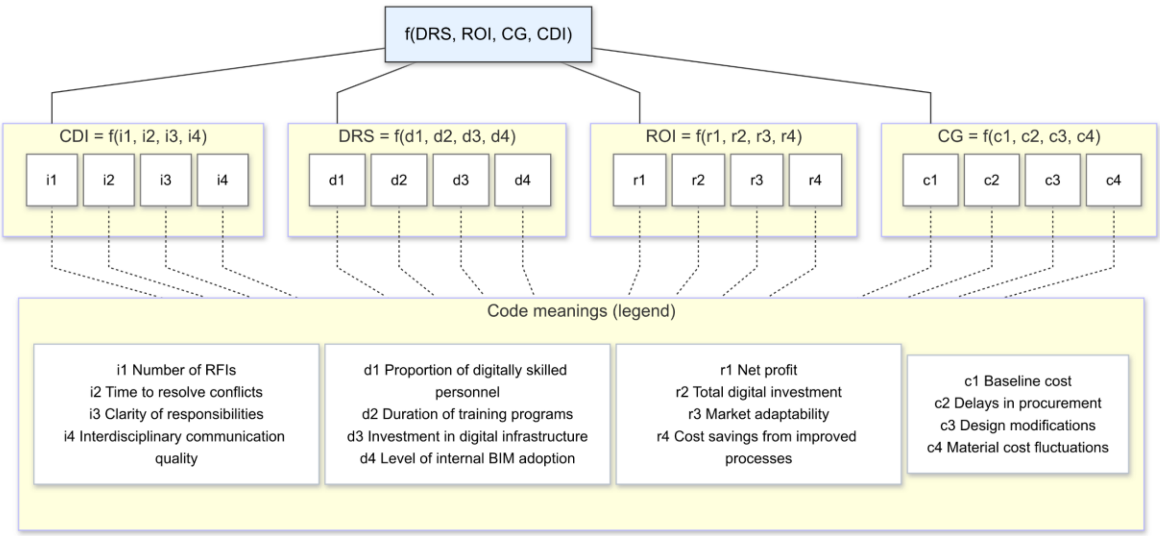


Figure 1. Matrix architecture and KPI subsystem mapping

The model's inputs consist of measurable project data validated through the Delphi process, including the proportion of digitally skilled staff, total digital investment, procurement delays, and the time required to resolve coordination conflicts.

The outputs are Pareto-optimal configurations of {DRS, ROI, CG, CDI} that expose trade-offs for decision-makers, enabling them to select solutions that align with project priorities.

The NSGA-II procedure begins by initializing a population based on empirical project data, then applies non-dominated sorting to classify solutions into Pareto layers. Crowding-distance computation preserves diversity within the population, while crossover and mutation operators generate improved offspring. This iterative process continues until convergence on a stable Pareto front is achieved, providing a set of optimal solutions that enhance project performance without compromising cost or coordination efficiency.

This approach empowers decision-makers to visualize multiple optimal configurations simultaneously and select the most appropriate trade-off in accordance with strategic objectives. By integrating expert-derived factors with algorithmic modeling, the framework ensures evidence-based decisions that balance efficiency, reliability, and adaptability in digitally enabled construction environments.

5. RESULTS

This section presents the outcomes of the multi-phase validation process, including survey diagnostics, Delphi consensus, simulation modeling, real-world implementation, sensitivity analysis, and multi-objective optimization. Together, these phases provide empirical evidence supporting the reliability, contextual adaptability, and predictive accuracy of the proposed digital-organizational transformation framework.

5.1 Survey findings

The baseline survey engaged 94 professionals from the Iraqi and Russian construction sectors. It aimed to evaluate the readiness and challenges of digital transformation within the AEC industry. A total of 45 unique input factors were identified across three domains—organizational, technological, and financial/interactional—using a combination of closed-ended Likert-scale items and open-ended narrative responses.

These raw inputs were refined through structured content analysis, resulting in 28 consolidated output factors, as shown in Table 2.

Subsequent analysis grouped the challenges into three dominant thematic clusters, highlighting critical constraints that influence project success.

Table 2. Baseline survey inputs and outputs

Domain	Inputs (Survey Findings)	Outputs (Baseline Survey)
Organizational	18 Inputs (13 closed-ended + 5 open-ended)	9 Outputs (8 core + 1 additional)
Technological	16 Inputs (13 closed-ended) + three open-ended)	11 Outputs (10 core + 1 additional)
Financial & Interactional	11 Inputs (10 closed-ended + 1 open-ended)	8 Outputs (7 core + 1 additional)

5.1.1 Human capacity and digital skills

Figure 2 summarizes the outcomes of the technological domain, specifically the digital skills subgroup. The results were derived from the Weighted Mean (WM) values presented in the corresponding analytical table and calculated in accordance with Eq. (5), which defines the DRS model introduced in Section 4.6.5.

The three critical factors—training program enhancement (2.91), digital communication tools (2.17), and responsiveness to new technologies (1.94)—represent the main technological components influencing the organization's digital readiness. Among these, structured training programs achieved the highest WM, reflecting their dominant role in improving staff competence and accelerating digital adoption.

Although digital communication tools and responsiveness to new technologies showed lower mean values, their contribution remains complementary, supporting knowledge sharing and adaptive capacity. These findings confirm that human–technological alignment is central to enhancing the overall DRS and facilitating sustainable BIM-based transformation in construction projects.

5.1.2 Digital infrastructure and systems modernization

Figure 3 presents the results of the technological domain, focusing on digital infrastructure and systems modernization, and is interpreted in relation to both technological readiness and financial efficiency. The results were obtained from the WM analysis in accordance with Eq. (5) for the DRS and cross-referenced with the financial implications derived from the ROI formulation presented in Eq. (3) of Section 4.6.3.

The three critical factors—upgrading and improving structures (2.73), technology sufficiency (1.89), and systems integration (1.87)—reflect not only the organization's digital maturity but also its capacity to generate economic value from technology investments. The relatively high means for upgrading structures indicate prioritized expenditure on modernization initiatives, which correlate with positive ROI trends identified in later simulation results.

Conversely, low scores in technology sufficiency and systems integration suggest that underutilization of digital tools and weak interoperability diminish potential financial returns, thereby reducing the efficiency of digital investment. Strengthening these areas is essential to enhance both technological and financial performance, ensuring that infrastructure modernization translates into measurable improvements in ROI and long-term value creation.

5.1.3 Coordination deficiencies

Figure 4 illustrates the results of the organizational dimension, emphasizing coordination-related inefficiencies derived from the WM analysis consistent with Eq. (5) of the DRS model presented in Section 4.6.5.

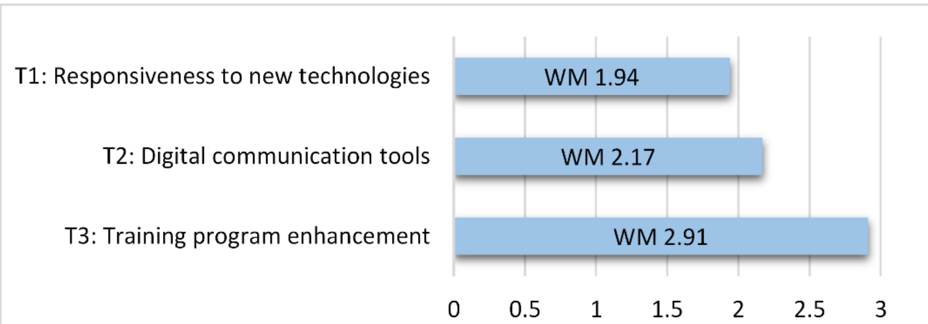


Figure 2. WM of digital skills factors

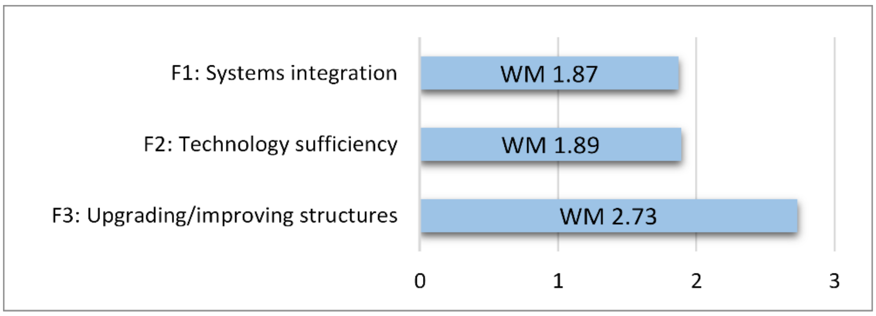


Figure 3. WM of digital infrastructure factors

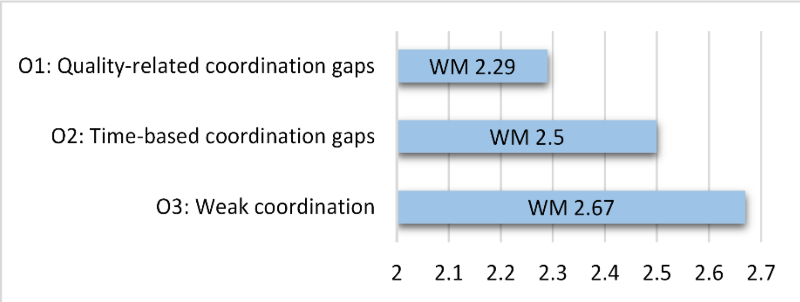


Figure 4. WM of coordination deficiency factors

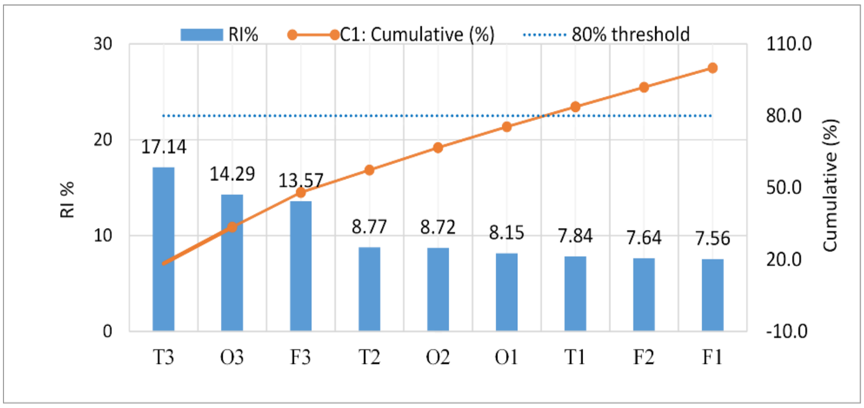


Figure 5. Pareto chart of cumulative challenge impact

Note: Each RI% value originates from a distinct sub-scale; cross-theme comparisons represent relative thematic weight rather than arithmetic summation.

The three critical coordination-related factors—weak coordination (2.67), time-based coordination gaps (2.50), and quality-related coordination gaps (2.29)—reveal persistent deficiencies within organizational and project communication structures. Among these, weak coordination recorded the highest mean value, signifying that communication fragmentation and lack of synchronized planning remain significant constraints affecting project performance.

Meanwhile, the relatively lower values for time-based and quality-related coordination gaps indicate that scheduling misalignments and quality feedback loops, although less severe, continue to disrupt consistency and workflow integration. These results underscore the need to enhance coordination mechanisms through BIM-supported communication systems and standardized protocols, thereby reducing discrepancies, improving real-time decision-making, and strengthening the organization's overall digital readiness.

5.1.4 Pareto analysis of critical challenges

As illustrated in Figure 5, the Pareto analysis shows that the highest-ranked challenges across technological, organizational, and financial dimensions account for approximately 80% of the overall impact on project performance. These nine factors represent the critical challenges previously analyzed in Sections 5.1.1–5.1.3 and were selected as the most influential variables for further modeling. This distribution validates their prioritization in subsequent optimization processes.

RI% represents RII expressed as a percentage, derived from survey-based weighting. The chart confirms that the most influential factors—particularly those related to training enhancement (T3), organizational upgrading (O3), and financial adaptability (F3)—represent the critical leverage points for digital transformation.

These results were further emphasized by Delphi experts, who confirmed the strategic significance of focusing on human capacity development, technological infrastructure investment, and real-time coordination mechanisms. Together, these findings guided the construction of the Delphi consensus matrix in the next phase.

5.2 Delphi consensus matrix

To refine and validate the baseline findings, a two-round Delphi process was conducted, involving 18 experts from Iraq and Russia. These experts represented diverse roles across the construction sector, ensuring a balanced integration of academic, operational, and executive perspectives.

Building on the 28 output factors generated by the baseline survey, Round I of the Delphi study reassessed these variables through a combination of structured quantitative ratings and open-ended expert feedback. As summarized in Table 3, the Delphi panel consolidated the input into 24 refined factors across three key domains:

Table 3. Delphi round I inputs and outputs

Domain	Inputs Round I (from Baseline Survey Outputs)	Outputs Round I
Organizational	9 Inputs (8 closed-ended + 1 open-ended)	9 Outputs (7 core +2 additional)
Technological	11 Inputs (10 closed-ended + 1 open-ended)	9 Outputs (6 core + 3 additional)
Financial & Interactional	8 Inputs (7 closed-ended + 1 open-ended)	6 Outputs (6 core + 0 additional)

These results reflect the panel's collective judgment in both consolidating and expanding upon previously identified challenges. The increased granularity in the technological and organizational domains underscores a strong consensus on emerging priorities. At the same time, the stability of these stabilizing financial factors, along with a clear consensus and interactive factors, reveals a type of economic factor that clearly demonstrates a consensus. Interactional factors also indicate their foundational role.

The refined outputs from Round I served as the inputs for Delphi Round II, during which statistical agreement was further strengthened using Kendall's W and the Kruskal-Wallis test. This process ultimately yielded a validated list of 16 sub-variables, which were mapped to four overarching performance indicators, previously defined in the methodology, guiding the simulation and optimization phases that followed.

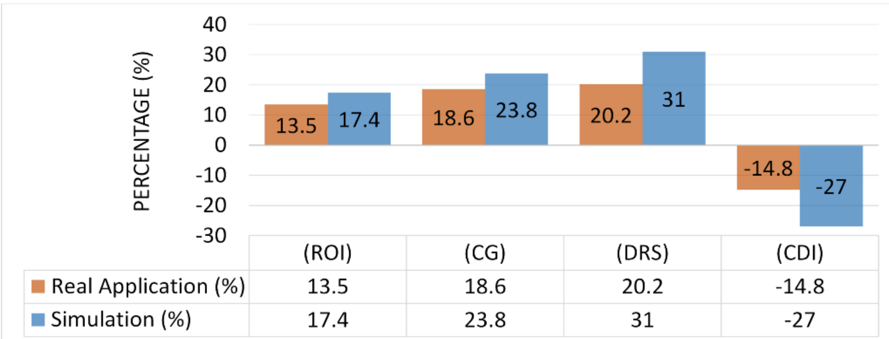
5.3 Simulation-based performance forecasts

Simulation experiments conducted across twelve historical projects (2003–2019) demonstrated the predictive reliability of the proposed framework.

The simulation model utilized aggregated KPI results, including the DRS, ROI, CG, and CDI, which were derived from validated sub-variables established in earlier analytical stages. Empirical project data extracted from company records served as the model inputs, while the simulated outputs were generated using the NSGA-II algorithm to estimate optimal performance configurations.

As illustrated in Figure 6, the comparison between the baseline (traditional management) and simulated digital scenarios revealed measurable improvement across all four KPIs. The simulation predicted higher digital readiness (+31%), more substantial ROI (+17.4%), better cost control (+23.8%), and shorter coordination delays (−27%) compared with baseline averages. These improvements stem from integrating structured digital workflows, interoperable data systems, and coordinated communication platforms.

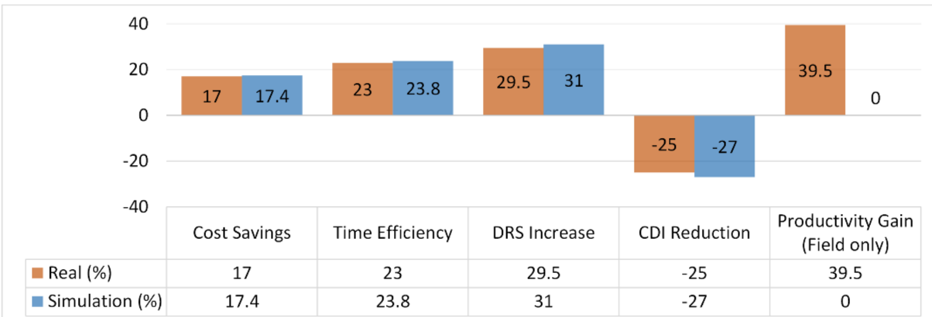
From a practical standpoint, these findings demonstrate that the simulation phase effectively captured the potential impact of digital transformation prior to its actual implementation. The results provided quantitative justification for applying the proposed digital–organizational model in practice, which is discussed in the following section.



	(ROI)	(CG)	(DRS)	(CDI)
Real Application (%)	13.5	18.6	20.2	-14.8
Simulation (%)	17.4	23.8	31	-27

Figure 6. Simulation–real KPI comparison

Note: The reported values are expressed as percentages rather than absolute monetary figures, ensuring interpretability for international readers regardless of currency or local cost structure.



	Cost Savings	Time Efficiency	DRS Increase	CDI Reduction	Productivity Gain (Field only)
Real (%)	17	23	29.5	-25	39.5
Simulation (%)	17.4	23.8	31	-27	0

Figure 7. Simulation–field KPI comparison

5.4 Field implementation results

Following the simulation phase, the proposed digital–organizational framework was implemented and validated through a real-world case study: a 29-story residential high-rise project executed between 2022 and 2025. This implementation phase represented the final verification step, designed to assess how closely real-world performance aligned with the NSGA-II–based simulation forecasts derived in Section 5.3.

At this stage, the project was executed in practice using the proposed digital transformation tools: BIM, iTWO 5D, Revizto, and MS Project. The researcher directly monitored and recorded cost, time, and coordination data throughout the construction process, ensuring the accuracy and independence of the empirical dataset.

Figure 7 presents a comparative analysis between the simulated optimized scenario (representing the predicted digital transformation case) and the actual field results achieved during implementation. The observed performance trends closely matched the NSGA-II simulation outputs, showing a DRS increase of +29.5%, a cost efficiency improvement of +17%, a schedule enhancement of +23%, and a reduction in CDI of –25%. Furthermore, field operations recorded an additional +39.5% gain in productivity, reflecting gains in real-time collaboration and enhanced communication workflows beyond the simulated scope.

These findings verify that the optimization-based simulation model accurately forecasted the dynamic interactions among cost, time, and coordination variables once the proposed framework was implemented. The close alignment between predicted and actual performance validates the operational feasibility and reliability of the NSGA-II approach within real construction environments.

Ultimately, this outcome highlights the broader benefits of integrating multi-objective optimization into construction management. Similar performance-based methodologies—such as Earned Value Management (EVM) systems implemented in Anbar Governorate projects—have demonstrated parallel advantages by synchronizing schedule and cost control functions, reinforcing the applicability of data-driven management approaches in regional construction contexts [18].

5.5 Sensitivity and optimization insights

The final phase of the study aimed to pinpoint the key factors influencing performance across the four KPIs: DRS, ROI, CG, and CDI. Sensitivity analysis through simulations identified two sub-variables with consistently high impact:

- r4 (cost savings from improved processes) within ROI;
- c3 (design modifications) within CG.

These results align with earlier Delphi findings and Pareto diagnostics, emphasizing the importance of process efficiency and design control in boosting project outcomes.

To evaluate the best trade-offs among the KPIs, the NSGA-II method was applied. The optimization model, structured as:

$$Performance = f(DRS, ROI, -CG, -CDI) \tag{7}$$

Created balanced scenarios that enhance digital performance while minimizing additional costs and delays. The model remained stable under a ±10% parameter variation, proving its robustness and flexibility.

This optimization validates the integrated framework as a reliable tool for strategic decision-making in digital transformation under practical constraints.

6. DISCUSSION

6.1 Interpretation and implications

The study's findings confirm the robustness of the proposed digital–organizational framework, with performance deviations between simulated forecasts and real-world implementation ranging from 3.9% to 7.4%, validating its predictive reliability and operational feasibility across distinct project environments. The close correspondence between simulated and field data demonstrates that the NSGA-II-based optimization model effectively captured the nonlinear relationships among cost, time, coordination, and digital maturity indicators.

Three major strengths emerged from this analysis:

(1) Reproducibility: The framework produced consistent outcomes across both simulation and field applications, including measurable reductions in cost growth (≈ 17%), time savings (≈ 24%), enhanced DRS, and decreased CDI. This reproducibility underscores the model's internal reliability and its ability to generalize predictive performance across projects of varying scale and complexity.

(2) Scalability: Application of the framework to twelve historical projects and a large-scale residential high-rise (2022–2025) confirmed its enterprise-level adaptability. The integration of BIM-based coordination, iTWO 5D cost forecasting, and Revizto communication platforms enabled the model to translate optimization outcomes into actionable management practices—bridging the gap between theoretical modeling and practical execution. Such outcomes align with recent digital transformation strategies reported in the AEC industry [14].

(3) Contextual Adaptability: Performance outcomes varied between Iraq and Russia, reflecting differences in infrastructure maturity, policy frameworks, and institutional readiness. In Iraq, limited digital infrastructure investment (d_3 ≈ 22%) and fragmented organizational coordination necessitated a phased implementation and targeted workforce training, consistent with the adoption challenges identified in emerging economies. Conversely, in Russia, higher BIM maturity levels (d_4 ≈ 78%) and more substantial regulatory alignment enabled the full integration of the proposed workflow with existing digitization initiatives [19].

While these contrasts reaffirm the contextual adaptability of the model, they also reveal that policy support, governance quality, and organizational culture have a substantial influence on the effectiveness of digital transformation. The findings suggest that in environments where regulatory frameworks and IT infrastructure are less mature, the same optimization algorithm may require recalibration of sub-variables such as d_3 (Digital Infrastructure Investment) and i_2 (Time to Resolve Conflicts) to maintain comparable performance outcomes.

From a critical perspective, the minor discrepancies between simulation and implementation (≤ 7%) can be attributed primarily to human-centric and contextual factors, including learning curves, communication delays, and unmodeled behavioral variability—rather than structural flaws in the optimization logic. This aligns with observations in comparable NSGA-II-based applications in infrastructure and energy sectors, where practical outcomes tend to diverge slightly from idealized simulations due to implementation complexity [20].

Furthermore, the sensitivity analysis confirmed r_4 and c_3 as the most influential sub-variables, reinforcing the Delphi consensus and Pareto findings that emphasized process efficiency and design coordination as key leverage points for enhancing digital performance. these insights underline that the framework's effectiveness depends on its strategic customization—balancing computational precision with managerial adaptability—to suit the technological maturity and governance conditions of each project context.

Ultimately, digital transformation in construction is not only a technical shift but an organizational evolution requiring alignment between technology, human expertise, and policy. The proposed model demonstrates how multi-objective optimization can operationalize this alignment, enabling decision-makers to implement context-sensitive strategies that sustain performance improvement across diverse project environments.

6.2 Limitations and future work

Although the framework was validated through simulation and field implementation, several methodological constraints limit its generalizability.

(1) Geographic Scope: The study focused on Iraq and Russia—contexts differing in digital maturity and regulatory advancement. While this contrast offered cross-comparative insights, broader validation across additional regions is needed to ensure global adaptability.

(2) Organizational Representation: The sample included contractors and consultants but lacked legal and administrative experts, whose roles are critical in digital governance. Future research should involve policymakers and legal specialists to capture the institutional factors that influence adoption and compliance.

(3) Financial Evaluation: The analysis relied mainly on ROI, which overlooks non-monetary benefits such as risk reduction and sustainability. Incorporating NPV, CPI, and SROI would provide a more holistic assessment of economic and social impacts.

(4) Computational Strategy: Exclusive use of NSGA-II ensured stability and reproducibility but limited comparison with other heuristics. Future studies should benchmark NSGA-II against methods such as MOPSO and ACO to enhance the robustness of the Pareto front.

Figure 8 summarizes these limitations and related research opportunities across five domains: geographic scope, organizational applicability, financial evaluation, optimization strategy, and scalability [21].

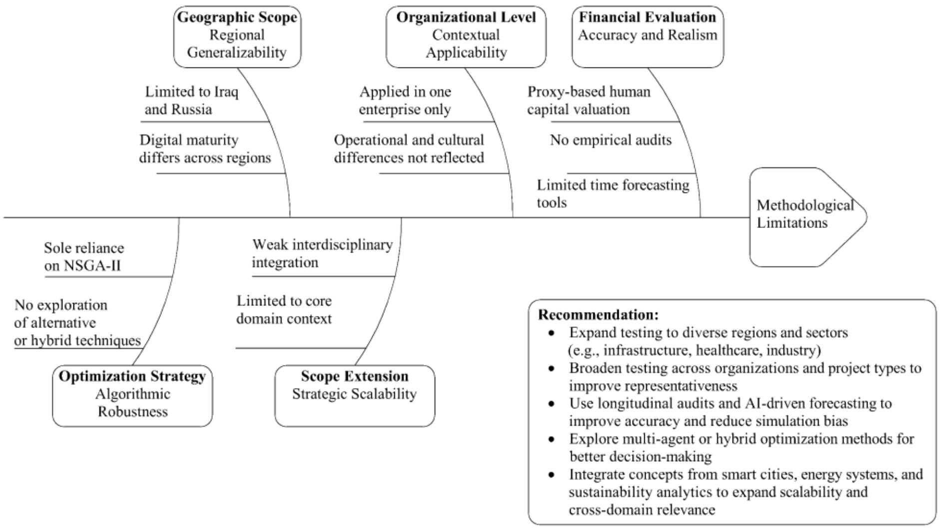


Figure 8. Methodological limitations and recommendations

Note: While the diagram presents recommendations tailored to each identified limitation, a more comprehensive set of strategic and stakeholder-specific recommendations is provided in Section 8 to support broader implementation and cross-sector applicability.

6.3 Practical implications for stakeholders

The study highlights the various ways in which different stakeholders interact with digital transformation dynamics in the construction industry. For firms, variations in DRS components—such as digital skills (d_1)—indicate that workforce capability has a strong influence on readiness, raising questions about the balance between training and recruitment. At the policy level, differences in infrastructure investment (d_3) between contexts suggest that governance and financial support have a significant impact on adoption speed, reflecting patterns observed in international strategies [19]. For research, the findings suggest opportunities to integrate AI-based predictive models and conduct cross-regional comparisons to understand adaptation strategies under varying technological and governance conditions [22]. Overall, these insights emphasize that digital transformation involves interconnected technical, organizational, and policy factors rather than isolated technological upgrades.

7. CONCLUSIONS

This study validated an integrated digital–organizational framework for enhancing construction project performance through simulation, mathematical modeling, and expert consensus. The framework demonstrated a strong predictive capability for KPIs—cost, time, coordination, and digital readiness—across varying levels of digital maturity.

Quantitative evaluation revealed a clear improvement: the ROI increased by 17.8%, CDI decreased by 23%, CG was reduced by 14%, and Digital Readiness (DRS) improved by over 25% after BIM integration. These results confirm the model's reliability and its ability to transform digital strategies into measurable organizational outcomes.

The close consistency between simulated and real project data further proves its robustness and scalability. Rather than offering a one-size-fits-all solution, the framework serves as a context-sensitive decision-support tool, guiding digital transformation in line with international BIM standards and best practices.

8. RECOMMENDATIONS

To enhance implementation and guide future development, the following recommendations are proposed across three stakeholder groups:

8.1 For policymakers

(1) Institutionalize Digital Readiness Assessments:

Given the 25% DRS improvement observed, policymakers should embed the DRS as a mandatory performance criterion in national project approval systems. DRS benchmarking should also be linked to tiered funding levels and digital transformation milestones, ensuring that higher-readiness organizations receive prioritized access to government contracts.

(2) Reinforce Policy and Incentive Mechanisms:

Since the ROI increased by 17.8%, fiscal incentives should be restructured to favor projects demonstrating measurable digital efficiency, such as tax credits, fast-track approvals, or co-funding schemes for BIM-based initiatives. Policies should specifically target digital infrastructure (d_3) and interoperability platforms that enable cross-stakeholder data exchange.

8.2 For project managers and construction firms

(1) Integrate Simulation-Driven Planning:

Implement NSGA-II–based simulation models during early planning to test trade-offs among cost growth, coordination delay, and ROI before execution. Firms should use these simulations to define risk-adjusted baselines and allocate contingencies proactively.

(2) Design Skill-Oriented Capacity-Building Programs:

Training should focus on the digital competencies (d_1–d_4) that showed the highest influence on DRS improvement, such as BIM coordination, data analytics, and digital procurement. Certification metrics should be aligned with these competencies to sustain long-term digital maturity.

(3) Standardize Post-Project Auditing Practices:

Post-project audits should quantify ROI variations, DRS progression, and CDI impact using the study's validated equations. Auditing results should feed into a national performance database for continuous benchmarking.

(4) Formalize Coordination Tools:

The 23% CDI reduction demonstrates the need for mandatory adoption of digital coordination platforms (e.g., Revizto, iTWO) across large-scale projects. Standard operating procedures should include digital issue-tracking and real-time model synchronization protocols.

8.3 For researchers and technology developers

(1) Expand Empirical Scope and Application Domains:

Future research should apply the model to different project typologies (infrastructure, healthcare, industrial) while comparing variations in KPI sensitivity—particularly how ROI and CDI respond to different contractual frameworks or cultural settings.

(2) Advanced Model Intelligence and Complexity Handling:

Integrate AI-driven sensitivity analysis to refine parameter weighting and apply hybrid optimization (e.g., NSGA-II + Monte Carlo) for better uncertainty quantification. This direction strengthens predictive precision and enhances decision-making robustness in high-risk environments.

REFERENCES

[1] Al-Musawi, R., Naimi, S. (2023). Evaluation of construction project's cost using BIM technology. Mathematical Modelling of Engineering Problems, 10(2): 469-476. https://doi.org/10.18280/mmep.100212

[2] Jasim, N.A., Ibrahim, A.A., Hatem, W.A. (2023). Leveraging support vector machine for predictive analysis of earned value performance indicators in Iraq's oil projects. Mathematical Modelling of Engineering Problems, 10(6): 2003-2013. https://doi.org/10.18280/mmep.100610

[3] Abanda, F.H., Balu, B.S., Adukpo, E., Akintola, A. (2025). Decoding ISO 19650 through process modelling for information management and stakeholder communication in BIM. Buildings, 15(3): 431. https://doi.org/10.3390/buildings15030431

[4] Choi, J., Leite, F., de Oliveira, D.P. (2020). BIM-based benchmarking for healthcare construction projects. Automation in Construction, 119: 103347. https://doi.org/10.1016/j.autcon.2020.103347

[5] Gharaibeh, L., Eriksson, K., Lantz, B. (2025). Quantifying BIM investment value: A systematic review. Journal of Engineering Design and Technology, 23(5): 1384-1403. https://doi.org/10.1108/JEDT-06-2023-0259

[6] Shehadeh, A., Alshboul, O., Taamneh, M.M., Jaradat, A.Q., Alomari, A.H. (2024). Enhanced clash detection in building information modeling: Leveraging modified extreme gradient boosting for predictive analytics. Results in Engineering, 24: 103439. https://doi.org/10.1016/j.rineng.2024.103439

[7] Rostamiasl, V., Jrade, A. (2024). A cloud-based integration of Building Information Modeling and Virtual Reality through game engine to facilitate the design of age-in-place homes at the conceptual stage. Journal of Information Technology in Construction, 29: 377-399. https://doi.org/10.36680/j.itcon.2024.018

[8] Magalhães, R.M., Mello, L.C.B. de B., Hippert, M.A.S. (2023). Organizational readiness for building information modeling. Frontiers in Engineering and Built Environment, 3(2): 137-152. https://doi.org/10.1108/FEBE-07-2022-0028

[9] Siebelink, S., Voordijk, H., Endedijk, M., Adriaanse, A. (2021). Understanding barriers to BIM implementation: Their impact across organizational levels in relation to BIM maturity. Frontiers of Engineering Management, 8(2): 236-257. https://doi.org/10.1007/s42524-019-0088-2

[10] Naji, K.K., Gunduz, M., Alhenzab, F., Al-Hababi, H., Al-Qahtani, A. (2024). Assessing the digital transformation readiness of the construction industry utilizing the Delphi method. Buildings, 14(3): 601. https://doi.org/10.3390/buildings14030601

[11] Osunsanmi, T.O., Aigbavboa, C.O., Emmanuel Oke, A., Liphadzi, M. (2020). Appraisal of stakeholders' willingness to adopt construction 4.0 technologies for construction projects. Built Environment Project and Asset Management, 10(4): 547-565. https://doi.org/10.1108/BEPAM-12-2018-0159

[12] Şahin O., Karayel, D. (2024). Generative Artificial Intelligence (GenAI) in business: A systematic review on the threshold of transformation. Journal of Smart Systems Research, 5(2): 156-175. https://doi.org/10.58769/joinssr.1597110

[13] Ma, X., Chan, A.P.C., Li, Y., Zhang, B., Xiong, F. (2020). Critical strategies for enhancing BIM implementation in AEC projects: Perspectives from Chinese practitioners. Journal of Construction Engineering and Management, 146(2).

https://doi.org/10.1061/(ASCE)CO.1943-7862.0001748

[14] Abdulwahhab, R., Naimi, S., Abdullah, R. (2022). Managing cost and schedule evaluation of a construction project via BIM technology and experts' points of view. Mathematical Modelling of Engineering Problems, 9(6): 1515-1522. https://doi.org/10.18280/mmep.090611

[15] Bayzidi, E., Kordestani Ghalenoei, N., Babaeian Jelodar, M. (2025). The effects of BIM maturity levels on modularization and standardization in the construction industry: A systematic literature review and case studies. Buildings, 15(12): 2124. https://doi.org/10.3390/buildings15122124

[16] Tao, G., Feng, H., Feng, J., Wang, T. (2022). Dynamic multi-objective construction site layout planning based on BIM. KSCE Journal of Civil Engineering, 26(4): 1522-1534. https://doi.org/10.1007/s12205-022-0708-y

[17] Hosseini Dehshiri, S.J., Yousefi Hanoomarvar, A., Amiri, M. (2023). Comparative performance of the NSGA-II and MOPSO algorithms and simulations for evaluating time–cost–quality–risk trade-off in multi-modal PERT networks. Soft Computing, 27(24): 18651-18666. https://doi.org/10.1007/s00500-023-09099-4

[18] Al-Somaydaii, J.A., Abdaljader, A. (2024). Earned value management application in construction projects of Anbar governorate. AIP Conference Proceedings, 3009: 030126. https://doi.org/10.1063/5.0190450

[19] Kassem, M., Succar, B. (2017). Macro BIM adoption: Comparative market analysis, Automation in Construction, 81: 286-299. https://doi.org/10.1016/j.autcon.2017.04.005

[20] Zhang, Z. (2024). Multi-objective optimization method for building energy-efficient design based on multi-agent-assisted NSGA-II. Energy Informatics, 7(1): 90. https://doi.org/10.1186/s42162-024-00394-4

[21] Elghaish, F., Hosseini, M.R., Matarneh, S., Talebi, S., Wu, S., Martek, I., Poshdar, M., Ghodrati, N. (2021). Blockchain and the 'Internet of Things' for the construction industry: Research trends and opportunities. Automation in Construction, 132: 103942. https://doi.org/10.1016/j.autcon.2021.103942

[22] Adebayo, Y., Udoh, P., Kamudyariwa, X.B., Osobajo, O.A. (2025). Artificial intelligence in construction project management: A structured literature review of its evolution in application and future trends. Digital, 5(3): 26. https://doi.org/10.3390/digital5030026

NOMENCLATURE

DRS	Digital Readiness Score
ROI	Return on Investment
CG	Cost Growth
CDI	Coordination Delay Index
BIM	Building Information Modeling
NSGA-II	Non-dominated Sorting Genetic Algorithm II
RII	Relative Importance Index
WM	Weighted Mean
KPIs	Key Performance Indicators
AEC	Architecture, Engineering, and Construction
ICU	Intensive Care Unit
AI	Artificial Intelligence
GA	Genetic Algorithms
MOPSO	Multi-Objective Particle Swarm Optimization

Greek symbols

TV_t	Total Transformation Value (theoretical maximum)
TV_p	Partial Transformation Value (realistic early-stage)
C_i	Project cost at time step i
C_{i+1}	Project cost at next time step
r	Cost escalation rate
x_1	Proportion of digitally skilled personnel
x_2	Average duration of training programs
x_3	Investment in digital infrastructure
x_4	Degree of BIM integration
$d_1 – d_4$	Sub-variables of DRS
d1	Proportion of digitally skilled personnel
d2	Average duration of training programs
d3	Investment in digital infrastructure
d4	Degree of BIM integration
$r_1 – r_4$	Sub-variables of ROI
r1	Net profit
r2	Total investment
r3	Market flexibility
r4	Process-related cost savings
$c_1 – c_4$	Sub-variables of CG (Cost Growth)
c1	Baseline cost
c2	Procurement delays
c3	Design modifications
c4	Material price volatility
$i_1 – i_4$	Sub-variables of CDI (Coordination Delay Index)
i1	Number of RFIs (Requests for Information)
i2	Conflict resolution time
i3	Clarity of responsibilities
i4	Communication quality
f (...)	Composite objective function
PD	Pareto front
RCA	Root Cause Analysis
FD	Fishbone Diagrams
RI%	Relative Importance Index, %
O1	Quality-related coordination gaps
O2	Time-based coordination gaps
O3	Weak coordination
F1	Systems integration
F2	Technology sufficiency
F3	Upgrading/improving structures
T1	Responsiveness to new technologies
T2	Digital communication tools
T3	Training program enhancement