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Evaluating the Digital Transformation of Construction Supervision in Building Projects Using PLS-SEM

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Abstract

Currently, a rapid digital revolution is occurring in the building industry due to the need to solve chronic challenges such as low productivity, inconsistent execution quality, and difficulty in controlling costs and schedules. Construction supervision is one area where digital transformation can have a significant impact, given the repetitive nature of its tasks, which rely heavily on human expertise and manual labor. The aim of this study is to develop a comprehensive framework to evaluate the role of the digital transformation in the supervision of construction projects using the modeling of structural equations (PLS-SEM). The data obtained was examined and evaluated utilizing the PLS-SEM software technique to build the proposed model. The results show a positive correlation between the supervisor's productivity and the utilization of digital technology, depending on the context of the task and the nature of the work. The study also proposes a methodology for the use of SEM in this area, comprising model construction steps and evaluation indicators, and it provides suggestions for researchers and practitioners to improve the effectiveness of using digital transformation in construction supervision.

Keywords: digital transformation; construction supervision; building projects; PLS-SEM; Iraq

1. Introduction

Construction supervision plays a key role when it comes to the achievement of building projects, making sure that the building is executed in keeping with the specs and plans. Traditional supervision processes, however, have numerous problems which have a negative effect on project quality and effectiveness. Manual inspection and monitoring process on site have been documented as displaying error rates of 20% to 30% in the detection of irregularities and defects, with significant consequences in terms of quality, cost and time [1].

These challenges were heightened during the COVID-19 pandemic, when home inspections were more critical than ever, and the research and practice community responded with creative digital solutions to modernize compliance and supervision. Manual measurements, paper-based document management, work documentation, etc., are typical supervision activities that are highly repetitive, require a lot of physical effort, and depend on a person's experience and ability, making them suitable for automation and digitalization [1,2]. Moreover, construction sites are dynamically changing and there is a gap between the design model and the reality of the construction site, which is one of the main sources of uncertainty in project work [3].

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Digital technologies automate repetitive tasks, like measurement, which are otherwise performed by hand. They reduce human error, document events, and have an up-to-the-minute view of project status. These features translate directly into genuinely improved supervision, productivity, and quality of supervision deliverables.

Digital transformation in construction supervision marks a shift in the way supervisors oversee the construction process, transforming it from a paper-based and visual inspection approach to an integrated system powered by advanced digital technology. Construction 5.0 [4] has introduced the concept of human–machine collaboration and a culture of learning, so the emphasis is now on a balanced use of AI and organizational processes and human expertise.

This transformation involved employing an integrated set of technologies that work together to offer a real-time and a comprehensive view of the status of the project. These technologies can be categorized according to the four-way integration model identified in recent studies [5], as shown in Table 1.

Table 1. Digital transformation technology models.

Technology Category	Key Applications in Supervision
Computer Vision	Visual comprehension, algorithms for monitoring labor, materials, equipment, and activities, visual analytics.
Internet of Things (IoT)	Sensors, data transmission, edge devices, signal processing.
Building Information Modeling (BIM)	Control, progress tracking, matching the implemented reality with the model.
Machine Learning	Data preparation, model training, forecasting and optimization, and immediate feedback.

Together, these technologies form what is known as the digital twin, a dynamic model that reflects the actual state of the project in real time and enables the simulation of future scenarios and the prediction of risks [5,6].

Some of the most important applications of digital technologies in the various stages of supervision for construction projects are outlined below.

2. Design and Planning Phase

2.1. Site Analysis and Design Improvement

We use Geographic Information Systems (GIS) and Hydrological Models (HEC-HMS) to analyze site data and identify optimal locations [7].

We apply virtual reality (VR) technologies to gather user feedback and improve designs [8].

2.2. Detecting Interferences

Numerous experiments have shown that the application of BIM has enabled the detection of many design interferences before the start of implementation for a large number of construction projects.

3. Implementation and Construction Phase

3.1. Real-Time Supervision

Monitoring work progress: Using drones every 6 days to collect and process images to detect problems (more than one problem can be identified in a single project).

Quality control: Using sensors in construction equipment to monitor the quality of work and construction components.

Safety monitoring: Using 4D digital systems to detect hazards and issue an immediate alarm [9].

3.2. Coordination Between Parties

The Spatial Sense platform provides collaborative capabilities that allow stakeholders to remotely review site data, comment on digital forms, and assign tasks, reducing delays caused by fragmented communication [10].

4. Operation and Maintenance Phase

4.1. Continuous Monitoring

We deploy a set of sensors at the project site to collect and analyze operational data using artificial intelligence.

We predict equipment failures using Long Short-Term Memory (LSTM) models to identify expected failure locations and times.

4.2. Improvement Results

It is possible to improve the maintenance response time from 36 h to 8 h (an improvement of 77.8%) in the project under consideration.

5. Literature Review

Over the past decade, there has been a lot of interest in the potential of digital transformation in construction project management. Basic research in this field was geared towards the recording of fundamental concepts and the application of new technologies on the construction site. This was the time when the first use of time-lapse photography and drones for progress tracking was introduced, as explained in a recent systematic review of 395 publications that sought to investigate their development and use [11].

As each technology advanced, people turned to ways to combine these different technologies into an integrated system. In a thorough study conducted by Abdelkader et al. [12] using the PRISM methodology, authors showed that BIM also gives a complete visualization of the project while low-cost sensors (IoT) allow researchers to follow the actual project progress in real time and perform simulations to predict future scenarios. The study demonstrated that one of the biggest value-adds of digital twins is for project managers determining potential opportunities and risks in the project prior to implementation.

The current period represents a paradigm shift with the proliferation of advanced artificial intelligence applications. A recent study by Mitra and Mulville [13] documents that technology can now enhance structural compliance in three key areas: defect detection, dimensional measurement, and conformity verification. The study also identifies the technology stacks best suited to each inspection purpose, providing a roadmap for commercial applications and future research.

Kim et al. [14] used SEM in an exploratory study to examine the digital technology' impact on productivity of a construction project's supervisors. It is a pioneering study for the evaluation of digital transformation of supervision with SEM methodology. The study offered a practical guide to how digital tools can improve productivity by emphasizing staged adoption and task-specific considerations.

Alqahtani et al. [15] investigated the factors of critical success (CSFs) that influence the efficiency of AI -enabled systems. The application of digital twins in the construction industry in Saudi Arabia has been examined by PLS-SEM. A reflective-hierarchical model

has been created that captures three dimensions of success factors: human factors (HCFs), infrastructure factors (TIFs) and technological factors, and standards and governance factors (GSFs). The study emphasized the significance of funding governance frameworks, scalable infrastructure, and high-quality data. To reap the advantages of AI-powered digital transformation, workforce training and incentives are required [15].

Naji et al. [16] used the Digital Transformation Readiness Level Index in Building Construction (DTRLIIBC) to measure the digital transformation's level of maturity in the construction sector by applying SEM. In order to get the most efficient model possible, Correlational relationships between variables were identified using SEM in order to minimize the measurement error. The research offers a framework to organize organizations by digital maturity levels, and can be applied by government agencies, construction companies and developers to track the level of digital transformation.

Okanlawon et al. used PLS-SEM to evaluate the impact of adopting augmented reality (AR) technologies on the construction lifecycle in Nigeria [17]. Dissemination of Innovation (DOI) theory and Technology Acceptance Model (TAM) were used to develop the conceptual framework. The study showed that integrating AR throughout the construction lifecycle can improve the construction process.

Kumar and Padala [18] created a framework based on PLS-SEM to recognize the key factors that impact the implementation of digital twin systems in construction projects. Multiple techniques (data-driven performance, real-time monitoring, significant integration with monitoring) were integrated by second-order latent variables, with significant results ($p < 0.001$).

With the ever-expanding use of digital technologies such as the Internet of Things (IoT), Building Information Modeling (BIM), digital twins in the construction sector, and artificial intelligence (AI) [14,19], the importance of measuring the of digital transformation on supervision is also growing. However, a systematic review of the literature reveals a significant gap in the research literature: the absence of comprehensive assessment models that combine several measures of digital transformation and examine the causal relationship between the introduction of technology and the measures of performance of the supervisors [14,15]. This study aims to fill this gap by developing a framework for the effect of digital transformation on supervision through structural equation modeling (SEM), a sophisticated statistical analysis technique that can be used to analyze complex relationships between observed variables and underlying variables.

Although numerous studies have employed PLS-SEM in the context of the digital transformation of the construction sector [14–18], the novelty of this study lies in three main aspects: First, it presents an integrated structural model that links the dimensions of the Organization–Technology–Environment (TOE) theory with two underlying mediating variables—the degree of digital technology adoption (DoT) and the maturity of digital transformation (DoM)—to the performance of construction supervision as the final output. This has not been tested in this integrated form in the previous literature. Second, it develops precise operational indicators specifically designed for the nature of repetitive supervisory tasks (such as monitoring accuracy, decision quality, and cost efficiency), rather than relying on general measures of productivity or project success. Third, testing the model in an Iraqi construction context provides new insights into the generalizability of digital transformation models in environments with economic and organizational conditions different from those covered by previous studies.

6. Materials and Methods

This study was conducted using a standard set of tools and software for data collection and analysis. The online questionnaire was designed and distributed using Google

Forms (Google LLC, Mountain View, CA, USA). For descriptive and structural data analysis, Microsoft Excel (Microsoft Corporation, Redmond, WA, USA) and SmartPLS version 4 (SmartPLS GmbH, Bönningstedt, Germany, https://www.smartpls.com, accessed on 10 October 2025) were used to implement partial least squares structural equation modeling (PLS-SEM). The study did not involve the use of any physical instruments, chemicals, or laboratory equipment, relying entirely on data collected from field questionnaires. The proposed structural model for this study, which is based on the applied studies framework, consists of three groups of indicators: indicators of the digital transformation process (independent variables), indicators measuring the impact of the digital transformation process on the performance of the construction supervision process dependent variables), and two latent (mediating) variables: degree of digital technology use and digital transformation maturity. See Figure 1 below [2,15,20,21]:

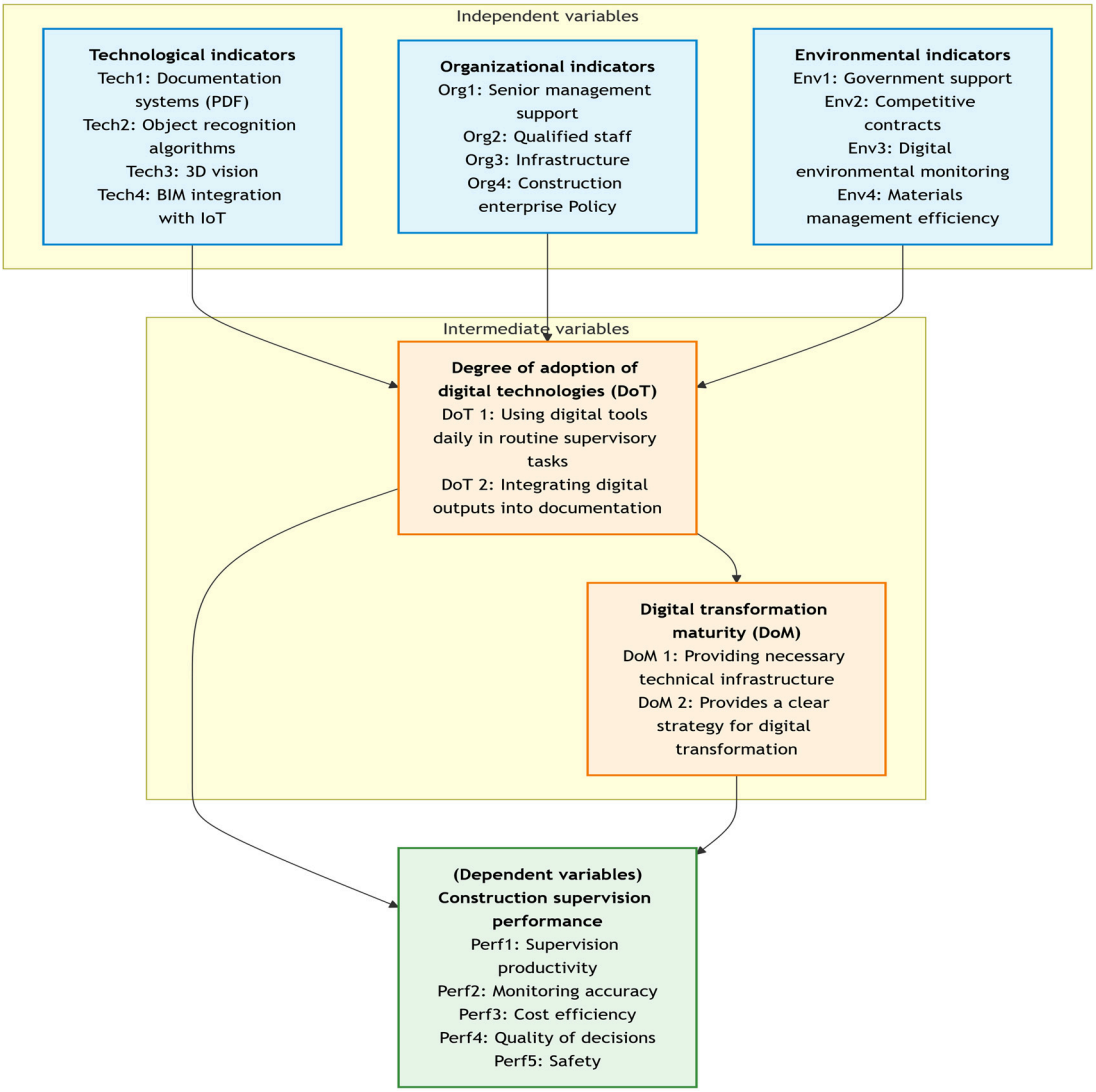


Figure 1. Study model.

Smart PLS is the most popular software for implementing PLS-SEM in construction management research. The software includes a suite of tools that enable researchers to build measurement models, evaluate model quality using multiple indicators, and test Correlational relationships by estimating path coefficients [22,23].

Based on the key variables and expected relationship between the indicators, a questionnaire using the five-point Likert scale was created as the main data collection and measurement tool, as displayed in Table 2. The questionnaire was sent to a sample of engineers, supervisors, project managers and construction industry experts to examine the relationship of technological, organizational and environmental digital transformation indicators with the performance of construction supervision in construction projects.

Table 2. Five-point Likert scale.

Likert Scale	**1**	**2**	**3**	**4**	**5**
Impact Degree	Minimal	Low	Moderate	High	Very High

Table 3 shows the study indicators (items) used to measure each latent variable in the model, indicating the sources from which they were quoted or adapted to fit the study context. The items were designed to fit the context of supervising construction projects in Iraq, while preserving the essential meaning of the original items.

Table 3. Study indicators and sources.

Latent Variable	**Variable Symbol**	**Subvariates**	**Source**
Technological	Tech1	Documentation systems	[2,14]
	Tech2	Object recognition algorithms	[14,15]
	Tech3	3D vision	[13,15]
	Tech4	BIM integration with IoT	[5,12]
Organizational	Org1	Senior management support	[15,16]
	Org2	Qualified staff	[15,16]
	Org3	Infrastructure	[15,16]
	Org4	Construction enterprise policy	[15,16]
Environmental	Env1	Government support	[15,17]
	Env2	Competitive contracts	[15,17]
	Env3	Digital environmental monitoring	[5,12]
	Env4	Materials management efficiency	[15,16]
Degree of digital technology adoption	DoT1	Using digital tools in daily in routine supervisory tasks	[14,15]
	DoT2	Integrating digital outputs into documentation	[14,15]
Digital transformation maturity	DoM1	Providing necessary technical infrastructure	[15,16]
	DoM2	Providing a clear strategy for digital transformation	[15,16]
Supervision Performance	Perf1	Supervision productivity	[14]
	Perf2	Monitoring accuracy	[14]
	Perf3	Cost efficiency	[14,15]
	Perf4	Quality of decisions	[14,15]
	Perf5	Safety	[14,15]

All indicators were measured using a five-point Likert scale (1 = minimal effect, 2 = low, 3 = medium, 4 = high, 5 = very high), as shown in Table 2. This scale is suitable for

the exploratory nature of the study, as it allows participants to assess the degree of relevance of each indicator to the supervision of construction projects. The questionnaire consists of five main sections: Section 1 collects participants' demographic information (type of work, educational level, years of experience); Section 2 measures the independent indicators (technological, organizational, environmental) through 12 items (Tech1–Tech4, Org1–Org4, Env1–Env4); Section 3 measures the mediating variables: the degree of digital technology adoption (DoT) with two items (DoT1–DoT2), and the maturity of digital transformation (DoM) with two items (DoM1–DoM2); and Section 4 measures the dependent variable, "supervisory performance," with five items (Perf1–Perf5). The fifth section includes open-ended (optional) questions to gather additional feedback from participants. Participants were asked to rate each item on a five-point Likert scale, with clear instructions emphasizing that there were no right or wrong answers, and that the goal was to measure their perceptions based on their actual experience.

To determine the appropriate sample size in this study, several equations are used depending on the type of study, the population, and the variables. Equation (1) was used to find the sample size of the respondents with a 95% confidence level and a 50% expected percentage, resulting in a margin of error of 8%, which is appropriate for the exploratory nature of the study.

$$\mathrm{n} = \frac{\mathrm{z}^2 \times p \times (1-p)}{\varepsilon^2} \quad (1)$$

where:

n: Sample size.

Z: Degree of confidence; for instance, 1.96, and 1.645 stand for 95%, and 90% confidence, respectively.

p: The coefficient of variance among the target sample's components (its value is often taken 0.5).

ε: The greatest estimate error, ranging from 8 to 9%.

Once all the questionnaires were completed, the data were analyzed, and the measurement model was tested using Smart PLS software, as shown in Figure 2. We performed assessment of the model's internal consistency reliability, convergent and discriminant validity [24–26].

Based on the proposed model, the following hypotheses can be formulated:

H1. *Technology indicators are positively correlated with supervisory performance across the degree of digital technology adoption (DoT).*

H2. *Organizational indicators are positively correlated with supervisory performance across the degree of digital technology adoption (DoT).*

H3. *Environmental indicators are positively correlated with supervisory performance across the degree of digital technology adoption (DoT).*

H4. *Technological indicators are positively correlated with supervisory performance across the sequential path: DoT then DoM.*

H5. *Organizational indicators are positively correlated with supervisory performance across the sequential path: DoT then DoM.*

H6. *Environmental indicators are positively correlated with supervisory performance across the sequential path: DoT then DoM.*

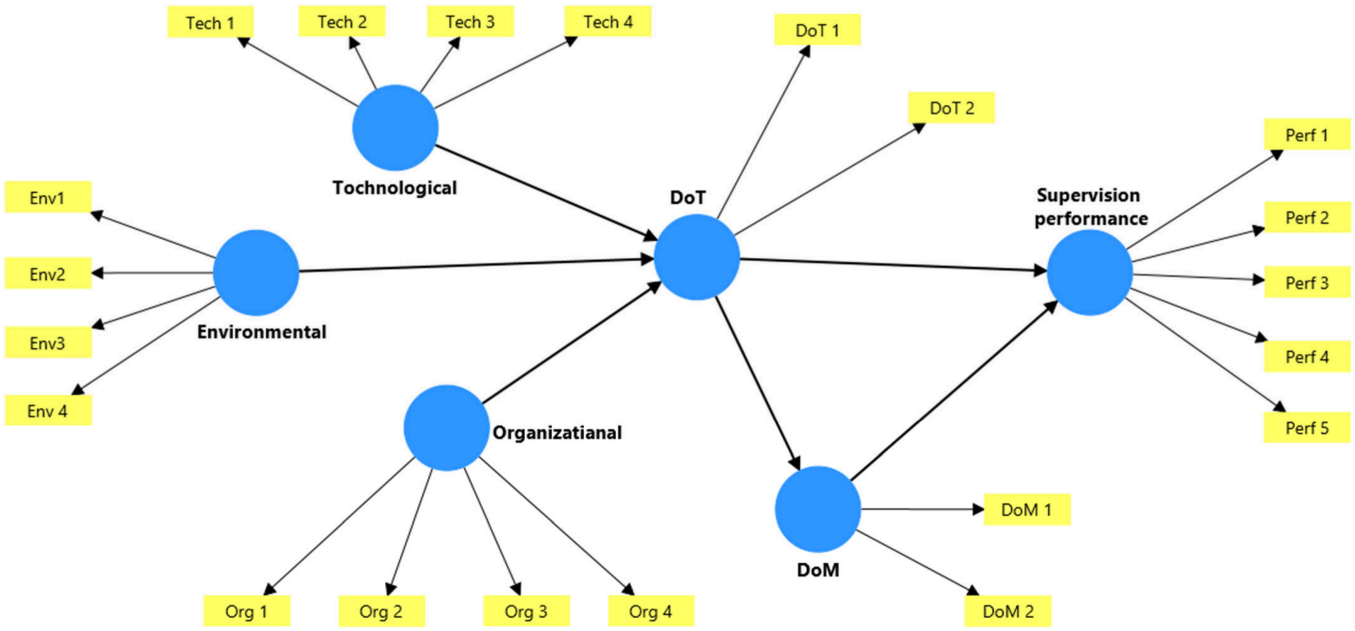


Figure 2. Structural model of dependent, mediating, and independent variables in Smart PLS.

From the perspective of "reliability and dependability," the study indicators are assessed [27]. While reliability demonstrates the correctness of the scale in representing the phenomena under investigation, dependability refers to the degree to which the measurement may provide comparable findings over repeated testing; hence, it illustrates the measurement sequence. To evaluate the proposed measurement model and its parameters, the Smart-PLS 4 software was used, as shown in Table 4. Additionally, the structural model was investigated by estimating path coefficients for determining the direction and strength of the relationships between the study variables. t-values and *p*-values were used to determine the significance of these relationships. In addition, the coefficient of determination (R^2) was computed to determine the ability of the model to explain variance, and the ability of the predictor variables to explain the variance of the endogenous variables [28–30].

Table 4. Assessment parameters of the measurement model [31,32].

	Criteria	Accepted Limit
1	Reliability of the internal dependability	Composite reliability ≥ 0.60, Cronbach alpha ≥ 0.70
2	Items stability	Standard loading of the items ≥ 0.70
3	Validity of the convergent	Average variance extracted (AVE) ≥ 0.50
4	Validity of the discriminant	Outer Loading
		(Correlation of variables-R^2-AVE)

Structural equation modeling (SEM) using the software Smart PLS is an advanced statistical method that can model and analyze complex Correlational relationships between independent variables (digital adoption factors) and dependent variables (supervision performance outcomes) in the context of digital transformation in construction projects [18,33]. These relationships are represented, ranging from conceptual models to mathematical equations and graphs [34–36].

7. Results

Based on Equation (1) detailed in the methodology section, the target sample size was calculated as follows:

$$n = \frac{(1.96)^2 \times (0.5) \times (1 - 0.5)}{(0.08)^2} \approx 150 \quad (2)$$

A total number of 150 surveys were given out. Nine surveys were removed for inaccurate completion, leaving 141 participant questionnaires used in the study. Table 4 displays the demographic characteristics and dispersion of the study sample (respondents).

The types of projects included in the study were divided into (residential 45%, infrastructure 30%, industrial/commercial 25%), the size of the institutions (small 20%, medium 55%, large 25%), and the job roles of the participants, shown in Table 5, in addition to the extent of actual use of digital technologies in their daily tasks (daily user 40%, weekly user 35%, rare user 25%).

Table 5. Demographic characteristics of the study sample.

Demographic Characteristics	Description of Properties	Frequency (*n*)	Percentage %
Nature of work	Consultants	54	38.3
	Contractors	24	17
	Investors	25	17.7
	Others *	38	27
	Total	141	100
Educational level	Secondary/Diploma	19	13.5
	Bachelor's Degree	69	48.9
	Master's Degree	33	23.4
	Ph.D.	20	14.2
	Total	141	100
Years of experience	Less than 5 years	0	0
	5 to less than 10 years	32	22.7
	10 to less than 15 years	52	36.9
	15 years or more	57	40.4
	Total	141	100

* The "Others" category includes government regulatory body employees (e.g., Ministry of Construction and Housing) and academic staff in civil engineering and architecture departments.

The data for this study were collected in the Republic of Iraq during the period from June 2025 to June 2026. The target population was supervising engineers, project managers, and consultants working on construction projects with experience in construction supervision and the use of digital technologies. The questionnaire was distributed electronically and in paper form using the convenience sampling method in cooperation with the Engineers Syndicate and the field research team. Overall, 150 questionnaires were distributed, and nine were excluded due to incompleteness, leaving 141 valid questionnaires for analysis, with a response rate of 94%. The demographic distribution of the sample (Table 5) reflects diversity in the nature of work (38.3% consultants, 17% contractors, 17.7% investors, 27% other) and in educational level and years of experience, which enhances the representativeness of the sample of different categories of workers in the construction supervision sector in Iraq and the generalizability of the results to the target population.

The values of the arrows in Figure 3 represent the outer loadings that show the association between the latent variables and their observed variables. An acceptable indicator would have an outer loading of 0.7 or higher, which means that it has a substantial contribution to the construct. The outer loading is a measure of the relationship between the measured indicators and a latent variable. In this type of model, it is assumed that changes in the observed variables are explained by changes in the latent variables, which is why the arrows in the model go from the latent constructs to the observed constructs. For example, a loading *p*-value of 0.708 or higher means that the indicator has for example more than 50% of the variance explained by the latent construct (0.708 squared is approximately 0.5), and is therefore considered excellent.

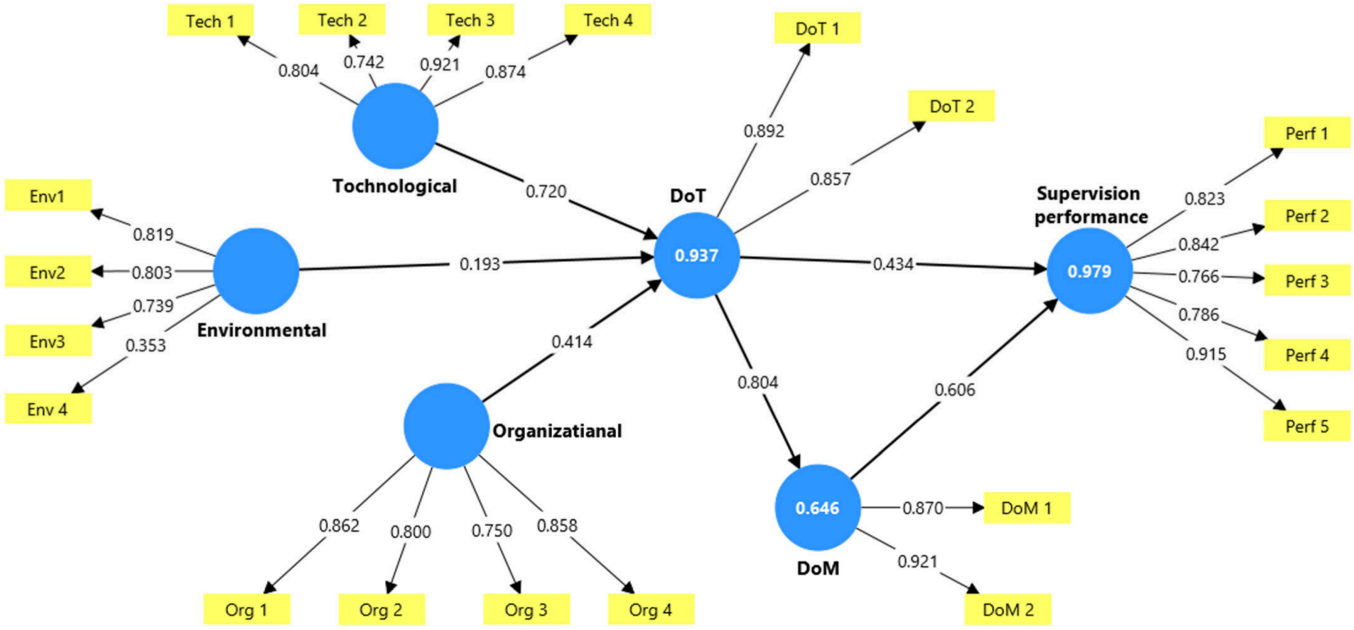


Figure 3. Outcomes of the impact of digital transformation on supervisory performance on construction projects.

However, if the external load of the variables is between 0.40 and 0.70, it should be removed because it affects the values of the external factors in the measurement model (Cronbach's alpha coefficient, composite reliability, extracted mean variance). It can be retained if it does not impact the parameters.

As mentioned previously, in Table 6, there is one external load for an indicator (material management efficiency) with a value less than 0.7 (less than the specified standard), although the Cronbach's coefficient and the reliability coefficient are not affected. However, there are other values and coefficients that may be affected, and therefore it is excluded.

Figure 4 shows that, after excluding the indicator with a value of less than 0.7, improving the model, and then retesting the model, the model for the impact of digital transformation indicators on the performance of supervision in the construction project meets the required criteria.

Table 6. Results of the measurement model assessment of the impact of digital transformation indicators on the performance of construction supervision.

Items	Outer L0	Cronbach Alpha > 0.7	CR (rho_a) > 0.7	CR (rho_c) > 0.7	AVE > 0.5
Tech 1	0.804	0.857	0.876	0.903	0.702
Tech 2	0.742				
Tech 3	0.921				
Tech 4	0.874				
Org 1	0.862	0.837	0.854	0.890	0.670
Org 2	0.800				
Org 3	0.750				
Org 4	0.858				
Env 1	0.819	0.708	0.724	0.714	0.478
Env 2	0.803				
Env 3	0.739				
Env 4	0.353				
DoT 1	0.892	0.723	0.701	0.867	0.692
DoT 2	0.857				
DoM 1	0.870	0.758	0.788	0.891	0.701
DoM 2	0.921				
Perf 1	0.823	0.884	0.892	0.916	0.686
Perf 2	0.842				
Perf 3	0.766				
Perf 4	0.786				
Perf 5	0.915				

Background color: demonstrate that both of these components fell short of the necessary limit.

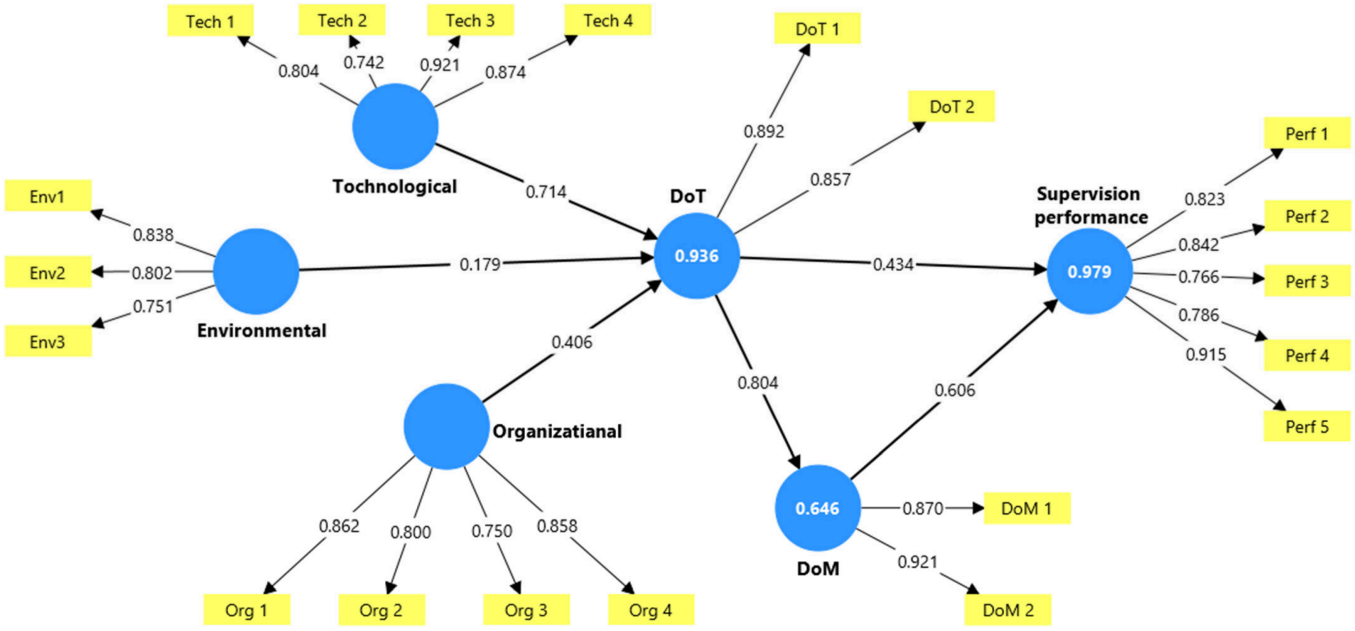


Figure 4. Results from assessing the measuring model following adjustment.

Eliminating indicators with factor loadings less than 0.7 is a fundamental methodological step in improving the quality of structural equation models using Smart-PLS. This process aims to:

- Improve the reliability of the internal consistency of the underlying variables.
- Improve convergent validity (AVE) by making at least two indicators for each latent construct explain over 50% of the variance.
- Reduce measurement error, leading to more accurate estimates of structural relationships.
- Achieve a more compact and reliable model with fewer indicators.

The external loads of all indicators were assessed. According to methodological guidelines [25,26], indicators with loads between 0.40 and 0.70 are not automatically excluded. Instead, the decision is based on their impact on reliability (CR) and extracted mean variance (AVE), as well as their theoretical significance.

One environmental indicator (Env4: Materials management efficiency) showed a low factor load of 0.353, which is below the acceptable minimum (0.40) shown in Table 7. Statistically, excluding this indicator resulted in a substantial improvement in the convergent validity of the environmental variable, with the AVE increasing from 0.478 (unacceptable) to 0.637 (very acceptable), and the composite reliability (CR) increasing from 0.714 to 0.840. Theoretically, the Env4 indicator represents an internal operational efficiency more closely related to organizational and technological processes (such as materials management using technology) than to external environmental factors. Since the three remaining environmental indicators (Env1: Government Support, Env2: Competitive Contracts, Env3: Digital Environmental Monitoring) comprehensively cover the conceptual domain of the external context, the deletion of (Env4) does not reduce the content validity of the environmental variable, but rather enhances the construction's accuracy and conceptual purity.

Table 7. Results of the adjusted measurement model assessment of the impact of digital transformation indicators on supervisory performance.

Items	Outer L0	Cronbach Alpha > 0.7	CR (rho_a) > 0.7	CR (rho_c) > 0.7	AVE > 0.5
Tech 1	0.804	0.857	0.876	0.903	0.702
Tech 2	0.742				
Tech 3	0.921				
Tech 4	0.874				
Org 1	0.862	0.837	0.854	0.890	0.670
Org 2	0.800				
Org 3	0.750				
Org 4	0.858				
Env 1	0.838	0.717	0.728	0.840	0.637
Env 2	0.802				
Env 3	0.751				
DoT 1	0.892	0.723	0.701	0.867	0.698
DoT 2	0.857				
DoM 1	0.870	0.758	0.788	0.891	0.711
DoM 2	0.921				
Perf 1	0.823	0.884	0.892	0.916	0.686
Perf 2	0.842				
Perf 3	0.766				
Perf 4	0.786				
Perf 5	0.915				

The discrimination is validated. This measure aims to ensure that the measure (the underlying variable) is strongly correlated with its own indices compared to its correlations with the indices of any other measure in the model. Table 8 shows that all variables have reached higher individual values.

Table 8. A matrix indicating the variables' correlations by discriminant validity (HTMT).

	DoM	DoT	Environmental	Organizational	Supervision Performance	Technological
DoM	0.843					
DoT	0.654	0.835				
Environmental	0.525	0.662	0.798			
Organizational	0.388	0.481	0.498	0.819		
Supervision_Performance	0.631	0.740	0.620	0.712	0.828	
Technological	0.702	0.635	0.587	0.708	0.696	0.837

It is noteworthy that the value (0.823) in the first column is greater than the other correlations in its rows (0.654, 0.525, 0.388, 0.631, 0.702) and so on for the remaining columns for the other variables; therefore, the results are acceptable. This means that these variables are characterized by a lack of overlap with the other variables, which confirms the validity of distinguishing between them.

8. Discussion

Figure 5 illustrates the results of path analysis in the structural equation model, where the numbers shown on the arrows indicate path coefficients (β) and statistical significance levels (*p*-value) in parentheses. The results show that technological indicators have a strong positive correlation with the degree of digital technology (DoT) adoption, with a path coefficient of 0.714, followed by organizational indicators with a moderate positive correlation of 0.406. In contrast, the correlation of environmental indicators was weak (0.179). As for the mediating variables, the degree of technology (DoT) adoption showed a strong positive correlation with digital transformation maturity (DoM), with a coefficient of 0.804, and with supervision performance, with a coefficient of 0.434. Digital transformation maturity (DoM) also had a strong positive correlation with supervision performance, with a coefficient of 0.606. It is worth noting that all these structural paths were statistically significant ($p < 0.05$).

The results of the bootstrapping procedure for estimating the T-statistic for all levels of variables are presented in Table 9. Bootstrapping is a non-parametric approach that is employed to evaluate the statistical significance of relationships between variables in structural equation modeling. The t-values for the path coefficients for the hypothesized relationships for all constructs are identified. Furthermore, *p*-values should be lower than the predetermined significance levels, generally 0.05 or 0.01, to establish statistical significance.

Multicollinearity was assessed using the Variance Inflation Factor (VIF) for all indicators (Outer VIF), as shown in Table 10. The accompanying table shows that the VIF values ranged from 1.325 (for Env2) to 3.145 (for Tech3). All these values fall within the acceptable upper limit of 5.0, and even within the stricter limit of 3.3, indicating the absence of a serious multicollinearity problem among the indicators. Tech3 has the highest value (3.145), followed by Perf5 (3.121), Perf2 (3.100), and Tech4 (3.108), all of which are relatively low and do not pose a risk to the accuracy of the path coefficient estimates. Therefore, it can be said that the model is free from multicollinearity problems that could affect the accuracy of the estimates.

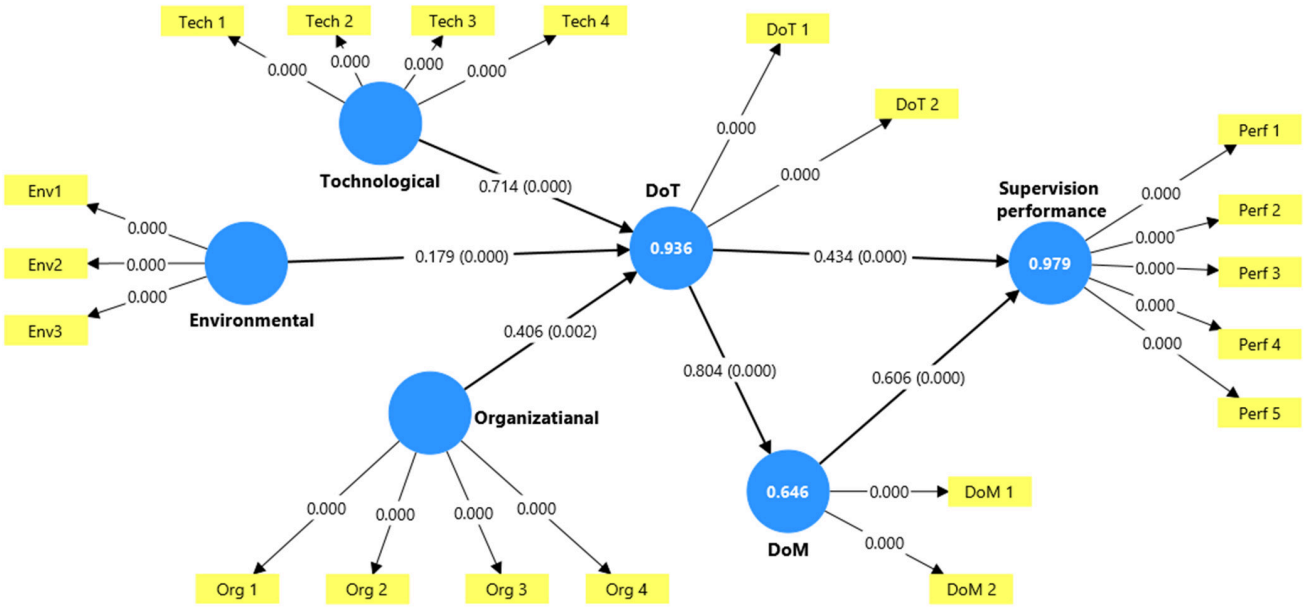


Figure 5. Path coefficients for all levels of variables.

Table 9. Results of path coefficients and hypothesis testing for all levels of variables.

	Original Sample (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	T Statistics (|O/STDEV|)	*p* Values	Results
Technological -> DoT -> Supervision Performance	0.310	0.318	0.054	5.764	<0.001	Significant Accepting hypothesis H1
Organizational -> DoT -> Supervision_Performance	0.176	0.164	0.057	3.106	0.002	Significant Accepting hypothesis H2
Environmental -> DoT -> Supervision_Performance	0.078	0.074	0.019	4.184	<0.001	Significant Accepting hypothesis H3
Technological -> DoT -> DoM -> Supervision_Performance	0.348	0.363	0.068	5.146	<0.001	Significant Accepting hypothesis H4
Organizational -> DoT -> DoM -> Supervision_Performance	0.198	0.185	0.063	3.126	0.002	Significant Accepting hypothesis H5
Environmental -> DoT -> DoM -> Supervision_Performance	0.087	0.086	0.025	3.462	0.001	Significant Accepting hypothesis H6

Table 10. Collinearity statistics (VIF).

DoM1	DoM1	DoT1	DoT2	Env1	Env2	Env3	Org1	Org2	Org3	Org4	Tech1	Tech2	Tech3	Tech4	Perf1	Perf2	Perf3	Perf4	Perf5
1.593	1.593	1.392	1.392	1.571	1.325	1.421	2.233	1.595	1.637	2.403	1.708	1.658	3.145	3.108	2.298	3.100	1.734	1.951	3.121

Table 11 presents the path coefficients and confidence intervals for all paths in the structural model, estimated using Bootstrap (5000 samples, 95% confidence interval). The table shows that all paths were positive and statistically significant, with none having zero confidence intervals. The table also presents the results of the mediation analysis, estimating the direct correlation, indirect correlation, and total correlation for each pathway, along with confidence intervals and *p*-values. The results showed that the indirect correlations of all mediating pathways were positive and statistically significant, as no confidence interval

was zero. This confirms the mediating role of both DoT and DoM in the relationship between independent indicators (technological, organizational, and environmental) and supervisory performance.

Table 11. Path coefficient–confidence interval.

	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
DoM -> Supervision_performance	0.606	0.607	0.539	0.671
DoT -> DoM	0.804	0.807	0.734	0.868
DoT -> Supervision_performance	0.434	0.432	0.370	0.500
Environmental -> DoT	0.179	0.174	0.082	0.267
Organizatianal -> DoT	0.406	0.379	0.077	0.581
Tochnological -> DoT	0.714	0.738	0.543	1.005

According to the table, the correlation of technological indicators on the degree of digital technology (DoT) adoption was 0.714 (CI: [0.543, 1.005]), a strong and positive correlation. This was followed by the correlation of organizational indicators at 0.406 (CI: [0.077, 0.581]), and then the correlation of environmental indicators at 0.179 (CI: [0.082, 0.267]). While the latter correlation was relatively weak, it was still statistically significant, consistent with the literature indicating that environmental factors are often less influential than internal factors.

The table also shows that the degree to which digital technology adoption (DoT) positively correlates with digital transformation maturity (DoM), with a coefficient of 0.804 (CI: [0.734, 0.868])—a very positive correlation. Additionally, the correlation of environmental indicators was 0.179 (CI: [0.082, 0.267]). The correlation was relatively weak between DoT and supervisory performance, standing at 0.434 (CI: [0.370, 0.500]), and the correlation of DoM with supervisory performance was 0.606 (CI: [0.539, 0.671]).

Thus, all six paths listed in the table are statistically significant and consistent with the trends assumed in the hypotheses. This supports the validity of the proposed model and confirms that digital transformation, in its various stages (adoption and then maturity), plays a pivotal role in improving the supervisory performance of construction projects in Iraq.

These results were interpreted as partial mediation in most pathways, where both direct and indirect correlations were significant. Regarding statistical support, it was confirmed that all indirect correlations exceeded the acceptable minimum, and the f^2 values (correlation sizes) of the mediating pathways supported the strength of the mediating relationships. Furthermore, the model quality indices ($Q^2 > 0$ and SRMR values) demonstrated acceptable predictive and matching power. Therefore, it can be concluded that the mediation analysis provides sufficient statistical support for the purported mediating relationships in the model.

The path analysis results showed that technological indicators were most strongly correlated with the degree of digital technology adoption ($\beta = 0.714$), followed by organizational indicators ($\beta = 0.406$), and then environmental indicators ($\beta = 0.179$). This finding is consistent with previous studies [14,15], which confirmed that technological infrastructure and organizational support are the two main drivers of digital transformation.

The weak correlation of environmental indicators reflects the limited government support and institutional incentives in the Iraqi context, which differs from other Gulf con-

texts [15], where government support is stronger. The results also showed that the degree of digital technology adoption (DoT) is positively correlated with the maturity of digital transformation (DoM) ($\beta = 0.804$), and that DoM, in turn, is positively correlated with supervisory performance ($\beta = 0.606$), thus confirming that adoption alone is insufficient; it must reach maturity to achieve tangible performance improvement.

This study presents an integrated structural model linking of Organization–Technology–Environment indicators (TOE), the mediating variables (DoT and DoM), and supervisory performance, thus expanding upon previous models [14–16] and providing a deeper understanding of how adoption translates into actual performance. The high correlation between DoT and supervisory performance has been interpreted as potentially reflecting conceptual overlap between the two variables, warranting future studies using more independent measures. In this way, the study contributes theoretical and practical insights regarding the importance of combining technological, organizational, and environmental factors to achieving effective digital transformation in construction project supervision.

The coefficient of determination (R^2), shown in Table 12, demonstrates the high explanatory power of the proposed model. The R^2 value for the dependent variable, supervision performance, reached 0.979, meaning that the independent and mediating variables in the model explain 97.9% of the variance in supervisory performance. The R^2 value for the mediating variable, digital transformation maturity (DoM), reached 0.646, meaning that the model explains 64.6% of the variance in DoM. The mediating variable, digital technology adoption (DoT), had an R^2 value of 0.936, indicating that technological, organizational, and environmental indicators explain 93.6% of the variance in DoT. These values are classified as very robust (greater than 0.26), supporting the model's validity and predictive power.

Table 12. Coefficient of determination (R^2).

	R-Square	**R-Square Adjusted**
DoM	0.646	0.642
DoT	0.936	0.934
Supervision_performance	0.979	0.976

This value is classified as a "strong" explanatory power according to the standards adopted in the PLS-SEM literature, and is considered a good result in the context of behavioral and organizational studies in the construction sector.

The findings of this study are consistent with the previous literature regarding the pivotal role of technological and organizational indicators. It demonstrated that technological indicators are the strongest driver of digital technology adoption and supervisory performance ($\beta = 0.714$, $p < 0.001$), followed by organizational indicators, which also have a significant positive impact ($\beta = 0.406$, $p < 0.001$). This aligns with the findings of Kim et al. [14], who emphasized that the availability of technological infrastructure is a prerequisite for improving supervisory productivity. It also agrees with Zhang et al. [32] and Alqahtani et al. [15], who found that senior management support and organizational readiness are crucial and motivating factors for digital transformation in construction companies.

However, this study offers a novel and distinct contribution by revealing the dual sequential path (DoT → DoM). While Kim et al. [14] focused on the direct effects of technology on productivity, Alqahtani et al.'s study did otherwise [15]. Regarding the role of critical success factors as a single mediator, this study demonstrates that the impact of technological and organizational indicators extends beyond direct application, progressing through two successive stages: first, the conversion of these indicators into actual use (DoT), and then the transformation of this use into sustainable organizational maturity (DoM). This broadens

the theoretical understanding of how technological and organizational investment translates into tangible performance.

As for environmental indicators, the results showed a positive impact, but with relatively lower significance compared to technological and organizational factors. This partially aligns with Zhang et al. [33], who indicated that government support is important but may be less influential than internal organizational factors. The study emphasizes that the success of digital transformation in supervision depends primarily on technological infrastructure and internal organizational readiness, while environmental factors play a supporting and complementary role.

Although the model proposed in this study demonstrated high explanatory power, it is possible to consider some alternative factors not measured in the current model that may influence the relationships identified. First, organizational size may play a pivotal role; larger companies typically possess greater financial and human resources, enabling them to adopt digital transformation more quickly than smaller organizations. Second, project complexity may influence the degree of need for digital technologies, as large-scale projects (such as infrastructure) require more complex digital oversight systems than residential projects. Third, the organization's digital readiness (which includes organizational culture and pre-existing technical capabilities) may be an important mediating or moderating factor. Fourth, the functional role of the participants (consultant, contractor, investor) may create a divergence in perceptions, as each party views the benefits of digital transformation from a different perspective. Finally, self-selection bias may exist, as some survey respondents may be more interested in digital technologies than others, potentially influencing the results. Therefore, it is recommended that future studies include these variables in their structural models, or use multi-group analysis to assess whether these factors modify the relationships between TOE indicators and supervisory performance.

9. Conclusions

This study aims to assess the impact of digital transformation, via its technological, organizational, and environmental dimensions, on supervisory performance in construction projects. The results obtained from the PLS-SEM structural equation analysis demonstrated that digital transformation plays a positive and significant role in improving this performance, confirming that the proposed framework provides a comprehensive and statistically supported answer to the study's main objective.

The hypothesis testing results confirmed that all pathways in the model were positive and statistically significant. The results showed that technological indicators are the strongest and most influential drivers of supervisory performance, followed by organizational indicators, while the impact of environmental indicators was positive but relatively less pronounced. Importantly, the structural analysis demonstrated that the relationship between these indicators and supervisory performance is subject to "partial complementary mediation." In response to the evaluators' feedback, a full mediation analysis was conducted based on the Bootstrapping outputs, which confirmed that indirect effects (via the degree of technology adoption (DoT) and the maturity of digital transformation (DoM)) were statistically significant. This underscores that technological and organizational factors directly impact performance, but also that their influence becomes more powerful and sustainable as they progress through this sequential pathway, demonstrating the crucial mediating role of digital transformation maturity.

Based on these findings, the study offers clear, practical guidance for construction companies and decision-makers in general, and in Iraq in particular. It emphasizes that investment in technological infrastructure (such as digital documentation systems and the integration of BIM with the Internet of Things) should be given top priority as the

cornerstone. However, the study stresses that simply providing technology is insufficient; it must be accompanied by a balanced investment in organizational factors, such as human resource training and the implementation of supportive policies. Moving from merely "using" digital tools to building sustainable "organizational maturity" is the key to ensuring improved supervisory performance in the long term.

This study, conducted in Iraq, presents statistically sound and acceptable results. However, for the sake of scientific accuracy, it is important to note some methodological limitations that define the context for interpreting these findings. The cross-sectional design of the study reflects participants' perceptions within a specific timeframe, which guides the interpretation of relationships as statistically valid and reliable correlations rather than absolute claims. While reliance on subjective data may raise theoretical concerns about co-bias, statistical tests confirmed the data's integrity and lack of such influence. Furthermore, the use of a convenient sample does not diminish the accuracy of the internal results but merely limits their generalizability to all contexts.

Regarding the sample size (141), it exceeds the statistically required minimum but remains limited given the complexity of the multipath model. One environmental indicator was excluded based on the existing sample criteria, and no out-of-sample validation was performed. Nevertheless, the use of advanced analyses (such as Bootstrap and predictive validation) lends these results a high degree of reliability and validity within the scope of the study.

Based on the findings, the study offers the following recommendations, which are presented as implications requiring evaluation in future practices:

1. Adopt a holistic investment approach: The results confirm that relying solely on technology is insufficient. Therefore, a balanced and comprehensive investment in appropriate technologies, human skills, governance frameworks, information management, and organizational readiness is the most logical and viable proposition. These elements should be viewed as a single, interconnected package, not as separate steps.
2. Focus on organizational and human readiness: Construction company management should direct investments toward training human resources (engineers and supervisors) to enable them to work with digital technologies and develop an organizational culture that embraces change. Without qualified personnel, technological tools will remain underutilized.
3. Develop governance and information management frameworks: It is recommended to establish clear policies to ensure data quality and information security. Data generated by technologies (such as BIM and IoT) must be managed within a shared data environment to ensure its accuracy and reliability, as the quality of information is what translates technology into sound supervisory decisions.
4. Assess the impact of environmental policies and incentives: Instead of assuming that government support or financial incentives will automatically lead to successful digital transformation, findings suggest that these (environmental) factors may be supportive. Therefore, policymakers should empirically assess the impact of these regulations and incentives before widespread implementation to ensure their alignment with internal organizational readiness.
5. Move from use to digital maturity: Organizations should not simply purchase technologies (actual use—DoT), but rather work to build "sustainable organizational maturity" (DoM). It is suggested that this maturity be assessed periodically using clear indicators to ensure the long-term sustainability of improvements in supervisory performance.
6. To finalize the proposed framework, it is recommended that longitudinal studies be conducted to monitor the relationship between digital transformation and supervisory performance over multiple time periods, and that objective measures of supervisory

performance (such as actual productivity data, response times, error rates, and costs) be used instead of relying solely on subjective perceptions.

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