CHAPTER 32

Strategies for Enhancing Productivity in Industrial Infrastructure Projects

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ABSTRACT

Industrial infrastructure projects are vital to economic growth, yet they continue to face persistent productivity challenges such as delays, cost overruns, and inefficiencies. This study aims to identify, analyse, and recommend effective strategies to enhance productivity within these large-scale, capital-intensive projects. By drawing on global research, a systematic literature review was conducted followed by reinforcing the collection of primary data through a questionnaire targeting engineers, contractors and project managers. The productivity of the industrial infrastructure projects can be studied using five sub-systems, namely, planning subsystem; engineering subsystem; industrial development, land use, and infrastructure sub-system; mining, robotics and industrial automation subsystem; and digital transformation, artificial intelligence (AI) and computational subsystem. The analysis highlights that integrated approaches involving digital transformation, artificial intelligence, and computational subsystem along with up-to-date engineering subsystem significantly improve the overall productivity of the industrial infrastructure projects.

Keywords: Industrial infrastructure, Strategic Management, Productivity, Standardized Processes, Digital Technology.

1.0 Introduction

Power plants, petrochemical plants, water & wastewater treatment facilities, industrial parks, logistics hubs, and other industrial infrastructure projects play a vital role in supporting national competitiveness and promoting long-term economic growth by creating manufacturing capacity, providing energy security and unlocking trade-potential. However, their delivery performance is always weak, reflected through systematic schedule slippage, quality fault and rework, leading to high costs and time overruns (Jarkas et al., 2015; Serdar and Ismail, 2016; Dixit, 2019).

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This problem is further exacerbated in emerging economies where structural issues, such as labour and skills shortages, unbalanced contracting activities, and lack of coordination among stakeholders make projects complex.

Therefore, related schedules increase the risk of rework, leading to disruptions and claims, further reducing on-site productivity in a vicious cycle. As a result, the productivity of industrial infrastructure projects is chronically low and heterogeneous across regions, inhibiting organisation's ability to standardise results or even best practices (Baráth and Fertő, 2020). At the same time, Industry 4.0 technologies such as automation, digital twins, Building Information Modelling (BIM), Internet of Things (IoT), and Artificial Intelligence (AI), boast transformational planning, coordination, quality control, and risks management outcomes (Angulo et al., 2017; Sanee et al., 2017; Santos Fonseca et al., 2025). BIM helps coordinate designs and reduce errors, but IoT, robotics, and AI can be used to schedule all processes in real time, guarantee quality, monitor safety, and optimize lifecycle. However, its implementation has been uneven because of the complexities of integration, standardisation, lack of skills, and organisational resistance, leaving much of its potential untapped.

There is a lack of empirical studies including systematic literature synthesis and practical data, especially in the context of an emerging economy like India, which has a massive infrastructure agenda at its core. The current mixed-methods research fills these gaps with statistical study on improving productivity analysed through literature review and survey-based hypotheses testing with data of practitioners. It has three goals: (i) to identify the key determinants that influence productivity in industrial infrastructure projects; (ii) to examine the strategies that are currently implemented to enhance productivity in industrial infrastructure projects; (iii) to analyse how the major subsystems of industrial infrastructure projects individually and jointly shape perceived productivity outcomes; and (iv) to evaluate the extent to which the identified strategies, when implemented within the various subsystems, contribute to improvements in performance indicators of industrial infrastructure projects. The research questions addressed in this study are the following: (RQ1) What are the key determinants that influence productivity in industrial infrastructure projects? (RQ2) Which strategies are currently implemented to enhance productivity in industrial infrastructure projects? (RQ3) How do the major subsystems of industrial infrastructure projects individually and jointly affect perceived productivity outcomes? (RQ4) To what extent do these strategies, as implemented within the various subsystems, contribute to improvements in performance indicators of industrial infrastructure projects?

2.0 Literature Review

The productivity of industrial infrastructure is multidimensional in nature. Inputs such as labour, equipment, materials, energy, and capital are converted into outputs such as

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installed capacity, manufactured/built volume, throughput or delivered services. In this regard, conventional measurements focus on calculations involving partial productivity comprising labour productivity (LP) and equipment productivity (Baráth and Fertő, 2020). Despite their simplicity – being easy to calculate yet being intuitively non-measurable when other inputs change – such metrics can be deceptive; it may appear that LP is increasing, and indeed it is, but this increase may be due to greater mechanization, not efficiency.

The most common techniques used to track cost and schedule performance against baseline standards are project-level indicators based on Earned Value Management (EVM). These indicators are dynamic and operationally useful but are sensitive to the quality of baseline standards and cannot be easily compared across projects and geographies. A more holistic approach to measuring system efficiency, total factor productivity (TFP), which is the ratio of output relative to a weighted average of labour, capital, materials, and sometimes energy. A better measure of system efficiency may be TFP, however, TFP requires high-quality and long-term data and assumptions about production functions. TFP experiments conducted on agriculture and high-voltage infrastructure show that it can be used as a benchmarking tool; however, TFP is rarely used in industrial construction (Baráth and Fertő, 2020; Wang et al., 2024; Lecina et al., 2011).

2.1 Global and geographical evidence

The anchor collection of literature on productivity in industrial infrastructure projects covers labour capacity maturity in irrigation systems (Abdi-Dehkordi et al., 2021; Laghari et al., 2012; Lecina et al., 2011), water resources management (Abdi-Dehkordi et al., 2021; Laghari et al., 2012; Lecina et al., 2011), sustainability models (Abdi-Dehkordi et al., 2021; Zhou et al., 2013), labour productivity (Jarkas et al., 2015; Serdar and Ismail, 2016; Dixit, 2019; Wang et al., 2024; Laitinen et al., 2022), digital tools (Sanee et al., 2017), and infrastructure (Duran-Fernandez, 2014; Santos Fonseca et al., 2025) in countries such as the United States (Duran-Fernandez, 2014), China (Wang et al., 2024), India (Dixit, 2019), Oman (Jarkas et al., 2015), and Malaysia (Serdar and Ismail, 2016).

This literature on productivity in industrial infrastructure projects spans the globe. Multi-country research provides contextual knowledge of water systems and agricultural productivity, while country-specific research studies the determinants of labour productivity in Oman (Jarkas et al., 2015), on-site productivity in Malaysian infrastructure (Serdar and Ismail, 2016), management practices in Indian building projects (Dixit, 2019), and ultra-high voltage construction in China (Wang et al., 2024). However, coverage is quite uneven in other parts of the world, particularly in parts of Africa and South America. Methodologically, case-study designs predominate, and there are relatively few large-sample or longitudinal studies, limiting the ability to establish cause-and-effect relationships.

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Motivated by Prakash et al. (2017) and Prasad et al. (2015), this study has focussed on generating several subsystem-level themes. The Planning Subsystem based studies focus on scheduling, allocating resources and project management strategy as an important instrument of productivity like advanced work packaging, integrated project delivery and strong risk management (Angulo et al., 2017; Santos Fonseca et al., 2025; Laitinen et al., 2022). The Engineering Subsystem studies focus on engineering and emphasises design quality, constructability, modular construction, and prefabricated construction to minimize rework and downtime and enhance safety (Forsythe, 2018; Serdar and Ismail, 2016; Jarkas et al., 2015; Dixit, 2019). The Industrial Development, Land Use, and Infrastructure Subsystem are connected to the sustainability of utility availability (power, water, telecom) to support smooth execution (Abdi-Dehkordi et al., 2021; Zhou et al., 2013; Laghari et al., 2012). The Mining, Robotics and Industrial Automation Subsystem connected to the sustainability of automation (robotics, drone, automated machinery, etc. to improve productivity in the operations (Li and Liu, 2019; Xiao et al., 2022). Finally, the subsystem connected to digital transformation, AI and computational models are automated systems in sustaining uninterrupted productivity (Angulo et al., 2017; Sanee et al., 2017; Santos Fonseca et al., 2025; Laitinen et al., 2022).

2.2 Gaps, contradictions, and conceptual framing

The literature shows there are serious gaps that inspire the current research. To begin with, the subsystem fragmentation is omnipresent: hardly any, even no, studies conceptualize planning, engineering, labour, compliance, sustainability and digital tools under the umbrella of one comprehensive framework and, thus, offer partial accounts and low transferability. Second, the research on digital integration is generally dedicated to the study of individual tools e.g. BIM or IoT; the interactions between several technologies and the enduring effect of them are hardly evaluated within the framework of the quasi-experimental or longitudinal studies. Third, human and organizational variables such as leadership, communication, workforce capacity and knowledge sharing are not adequately represented in contrast to technological and material variables yet they are supported by practitioner evidence that organizational factors are frequently the causes of rework and delays (Saeed et al., 2023; Laitinen et al., 2022).

To this, the underlying thesis suggests a conceptual framework according to which productivity is an outcome of interacting subsystems, attenuated by the context of a project and quantified by a combination of partial metrics and project metrics. The subsystems of planning, engineering, industrial development and infrastructure, sustainability and digital transformation are addressed with practices and tools shaping the time, cost, quality, safety, and sustainability performance.

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3.0 Research Methodology

The paper takes mixed-methods focus and integrates both a systematic literature review and empirical survey research to answer both the question of what and how to such productivity strategies in industrial infrastructures projects. The literature review summarized above is based on databases such as Scopus, Google Scholar, Wiley Online Library, ResearchGate, and others, using inclusion criteria related to aspects such as time frame (2011–2025), focus on productivity and system performance, full-text availability, and English language.

The structured questionnaire used as the primary means of data collection is based on the conceptual framework and gaps defined in the identified subsystems. The instrument is divided into four major sections:

1. Demographics of the respondents (position, experience, and age bracket and gender).
2. Characteristics of the project (infrastructure of the type, scale of the project, average project length)
3. Possible perceived effectiveness and use of planning, engineering, and associated subsystems based on Likert-scale items, and
4. Implementation and perceived effectiveness of particular strategies of productivity including the use of process standardization, vendor performance systems, introduction of digital tools, capacity building, lean construction, and predictive analytics.

A snowball and purposive sampling method had been applied in order to focus on practitioners with active roles in the infrastructure planning and implementation, which also encompassed engineers, project managers and contractors.

The survey had 85 valid responses giving a diversified but non-probabilistic sample that cuts across the different project types, including transportation, water and wastewater, urban development, industrial projects, and the IT and communication infrastructure. The scale of the projects was below 100 crores to the value that was more than 1000 crore, with average project life of less than a year to over five years.

Analysis of the data was done in three steps:

- To start with, descriptive statistics were used to describe the distribution of demographic and project characteristics.
- Second, cross-tabulations and chi-square methods were used to determine the relation between variables including gender and average time of a project, age bracket and years of experience, age bracket and project, age bracket and project scale, project scale and project duration, project type and project duration.
- Third, the multi-regression models were estimated and key sub systems were taken namely planning, engineering and industrial development where the dependent variable

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would be the overall subsystem application or effectiveness and the predictors would be specific practices (e.g., minimal delays, resource utilisation, risk management, safety enhancement, innovative methods, re-work reduction).

The methodologies used include the use of self-reporting perceptions, non-probability sampling, and a sample size that, as large as it is in terms of exploratory regression, might not be sufficient to represent the entire heterogeneity of the infrastructure sector in India. However, the integrative design provides a systematic and empirically based perspective on the productivity strategies that can be used to complement the literature which is predominantly qualitative and case-based.

4.0 Findings

Table 1 shows that stakeholder coordination within planning subsystem is the only statistically strong determinant, while routine planning questions on delays, resource use, and generic risk management do not yet show a clear effect at the sites of industrial infrastructure projects. The regression suggests that, among the planning-related determinants measured, stakeholder coordination is emerging as a primary planning determinant of perceived productivity, while delay-control and resource-efficiency items are weaker or salient (RQ1).

Table 1: Planning Subsystem [a]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	1.54	0.57		2.71	0.01
How effective are project planning practices in minimizing delays?	-0.07	0.08	-0.10	-0.95	0.35
To what extent does planning ensure efficient resource utilization?	0.03	0.07	0.04	0.35	0.73
How well does planning incorporate risk management to improve productivity?	0.21	0.15	0.17	1.41	0.16
How effective is planning in coordinating multiple stakeholders?	0.39	0.14	0.33	2.76	0.01

[a] *Dependent Variable: Rate the overall application of the Planning Subsystem at your site.*
Source: Created by authors

Forward-looking, this implies that strategies which explicitly strengthen multi-stakeholder coordination (e.g., integrated planning workshops, collaborative platforms, formal stakeholder engagement processes) are more likely to shift how practitioners rate planning performance than incremental tweaks to conventional scheduling or

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resource-allocation alone (RQ2). Within the Planning Subsystem, the evidence supports a subsystem narrative where coordination capability is the main active lever (RQ3). Going forward, the Planning Subsystem should act as a mediator between planning-coordination practices and project-level performance indicators (for example, time, cost, quality, safety, sustainability) to report better KPI outcomes (RQ4).

Table 2 shows that safety-oriented related engineering practices are the dominant determinant of perceived productivity, while design timeliness, rework reduction, and innovation do not yet emerge as statistically strong levers in the sample. The results suggest that, within engineering, safety and downtime control are the primary perceived determinants of subsystem performance and, by extension, of productivity, whereas design speed, error reduction, and visible innovation are currently secondary in practitioners' perceptions (RQ1). Despite widespread rhetoric on modularization and advanced methods, the findings justify foregrounding strategies that explicitly strengthen engineering-led safety and reliability (e.g., safer constructible design details, maintenance-friendly layouts, engineered temporary works that minimize stoppages, robust equipment planning) as core productivity strategies, rather than treating safety as merely a compliance add-on (RQ2). In the cross-subsystem narrative, Planning appears to be driven mainly by stakeholder coordination, while Engineering is driven mainly by safety/downtime performance (RQ3). Practically, this means future KPI analysis should include safety frequency/severity and downtime metrics alongside traditional time–cost–quality to capture the full impact of engineering-subsystem strategies (RQ4).

Table 2: Engineering Sub System [b]

Model	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
	B	Std. Error	Beta		
(Constant)	1.44	0.43		3.39	0.00
How effectively does engineering design contribute to timely project delivery?	0.04	0.08	0.06	0.54	0.59
To what extent do engineering solutions (technical methods, tools, and practices) reduce rework and errors?	0.04	0.07	0.06	0.57	0.57
How well does engineering integrate innovative methods (prefabrication, modular design, etc.)?	0.02	0.09	0.02	0.25	0.80
How effective is engineering in improving safety and reducing downtime?	0.53	0.10	0.54	5.23	0.00

[b] *Dependent Variable: Rate the overall application of engineering practices on your site.*
Source: Created by authors

Table 3 suggests that reliable utilities are the central industrial-development determinant of perceived productivity, while logistics support is emerging but not yet

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statistically firm, and land-use and connectivity are currently weak levers in the data. The results indicate that site-level utility reliability (continuous power, water, and telecom) is a key determinant of perceived productivity potential (RQ1). Looking ahead, strategies actually shaping perceptions in this subsystem are those that secure robust utilities on site (e.g., redundant power arrangements, reliable water supply, telecom/data resilience) (RQ2). In the cross-subsystem narrative, this table supports for physical-enabling environment as the most influential capability (RQ3). Therefore, tracking utility uptime as explicit KPI, and integrating utility-resilience decisions into early project planning, should be central to productivity-oriented industrial-infrastructure strategies (RQ4).

Table 3: Industrial Development, Land Use, and Infrastructure Sub-System [c]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	1.19	0.51		2.33	0.02
How adequately does infrastructure support project logistics and productivity?	0.19	0.11	0.21	1.85	0.07
To what extent does land-use planning enable efficient site utilization?	0.00	0.09	0.00	-0.04	0.97
How effective are transportation and connectivity facilities in reducing delays?	0.13	0.13	0.12	1.00	0.32
How well does utility availability (power, water, telecom) support smooth execution?	0.39	0.12	0.36	3.34	0.00

[c] *Dependent Variable: Rate the overall application of Industrial Development, Land Use, and Infrastructure at your site.*

Source: Created by authors

Table 4 shows that automation use and the reliability of automated systems are the main determinants of perceived productivity for the mining, robotics and industrial automation subsystem, while robotics-for-error-reduction and automation-for-safety are not yet driving perceptions in the sample. That is, within this subsystem, the key perceived determinants are (a) the extent to which automation is actually deployed in operations and (b) the reliability of those automated systems over time (RQ1). The significant coefficients suggest that current, impactful strategies are those that scale up automation use in core tasks (robots, drones, automated machinery on site) and invest in maintenance, redundancy, and robustness so that these systems do not fail frequently (RQ2). This table supports the view that the automation-intensity and reliability engine contribute to productivity outcomes for the mining, robotics and industrial automation subsystem (RQ3). Therefore, projects with

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higher scores on "automation improves productivity" and "automated systems are reliable" will show better throughput, labour productivity, and schedule adherence KPIs, especially in repetitive or hazardous tasks (RQ4).

Table 4: Mining, Robotics and Industrial Automation Sub-System [d]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.76	0.63		1.20	0.24
To what extent does automation (robotics, drone, automated machinery, etc.) improve productivity in your operations?	0.33	0.15	0.31	2.29	0.03
How effectively are robotics used to reduce manual errors and increase efficiency?	-0.01	0.18	-0.01	-0.06	0.95
How reliable are automated systems in sustaining uninterrupted productivity?	0.40	0.20	0.26	2.06	0.04
How effectively does automation enhance safety and reduce downtime losses?	-0.01	0.20	-0.01	-0.07	0.94

[d] *Dependent Variable: Rate the overall application of Mining, Robotics, and Industrial Automation at your site.*
Source: Created by authors

Table 5 indicates that AI-driven scheduling and resource optimization is the primary determinant of perceived productivity of the digital transformation, AI and computational models. Within this subsystem, the key determinant is the extent to which AI and analytics are actually used to optimize schedules and resource allocation, not digitalization in general (RQ1).

Table 5: Digital Transformation, AI and Computational Models [e]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.31	0.51		0.61	0.55
How effectively does digitalization (AI, IoT, big data) enhance decision-making in projects?	0.20	0.14	0.18	1.47	0.15
To what extent do computational models improve productivity forecasting?	-0.06	0.16	-0.05	-0.38	0.71
How well do digital tools improve coordination and communication across teams?	0.24	0.16	0.17	1.48	0.14
How effectively do AI and analytics optimize scheduling and resource allocation?	0.48	0.13	0.43	3.73	0.00

[e] *Dependent Variable: Rate the overall application of Digital Transformation, AI, and Computational Models at your site.*
Source: Created by authors

The evidence suggests that the strategies currently making a difference are those that embed AI in core planning workflows (AI schedulers, predictive resource planning, analytics-driven look-ahead planning), rather than standalone dashboards or experimental computational models (RQ2). This supports that the intelligence layer that sharpens planning and resource deployment (RQ3). Therefore, AI and analytics optimize scheduling and resource allocation will associate with better time and cost performance, fewer delays, and smoother resource utilization, in line with practice evidence that AI scheduling reduces overruns and improves predictability (RQ4).

Table 6 shows that engineering and digital transformation emerge as the two dominant subsystems of overall perceived productivity influence, while automation is emerging but weaker, and planning plus industrial development are not yet significant once the others are controlled for. The key system-level determinants of perceived productivity influence are up-to-date engineering practices and digital/AI capabilities, with automation following behind them (RQ1). Data suggest that strategies currently "moving the needle" for productivity are those that modernize and professionalize engineering practices (engineering for safety, reduced downtime, constructability, etc.), and embed digital and AI tools into scheduling, resource allocation, and project management, with automation strategies adding some value, but less decisively at present (RQ2).

Table 6: Overall System [f]

Model	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
	B	Std. Error	Beta		
(Constant)	-0.08	0.43		-0.19	0.85
Rate the overall application of Digital Transformation, AI, and Computational Models at your site.	0.34	0.08	0.40	4.42	0.00
Rate the overall application of Mining, Robotics, and Industrial Automation at your site.	0.15	0.08	0.18	1.86	0.07
Rate the overall application of Industrial Development, Land Use, and Infrastructure at your site.	0.08	0.11	0.07	0.69	0.49
Rate the overall application of engineering up-to-date practices on your site.	0.57	0.12	0.44	4.65	0.00
Rate the overall application of the planning subsystem at your site.	-0.09	0.11	-0.08	-0.82	0.41

[f]*Dependent Variable: Overall, how would you rate the influence of various subsystems on enhancing productivity in industrial infrastructure projects?*
Source: Created by authors

With Tables 1–5, on overall-basis the model supports a differentiated subsystem narrative: planning requires stakeholder coordination, engineering requires to focus on

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safety/downtime control, industrial development requires to focus on reliable utilities, automation should focus on extent and reliability of automation, and digital should focus on AI-enabled scheduling and resource optimization; but only engineering and digital subsystems currently have strong, system-wide influence on perceived productivity when all are entered in one model (RQ3). For impact on performance, engineering and digital-transformation should be treated as primary predictors; automation can be treated as a secondary/mediating predictor; and planning and industrial development can be treated as enabling/contextual subsystems whose effects may be indirect (RQ4).

5.0 Conclusion and Implications

This study has explored research methods that seek to study productivity in the industrial infrastructure projects through systematic literature and the survey-based hypothesis testing with 85 practitioners. The literature reviews summarised international evidence in terms of massive coverage of the planning and engineering subsystems, the emergent but disparate evidence of virtual transformation, and instances of pertinent gaps related to human and organisational issues.

This empirical research ensured that engineering and digital-transformation practices are primary predictors of perceived productivity in the industrial infrastructure projects followed by automation, planning and industrial development. Theoretically, the results support a subsystem integration viewpoint of the productivity with the interaction of different subsystems to influence the results of temporal, cost, quality, safety, and sustainability.

Practically, the study suggests that organisational planning of high quality should be based subsystems thinking. Its implications at the policy level are crucial for implementing standardized KPI frameworks, facilitating information sharing and benchmarking, and capacity-building efforts to digitally enable the workforce to drive mission-based projects.

Study limitations include non-probability sampling, use of self-reported perceptions and consideration of perceived instead of actively measured productivity measures. This study can be furthered by future research using longitudinal designs, greater substantive and more heterogeneous sample sizes as well as more comprehensive factors that combine human and organisational variables, including technical and digital ones.

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