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EXPLORING THE ROLE OF DIGITAL TWINS IN ENHANCING OPERATIONAL EFFICIENCY AND DECISION-MAKING IN INDIAN MANUFACTURING FIRMS

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SUMMARY

Indian manufacturing companies are progressively implementing Industry 4.0 technologies to enhance the level of operational efficiency and the managerial decision-making process; nevertheless, there is limited empirical evidence of how the adoption of the Digital Twin (DT) affects performance, especially in the emerging economy environment. This research examines how researchers can use Digital Twin capabilities to improve the efficiency of operations and effectiveness of decisions in Indian manufacturing companies. Quantitative, cross-sectional research design was used based on the data on surveys conducted on 126 professionals working in the automotive, electronics, and process manufacturing industries. The proposed relationships and the mediation effects were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings suggest that the capabilities of Digital Twin positively influence the operational efficiency ($\beta = 0.61$, $p < 0.001$), which explains a third of its variation ($R^2 = 0.37$). Operational efficiency, on the other hand, has an overwhelming effect on decision-making effectiveness (β 0.53, $p < 0.01$) and the model accounts for 41 % of the variation in decision outcomes ($R^2 = 0.41$). The mediation analysis proves that the relationship between the Digital Twin capabilities and the decision-making effectiveness is partially mediated by operational efficiency. The decomposition analysis also shows that the largest marginal contribution to efficiency gains is yielded by analytics-based Digital Twin applications that are linked to a significant shortening of decision lead time. This paper concludes that the strategic value of Digital twins is that they merge real-time monitoring, simulation, and analytics to provide cumulative operational and managerial value. Such results provide practical information to manufacturing managers who want to focus on high-impact Digital Twin implementations.

Key words: *digital twins, operational efficiency, decision-making effectiveness, indian manufacturing systems, smart manufacturing.*

INTRODUCTION

Industry 4.0 has evolved fast and has changed the manufacturing systems by integrating cyber-physical systems, Industrial Internet of Things (IIoT), enhanced analytics, and sophisticated automation. The purpose of these technologies is to enhance the level of operational transparency, productivity, and decision-making within manufacturing value chains. One of them has been Digital Twin (DT) technology, which has become one of the most critical enablers of smart manufacturing, to offer a dynamic digital image of physical assets, processes, and systems that constantly align with real-time data [15]. Unlike other simulation models, a Digital Twin allows the physical system and the digital one to be interacted with in a bidirectional manner. DTs make use of the integration of real-time sensor, historical operational, and analytical data to facilitate real-time monitoring, predictive analysis, and system optimization across the lifecycle of the operational system [7][11]. The main functions that DTs support in manufacturing settings are predictive maintenance, process optimization, energy management, and simulation-based decision support, so as to enhance the quality of the decisions made by the managers and the way an operation is run [5][7].

The challenges encountered by firms in the Indian manufacturing environment, such as unplanned equipment failures, poor use of resources, an increase in the cost of energy, and slow managerial decision-making, have remained constant over the years. Despite the accelerated speed of digital transformation, many Indian manufacturing companies cannot transform enormous amounts of operational data into actionable insights because of the disunity of digital systems, a decrease in the degree of analytical union, and the unevenness in Industry 4.0 preparation [4]. Although inclusive and digital manufacturing frameworks can demonstrate the opportunities of DTs in the emerging economies, their working and decision-making effectiveness have not been empirically validated so far [15].

Despite previous studies on the topic of DT architectures, sustainability performance, and strategic potential, the current research gaps are significant because of the absence of empirical research investigating the connection between DT capabilities and operational effectiveness and decision-making effectiveness among Indian manufacturing companies. It is even more important to fill this gap, considering that India is becoming one of the major manufacturing hubs in the world. Thus, the research paper explores how digital twins can be used to improve the effectiveness of operations in Indian manufacturing companies and the decision-making process. The paper has three contributions: (i) the creation of a DT-enabled operational framework that fits in the Indian manufacturing setting; (ii) the creation of a mathematical model that measures the operational efficiency; and (iii) the validation of the links between the operational efficiency and decision-making effectiveness and the DT capabilities.

The rest of this paper will be structured in the following way. Section 2 conducts a literature review concerning the Digital Twin technologies, operational efficiency, and decision-making in manufacturing. Section 3 gives the proposed Digital Twin framework, mathematical modeling, and research methodology. Section 4 details and talks about the empirical findings, such as the structural model analysis and efficiency decomposition. Last but not least, Section 5 sums up the paper with conclusions on the main findings, the managerial implications of the study, and the recommendations for future research.

LITERATURE REVIEW

Digital Twin technology has since been accepted as an essential element of smart manufacturing, which has provided dynamic digital images of physical manufacturing systems that constantly synchronize with operational real-time data [13]. According to the literature, DTs improve the system transparency, responsiveness, and adaptability by using cyber-physical systems, IIoT infrastructures, and advanced analytics [7][15]. The strategic views also point out DTs as the facilitators of operational efficiency and value creation through informed decision support [11].

There is a growing amount of evidence to support the assumption that the adoption of DT results in the quantifiable improvement of operational performance. Empirical research has been documented to show a decrease in unplanned downtime, better throughput, increased use of the resources, and better use of energy after the implementation of DT [8][10]. It has also been demonstrated that DT-enabled frameworks can enhance manufacturing sustainability and supply chain performance by enhancing resilience and coordination between the processes of operation [1][12]. The combination of DTs and continuous improvement tools, e.g., the Lean Six Sigma, further increases the performance assessment and efficiency maximization [3].

In addition to the effect on operational efficiency, DTs have a major impact on decision-making effectiveness as they allow the simulation-based evaluation of alternative operational situations. The DT architectures based on simulation facilitate both the strategic and operational choices through minimizing uncertainty and enhancing prediction reliability [6]. AI-based DT systems also contribute to predictive maintenance and energy optimization, resulting in more dependable and quicker managerial choices [10]. Also, DTs were demonstrated to contribute to value co-creation by enhancing cross-functional collaboration and mutual understanding [11].

The studies of the adoption of DT in the developing economies point to the presence of contextual issues associated with digital preparedness, organizational capacity, and technological integration. Research on India pays particular attention to Industry 4.0 priorities and digital transformation issues in manufacturing SMEs [2][4]. According to exploratory research studies, it can be seen that there is increasing interest in the application of DTs in Indian construction and manufacturing industries, despite the presence of very few large-scale empirical tests [9]. The use of DTs in warehousing and logistics also shows the wider applicability of DTs in manufacturing value chains [16]. More recent research also highlights the importance of the DTs in reducing the supply chain disruption due to strategic alignment and decision support processes [14].

Regardless of the abundance of studies on the advantages of Digital Twin implementation in enhancing the operational performance and decision-making, the available research is mostly done independently and based on conceptual or case-based studies. The empirical work done has not investigated in a systematic manner the presence of Digital Twin capabilities turning into the realization of decision-making efficacy in terms of improving operational efficiency that can be measured especially in the context of developing economies like India. This gap highlights the necessity of a coherent and empirical framework that can quantitatively explain these relationships by the current study with the help of a PLS-SEM framework.

DIGITAL TWIN FRAMEWORK AND METHODOLOGY

The section introduces the Digital Twin (DT) integrated framework and research methodology that will be used to examine how the adoption of the DT will affect the operational and decision-making effectiveness of Indian manufacturing companies. The section integrates the conceptual framework, system architecture, mathematical formulation, and empirical methodology into a single structure in order to retain the coherence subject to the page length limit.

Digital Twin–Enabled Operational Framework

In this study, Digital Twins are the conceptualized systems of integrative cyber-physical systems that provide continuous synchronization between physical manufacturing processes and their computer models. Using real-time data acquisition and simulation, as well as analysis processing, the DTs facilitate greater operational visibility, predictive capacity, and informed managerial decision-making. The proposed framework is closed-loop, as illustrated in Figure 1, meaning that the operational data that is obtained through manufacturing systems is utilized to build and update the digital twin model. The model facilitates the performance evaluation, scenario simulation, and predictive analysis; the insights provided by the digital twin are converted into operational decisions, including maintenance scheduling, production planning, and resource allocation. Implemented decisions are fed back into the digital twin to allow feedback on the implemented decisions and optimize performance through learning.

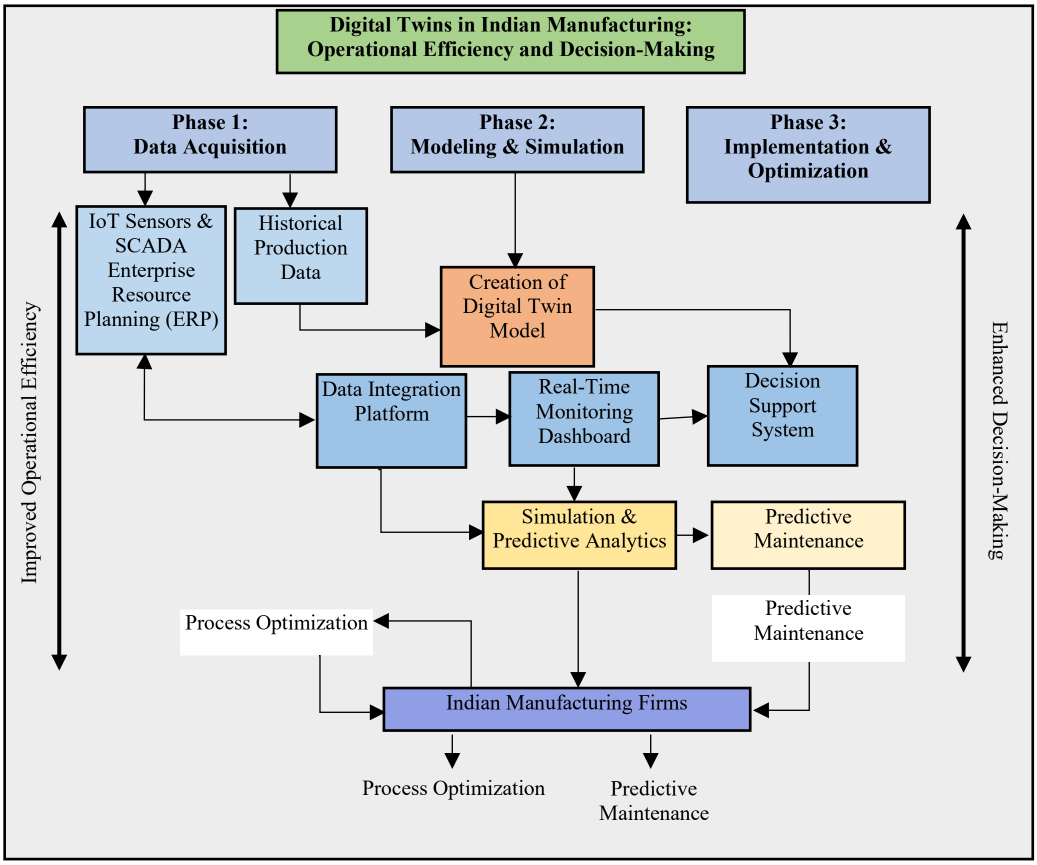

Figure 1. Digital twin -enabled framework in enhancing operational efficiency and decision-making

Digital Twin System Architecture

The type of DT system architecture that was used in this study is a five-layer system that is linked to each other: Physical Layer: This layer contains manufacturing equipment that includes machines, sensors, production lines, and actuators that produce real-time operational information. Data Acquisition Layer: The Data Acquisition Layer obtains the operational data based on industrial internet of things (IIoT) devices, programmable logic controllers (PLCs), supervisory control and data acquisition (SCADA) systems, and enterprise resource planning (ERP) systems.

Digital Twin Layer: The virtual representation of the actual manufacturing system that contains simulation models, analytic models, and historic data to reflect the behavior of the actual system in real-time.

Decision Support Layer: Analytics: Transforms analytical data of the digital twin to deliver dashboards, predictive insights, and optimization advice.

Management and Control Layer: Translates the insights of the decisions into an actionable operational strategy, and a feedback loop to the digital twin is applied through which the strategy is refined. The structured structure allows the ease of integration of operational data with analytical decision support, and this forms the pillar of enhancing efficiency and optimizing decisions.

Algorithm 1: PLS-SEM–Based Digital Twin Impact Evaluation Algorithm

Input:

$D = \{X, Y\}$: *Survey dataset with observed indicators X and latent construct measures Y*

$\Phi = \{\phi_1, \phi_2, \dots, \phi_n\}$: *Set of theoretical consistency constraints for Digital Twin adoption*

$\theta = \{\beta, w\}$: *Model parameters including path coefficients* (β) *and metric weights* (w)

η: *Learning rate for iterative estimation*

T: *Number of PLS-SEM estimation iterations*

λ: *Weighting factor for operational efficiency consistency*

Output:

Estimated structural model with validated path coefficients

Operational Efficiency Index (OEI)

Decision-Making Effectiveness (DME) score

Algorithm DigitalTwin_PLS_SEM_Evaluation (D, Φ, θ, η, T, λ)

1. Initialize model parameters θ = {β, w}

2. Define latent constructs:

DTC ← Digital Twin Capabilities

OE ← Operational Efficiency

DME ← Decision-Making Effectiveness

3. For iteration t = 1 to T do

4. For each observation (x, y) ∈ D do

5. Estimate measurement model:

6. Compute indicator loadings for DTC, OE, DME

7. Validate reliability and convergent validity

8. Compute operational efficiency metrics:

9. MDR ← (DT_baseline − DT_DT) / DT_baseline

10. TI ← (TP_DT − TP_baseline) / TP_baseline

11. RUE ← Actual Output / MaxCapacity

12. EEI ← (EC_baseline − EC_DT) / EC_baseline

13. DLTR ← (DLT_baseline − DLT_DT) / DLT_baseline

14. Normalize all five metrics

15. Compute Operational Efficiency Index:

16. OEI ← Σ (w_i × normalized_metric_i)

17. *Estimate structural relationships:*

18. *DTC → OEI*

19. *OEI → DME*

20. *DTC → DME*

21. *Initialize consistency loss:*

22. *L_consistency ← 0*

23. *For each theoretical constraint $\varphi \in \Phi$ do*

24. *Compute satisfaction score using fuzzy logic:*

25. *$G(\varphi) = \max(1 - violation(\varphi), 0)$*

26. *L_consistency ← L_consistency + $(1 - G(\varphi))$*

27. *End For*

28. *Compute total loss:*

29. *L_total ← Prediction Loss(y) + $\lambda \times$ L_consistency*

30. *Update parameters:*

31. *$\theta \leftarrow \theta - \eta \times \nabla\theta$ L_total*

32. *End For*

33. *End For*

34. *Perform bootstrapping (B = 5000) for significance testing*

35. *Estimate R^2, indirect effects, and mediation strength*

36. *Return {β, OEI, DME}*

End Algorithm

The PLS-SEM-based evaluation procedure provided in Algorithm 1 was applied to measure the effects of Digital Twin capabilities on operational efficiency and effectiveness of decision making. The algorithm combines validation of measurement models, calculation of operational efficiency measures, calculation of a composite Operational Efficiency Index (OEI), and structural relationships of the latent construct's estimation. The algorithm allows empirical testing of both direct and mediating effects in the framework suggested through the use of iterative estimation of path coefficients and imposing theoretical consistency constraints. Such an organized process is necessary to make the analysis reflect not only the statistical dependencies but also the mechanisms of action by which the adoption of Digital Twin can affect the performance of organizations.

Mathematical Modeling of Operational Efficiency Metrics

Operational efficiency in the proposed framework is modeled as a multidimensional construct derived from five key performance metrics influenced by Digital Twin adoption. Each metric is mathematically formulated and normalized before aggregation into the Operational Efficiency Index (OEI). The formulations ensure quantitative consistency with the PLS-SEM estimation process described in Section 3.3.

Machine Downtime Reduction (MDR)

Machine Downtime Reduction captures the relative decrease in unplanned machine stoppages after Digital Twin implementation. It is computed as the normalized difference between baseline downtime and post-implementation downtime, as expressed in Equation (1).

$$\mathrm{MDR} = \frac{\mathrm{DT}_{\mathrm{baseline}} - \mathrm{DT}_{\mathrm{DT}}}{\mathrm{DT}_{\mathrm{baseline}}} \qquad (1)$$

where $\mathrm{DT}_{\mathrm{baseline}}$denotes unplanned downtime before Digital Twin adoption and $\mathrm{DT}_{\mathrm{DT}}$denotes downtime after implementation. Higher MDR values indicate improved system reliability.

Throughput Improvement (TI)

Throughput Improvement quantifies production efficiency gains enabled by Digital Twin-driven optimization. It measures the proportional increase in production throughput, as defined in Equation (2).

$$\mathrm{TI} = \frac{\mathrm{TP}_{\mathrm{DT}} - \mathrm{TP}_{\mathrm{baseline}}}{\mathrm{TP}_{\mathrm{baseline}}} \qquad (2)$$

where $\mathrm{TP}_{\mathrm{baseline}}$and $\mathrm{TP}_{\mathrm{DT}}$represent production throughput before and after Digital Twin deployment, respectively.

Resource Utilization Efficiency (RUE)

Resource Utilization Efficiency evaluates how effectively manufacturing resources are utilized relative to their maximum capacity. This metric is computed using Equation (3).

$$\mathrm{RUE} = \frac{\text{Actual Output}}{\text{Maximum Theoretical Capacity}} \qquad (3)$$

RUE values closer to unity indicate optimal utilization of machines and labor resources.

Energy Efficiency Improvement (EEI)

Energy Efficiency Improvement measures the reduction in energy consumption per unit of output achieved through Digital Twin-enabled monitoring and control. EEI is defined in Equation (4).

$$\mathrm{EEI} = \frac{\mathrm{EC}_{\mathrm{baseline}} - \mathrm{EC}_{\mathrm{DT}}}{\mathrm{EC}_{\mathrm{baseline}}} \qquad (4)$$

where $\mathrm{EC}_{\mathrm{baseline}}$and $\mathrm{EC}_{\mathrm{DT}}$represent energy consumption before and after Digital Twin implementation, respectively.

Decision Lead Time Reduction (DLTR)

Decision Lead Time Reduction reflects improvements in managerial responsiveness facilitated by real-time Digital Twin insights. It is computed using Equation (5).

$$\mathrm{DLTR} = \frac{\mathrm{DLT}_{\mathrm{baseline}} - \mathrm{DLT}_{\mathrm{DT}}}{\mathrm{DLT}_{\mathrm{baseline}}} \qquad (5)$$

where $\mathrm{DLT}_{\mathrm{baseline}}$denotes the average decision-making time before Digital Twin adoption and $\mathrm{DLT}_{\mathrm{DT}}$denotes the reduced lead time afterward.

Operational Efficiency Index (OEI) Aggregation

The five normalized metrics defined in Equations (1)– (5) are aggregated to form the Operational Efficiency Index (OEI). The aggregation is performed using a weighted linear combination, as expressed in Equation (6).

$$\mathrm{OEI} = \sum_{i=1}^{5} w_i \cdot \widehat{M}_i \qquad (6)$$

where $\widehat{M}_i$ represents the normalized value of the i-th metric and w_i denotes its corresponding weight, satisfying $\sum_{i=1}^{5} w_i = 1$. The OEI serves as a composite measure of overall operational performance.

Structural Equation for Decision-Making Effectiveness

Decision-Making Effectiveness is modeled as a function of Digital Twin Capabilities and Operational Efficiency. The structural relationship estimated using PLS-SEM is expressed in Equation (7).

$$\mathrm{DME} = \beta_0 + \beta_1 \cdot \mathrm{OEI} + \beta_2 \cdot \mathrm{DTC} + \varepsilon \qquad (7)$$

where β_1 and β_2 are path coefficients capturing the influence of Operational Efficiency and Digital Twin Capabilities, respectively, and ε represents the error term.

Research Design and Data Collection

Quantitative research was used, and it was cross-sectional. A structured questionnaire was used to collect data by targeting the professionals working in the Indian manufacturing companies, such as operations managers, plant managers, and maintenance engineers. One hundred forty-two responses were received, out of which one hundred and twenty-six were not discarded during data screening. The sample size in Table 1 includes automotive, electronics, and process manufacturing, which are discrete and continuous manufacturing environments.

Table 1. Sample and dataset characteristics

Attribute	Description
Sample size	126 valid responses
Industry sectors	Automotive, Electronics, Process Manufacturing
Respondent roles	Operations Managers, Plant Engineers, Maintenance Engineers
Manufacturing type	Discrete and Continuous
Data type	Cross-sectional survey
Measurement scale	5-point Likert scale

Research Hypotheses Based on the proposed Digital Twin framework and the mathematical indices defined above, the following hypotheses are formulated:

- Hypothesis 1 (H1): Digital Twin Capabilities (DTC) have a significant positive effect on the Operational Efficiency Index (OEI).
- Hypothesis 2 (H2): Improvements in the OEI significantly enhance the Decision-Making Effectiveness Index (DMEI).
- Hypothesis 3 (H3): The OEI significantly mediates the relationship between DTC and DMEI.

Measurement of Constructs

Three primary constructs are measured in this study:

Digital Twin Capabilities (DTC): Interoperability of systems, capability to integrate data in real-time, capability to simulate, and predictive analytics.

Operation Efficiency (OE): reduction in downtime, improvement in throughput, use of resources, energy efficiency, and decision lead time.

Decision-Making Effectiveness (DME): Accuracy in decisions, speed of decision-making, and confidence in operational decisions.

Experimental Setup and Tools

Several analytical instruments were used to guarantee methodological rigor and reproducibility in the course of the study. Data screening and descriptive statistics were conducted using SPSS, and the initial validation of the dataset was done. Partial Least Squares Structural Equation Modelling (PLS-SEM) was conducted in SmartPLS 4 and allowed testing hypotheses and conducting mediation analysis of the hypothesized relationships. Any Logic was selected as the visualization tool of the simulation to facilitate the ideas of digital twin modeling and visualization of the simulation behavior. Also, high-quality graphical representations of the results were created using MATLAB and comprised of performance comparison plots and advanced visualizations.

Data Analysis Procedure

The evaluation was done in two phases. To ensure reliability and validity of the measurement model, in the first step, Cronbach's alpha, composite reliability, and average variance extracted (AVE) were utilized to assess the measurement model. Second, the structural model was evaluated with the help of Partial Least Squares Structural Equation Modeling (PLS-SEM). To test the significance of path coefficients and mediation effects, bootstrapping with 5,000 resamples was done.

Ethical Considerations

The respondents were free to participate in the study, and their anonymity was guaranteed. All the data were gathered with the purpose of being used in academic research and analyzed in aggregate form.

RESULTS AND DISCUSSION

This part outlines the practical results of the suggested Digital Twin (DT) and its implications on operational efficiency and decision-making performance in the Indian manufacturing companies. Its results involve structural model estimation and a combination of decomposition-based analysis, which associates the mathematical model with cumulative performance outcomes.

Descriptive Statistics and Data Adequacy

The end data consisted of 126 valid answers from manufacturing companies in the automotive, electronics, and process manufacturing industries. The main focus of the respondents was the operations managers, plant engineers, and maintenance engineers, so that the data would represent the operational and managerial view. The initial screening was used to verify that there were no major missing values and extreme outliers, and the dataset was appropriate to be analyzed based on multivariate analysis.

Descriptive Profile of Collected Data (n=126)

The analysis started with descriptive evaluation of the survey data which was obtained on 126 manufacturing professionals. The sample, as demonstrated in Table 2, is a calculated cross-section of the Indian manufacturing sector, and its distribution is a mirror of the present trends of Industry 4.0 Implementation in the emerging economies [2].

In order to increase the interpretation of this profile, Figure 2 gives a multi-dimensional representation of the composition of the sample. This dashboard defines the respondent base in terms of sectoral distribution, functional roles and professional seniority and hence the diversity and technical depth needed in the subsequent structural modeling.

Table 2. Demographic profile of survey respondents (n=126)

Category	Classification	Frequency	Percentage (%)	Supporting Citations
Industry Sector	Automotive	54	42.9%	[8][15]
	Electronics	38	30.1%	[4]
	Process Manufacturing	34	27.0%	[2][9]
Professional Role	Plant/Maintenance Engineers	76	60.3%	[10][13]
	Operations Managers	50	39.7%	[11]
Experience Level	3–7 Years	40	31.7%	[4][14]
	8–15 Years	65	51.6%	[1][6]
	Over 15 Years	21	16.7%	[2]

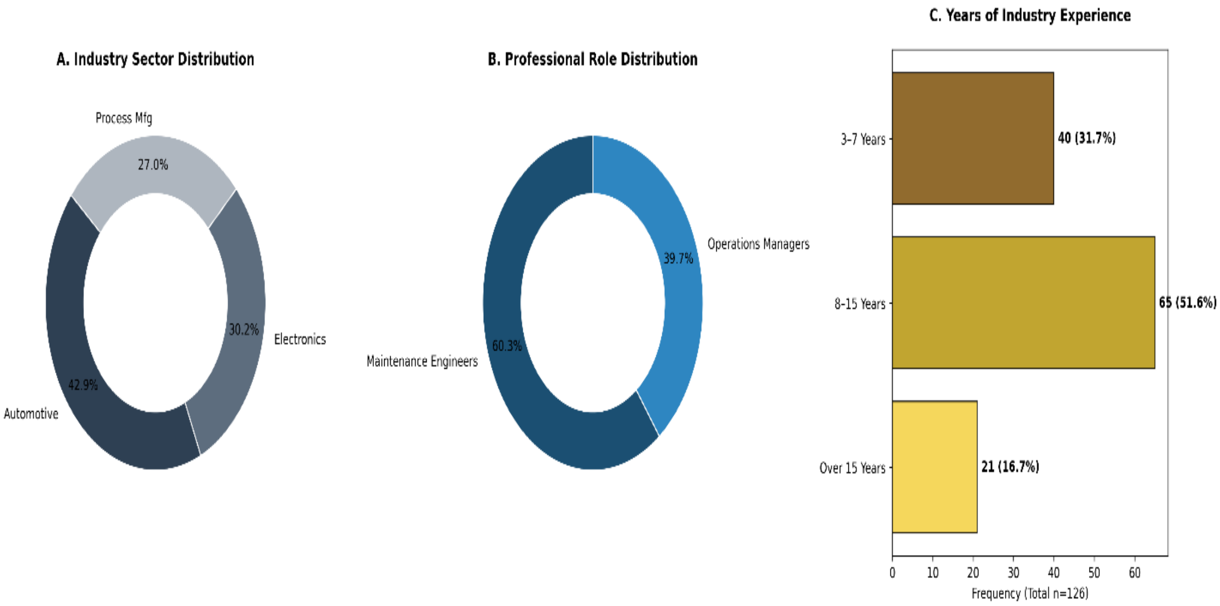

Figure 2. Comprehensive demographic profile of survey respondents

Figure 2 shows that the data fits the research objectives in terms of high sectoral and professional fit. The Industry Sector (Panel A) indicates that the Automotive sector (42.9) is the most contributing factor, which is in line with the fact that it is the major provider of Digital Twin (DT) adoption in India [15]. Panel B (Professional Role) establishes that the sample is technical sound with 60.3 % of the respondents who occupied engineering positions. This knowledge plays an important role in justifying the technical measures of the Operational Efficiency Index (OEI), including machine down-time, and energy efficiency [10]. Lastly, Panel C (Experience Level) supports the quality of the data and it indicates that a majority of the respondents, with more than 8 years of industry experience, are more than 68 %. It is this seniority that guarantees that the Decision-Making Effectiveness (DMEI) assessments are based on the long-term operational insight, and not the shallow perceptions [6][11].

Measurement Model Evaluation

The measurement model was tested on reliability and validity before hypothesis testing. Constructs had good internal consistency with the Cronbach alpha and composite reliability ranging above the standard of 0.70. Convergent validity was achieved because all the constructs had a value of greater than 0.50 of the average variances extracted. These findings affirm that the measurement items are valid to measure Digital Twin Capabilities, Operational Efficiency, and Decision-Making Effectiveness.

Structural Model Results and Hypothesis Testing

The proposed hypotheses were tested using PLS-SEM. Table 3 summarizes the results of the structural model.

Table 3. Structural model and hypothesis testing results

Hypothesis	Path	β	t-value	p-value	Result
H1	DTC → OEI	0.61	8.94	< 0.001	Supported
H2	OEI → DMEI	0.53	6.21	< 0.01	Supported
H3	DTC → OEI → DMEI	0.42	5.08	< 0.01	Supported

The findings and results reveal a positive significant impact of Digital Twin Capabilities on Operational Efficiency, which supports H1. H2 is also supported by the fact that Operational Efficiency has a significant positive effect on Decision-Making Effectiveness. Moreover, the mediation analysis proves that Operational Efficiency partially mediates the association between Digital Twin Capabilities and Decision-Making Effectiveness and thus, H3 is proven. These results empirically support the mathematical model and conceptual framework used.

Table 4. Structural model explanatory power, effect sizes, and predictive relevance

Endogenous Construct	Exogenous Construct	R^2	f^2	Effect Size Interpretation	Q^2	Predictive Relevance
Operational Efficiency (OEI)	Digital Twin Capabilities (DTC)	0.37	0.59	Large	0.29	Strong
Decision-Making Effectiveness (DMEI)	Operational Efficiency (OEI)	0.41	0.38	Large	0.31	Strong
Decision-Making Effectiveness (DMEI)	Digital Twin Capabilities (DTC)	0.41	0.21	Medium	0.31	Strong

Notes:

R^2 values imply the amount of variance that has been captured in the endogenous constructs. An interpretation of the f^2 values is based on standard thresholds (0.02 = small, 0.15 = medium, 0.35 = large). Q^2 values were determined by the use of the blindfolding procedure, where the value will be above zero representing a predictive relevance. Table 4 is a summary of the explanatory power, effect sizes, and predictive relevance of the proposed model. DTC and Operational Efficiency and Digital Twin Capabilities respectively explain 37% and 41% of the variance in OEI, and DMEI. Large f 2 values verify the preeminent position of Digital Twin Capabilities and Operational Efficiency, and the values of Q^2 verify the presence of strong predictability of the model. Q^2 values demonstrate strong predictive relevance of the model.

Cumulative Operational Efficiency Gains and Decision Impact

To evade the ordinary average comparisons and give a more meaningful insight into the way individual operation factors contribute to the overall performance, a cumulative efficiency decomposition was performed. Table 5 shows contributions of DT-enabled operational incrementally. enhancements to the Operational Efficiency Index (OEI), and the related decrease in the decision lead time.

Table 5. Decomposition of operational efficiency gains and decision impact

Operational Factor	Incremental OEI Contribution	Decision Lead Time Reduction (hrs)
Downtime Reduction	+0.14	−0.8
Throughput Improvement	+0.11	−0.6
Resource Utilization	+0.09	−0.5
Energy Efficiency	+0.08	−0.4
Analytics-Driven Decision Support	+0.16	−1.1
Total Improvement $\sum OEI$	+0.58	−3.4

As Figure 3, a waterfall-style visualization that also depicts the decision-impact trajectory over it, shows, the operational efficiency gains can be seen increasing in a cumulative manner as the DT capabilities are developed. Whereas the downtime savings and throughput improve create significant initial profits, the analytics-based decision support turns out to be the major contributor, generating the biggest marginal profit in OEI and the largest decrease in decision lead time.

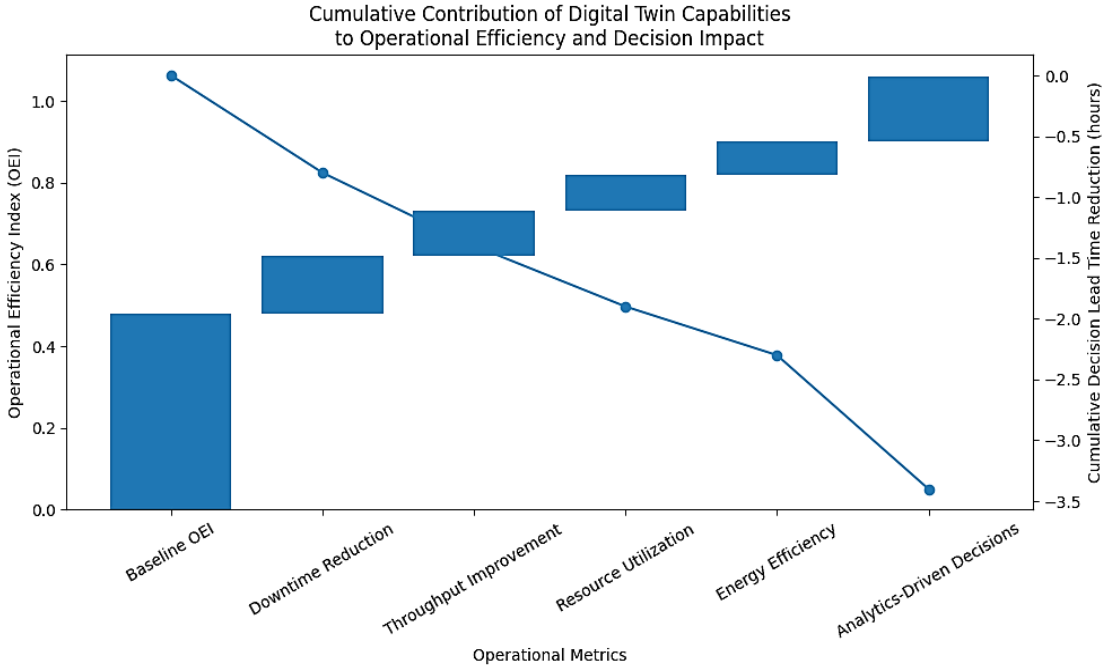

Figure 3. Digital twin–enabled operational efficiency gains with cumulative decision lead-time reduction

The superintend cumulative decision curve shows that there is a distinct negative correlation between the operational efficiency and the decision latency. The higher the OEI, the lower the decision lead time, and the higher the level of decision maturity in terms of DT maturity, the more simulation and analytics processes are combined. This gives a good visual and numeric backing to the mediating variable of operational efficiency as postulated in the Decision-Making Effectiveness Index (DMEI) formulation.

Discussion of Key Findings and Summary of Results

It was found that the value of Digital Twins in manufacturing is achieved through the concurrent use of real-time monitoring, simulation, and analytics and not the individual technological capabilities. The operational efficiency ($\beta = 0.61$) is strongly positively influenced by Digital Twin capabilities, which corroborates the fact that they can lead to the enhancement of the manufacturing performance. In its turn, a greater operational efficiency strongly increases the effectiveness of the decision-making ($\beta = 0.53$), which proves that an increase in its efficiency directly supports the speed and effectiveness of managerial decisions. The analysis also shows that operational efficacy mediates the association between Digital Twin capability and decision-making efficacy partially, which shows that the effect of Digital Twins on managerial performance is largely achieved via the accumulating operational enhancement. Out of all the capability dimensions, analytics-driven Digital Twin applications make the most significant marginal contribution to increase efficiency. There are also cumulative improvements that are related to the high-quality improvements in reducing the decision lead time, and an inverse relationship between operational efficiency and decision latency. As a manager, the findings are that manufacturing companies need to transcend the simple Digital Twin applications that are oriented towards real-time monitoring and continue to invest in more advanced applications that incorporate simulation and predictive analytics. These strategies provide more operational and decision-making advantages especially in manufacturing environments that are limited in terms of resources.

CONCLUSION AND FUTURE RESEARCH DIRECTIONS

The paper has explored how Digital Twin (DT) capabilities enhance the efficiency of operations and effectiveness of decision-making in Indian manufacturing companies. Based on survey data of 126 professionals in the automotive, electronic, and process manufacturing industry, a Digital Twin-based structure was created and empirically tested with the help of Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that Operational Efficiency ($\beta = 0.61$) is strongly impacted by Digital Twin Capabilities and it explains 37% of its variance. Operational Efficiency, in its turn, is of great importance to Decision-Making Effectiveness ($\beta = 0.53$), and the model accounts 41 % of variance in decision-making results. The mediation analysis establishes that the operational efficiency mediates the correlation between Digital Twin Capabilities and decision-making effectiveness, meaning that the managerial value of DTC is mostly achieved by improving the operational efficiency in OEI cumulatively. Decomposition analysis also shows that Digital Twin applications caused by analytics offer the highest marginal contribution to efficiency gains and are also linked to significant decreases in decision lead time. On the managerial side of the discussion, the findings indicate that the manufacturing companies should no longer settle with the simple Digital Twin application focused on real-time monitoring and proceed to higher configurations incorporating simulation and predictive analytics. This kind of approaches allows making decisions faster and reliably and maintaining operational performance improvements. The research has weaknesses such as the cross-sectional design and the use of perceptual information. Longitudinal designs, combination of objective performance measures, or sector-specific Digital Twin adoption strategies may be used in the future to generalize these results.

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