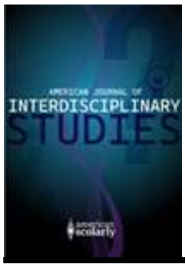

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DIGITAL TWIN-DRIVEN PROCESS MODELING FOR ENERGY EFFICIENCY AND LIFECYCLE OPTIMIZATION IN INDUSTRIAL FACILITIES

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Abstract

This quantitative cross-sectional, case-based study investigates how digital twin driven process modeling supports energy efficiency and lifecycle optimization in industrial facilities. The problem addressed is the limited empirical evidence on whether digital twin capabilities translate into measurable improvements in plant level performance. Using a structured survey, data were collected from 180 cloud or enterprise facility cases, targeting operations, maintenance, energy and digitalization professionals. Key independent variables were digital twin implementation level, data integration and quality, real time analytics capability and process model fidelity, measured on Likert 5-point scales, while dependent variables captured perceived energy efficiency performance and lifecycle optimization performance. The analysis plan combined dehmmscriptive statistics, reliability testing, Pearson correlations and multiple regression with controls for facility size, industry type and equipment age. Results show moderate to high maturity of digital twin practices (means 3.55 to 3.92) and positive outcomes for energy and lifecycle performance (means 3.58 to 3.65). Digital twin dimensions were moderately to strongly correlated with energy and lifecycle indices ($r = 0.42$ to 0.57, $p < 0.001$). Regression models explained 49 percent of the variance in energy efficiency and 46 percent in lifecycle optimization; data integration and implementation were the strongest predictors of energy efficiency ($\beta = 0.29$ and 0.24), while real time analytics, implementation, data integration and model fidelity significantly predicted lifecycle performance ($\beta = 0.27, 0.23, 0.21, 0.15$). The findings imply that industrial facilities should prioritize robust data integration and embedded analytics when scaling digital twin initiatives to secure durable gains in energy efficiency and asset lifecycle performance.

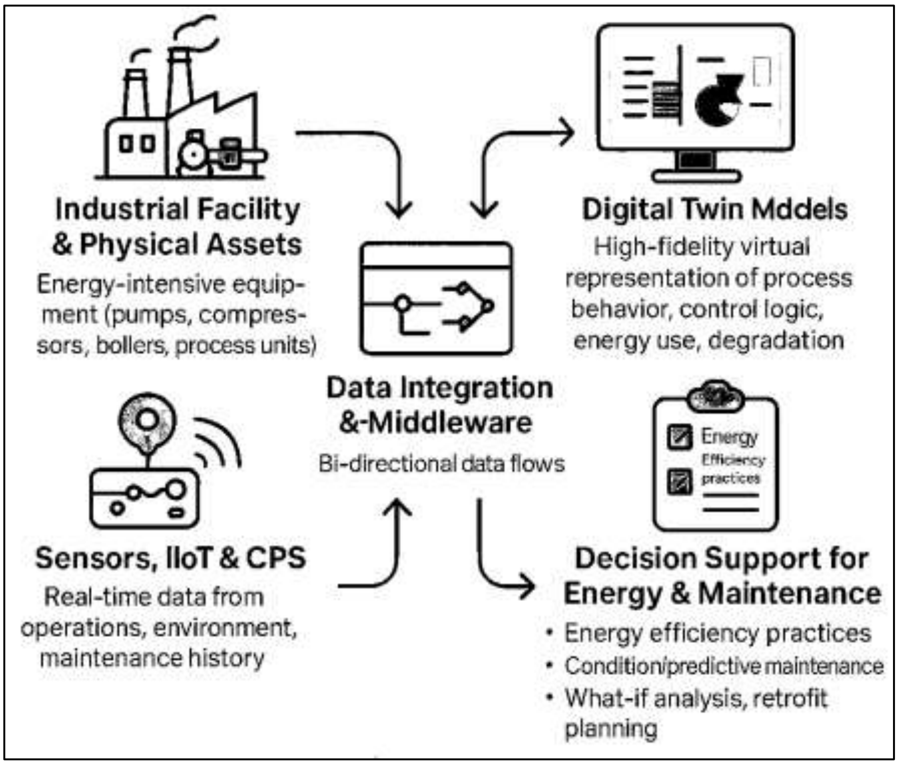
Keywords

Digital Twin Driven Process Modeling, Energy Efficiency, Lifecycle Optimization, Industrial Facilities, Real Time Analytics

INTRODUCTION

Digital twin–driven process modeling has emerged as a central concept in the broader transformation of industrial systems toward data-driven, cyber-physical, and intelligent operation. A digital twin is frequently defined as a high-fidelity virtual representation of a physical asset, system, or process that remains tightly linked to its real-world counterpart through bi-directional data flows across the entire lifecycle (Liu et al., 2020; Qi & Tao, 2018). In early aerospace work, the digital twin paradigm was described as an ultra-high-fidelity model continuously updated with sensor data, maintenance history, and operational context to mirror the state and behavior of a specific vehicle over time (Glaessgen & Stargel, 2012). In manufacturing and process industries, this concept extends beyond static computer-aided design models to encompass dynamic process behavior, control logic, and performance trajectories (Kritzinger et al., 2018). At the same time, industrial facilities remain among the largest global energy consumers and emitters, accounting for a substantial share of final energy use and greenhouse gas emissions, so that improvements in process-level efficiency directly support international climate and sustainability goals (Ghobakhloo & Fathi, 2021). Empirical studies on industrial energy management repeatedly show persistent technical, organizational, and economic barriers that limit the realization of cost-effective efficiency measures in plants of different sizes and sectors (Fuller et al., 2020). In this global context, digital twin–driven process modeling offers a way to continuously monitor, simulate, and optimize energy-intensive processes within industrial facilities, while simultaneously informing lifecycle decisions about maintenance, retrofit, and asset renewal (Cimino et al., 2019).

Figure 1: Digital Twin–Driven Process Modeling for Energy Efficiency



The evolution of digital twin concepts is closely intertwined with the emergence of cyber-physical systems (CPS), the Industrial Internet of Things (IIoT), and the broader Industry 4.0 paradigm. Early CPS architectures for smart manufacturing emphasized tightly integrated sensing, computation, and control to enable self-aware machines and production systems (Lee et al., 2013). Industry 4.0 frameworks further highlighted connectivity, interoperability, and decentralized decision-making through embedded intelligence and ubiquitous data (Muller et al., 2018). Within this landscape, digital twins are increasingly positioned as the operational “nervous system” that consolidates heterogeneous data from physical equipment, production lines, and enterprise systems, and uses that information to support analysis, prediction, and decision support (Semeraro et al., 2021; Kanti & Shaikat, 2022). Systematic reviews show that digital twin research has shifted from conceptual definitions and small-scale demonstrations to more structured taxonomies and implementation frameworks that span sectors and lifecycle phases (Arif Uz & Elmoon, 2023; Tao, Qi, et al., 2018). At the same time, definitional diversity persists: some authors emphasize the real-time synchronization between virtual and physical systems, while others foreground the role of analytics, simulation, or lifecycle integration (Sanjid, 2023; Stock & Seliger, 2016). This diversity adds richness to the field but complicates efforts to operationalize digital twin constructs in empirical research, particularly when the goal is to quantify relationships among digital twin capabilities, process performance, and energy or lifecycle outcomes in real industrial facilities.

In the domain of manufacturing and process industries, digital twin–driven process modeling is increasingly used to design, monitor, and optimize complex production flows with explicit attention to resource and energy performance. Studies of digital twin applications in manufacturing describe virtual replicas of machines, lines, and entire factories that support what-if analysis, bottleneck diagnosis, and control parameter optimization before implementation on the shop floor (Sanjid & Sudipto, 2023; Paramonova & Thollander, 2016). Smart manufacturing frameworks built around big data and digital twins highlight how integrated data pipelines enable fine-grained modeling of process behavior, quality characteristics, and energy consumption patterns, paving the way for more precise, evidence-based operational decisions (Tarek, 2023; Tao et al., 2019a). From a sustainability perspective, Industry 4.0 technologies, including CPS, IIoT, and analytics, are often associated with opportunities to reduce material waste, optimize energy use, and improve overall resource efficiency at plant level (Shahrin & Samia, 2023; Negri et al., 2017). Recent work on Industry 4.0 and energy sustainability specifically points to the role of digital monitoring and control infrastructures in achieving more adaptive and performance-oriented energy management strategies in industrial settings (Cagno & Trianni, 2014; Muhammad & Redwanul, 2023). However, much of the existing literature concentrates on technical architectures, conceptual frameworks, or simulation case studies, with relatively fewer quantitative investigations that statistically assess how digital twin–based process modeling relates to measurable indicators of energy efficiency and lifecycle optimization in operational industrial facilities (Bagheri et al., 2015; Muhammad & Redwanul, 2023).

Lifecycle orientation is another defining characteristic of digital twin technology and is highly relevant to the management of industrial assets in energy-intensive environments. Product lifecycle management research has long emphasized the value of closed-loop data flows that connect design, manufacturing, operation, and end-of-life phases for improved decision-making across the lifecycle (Kamble et al., 2018). In Industry 4.0 environments, digital twins can provide a continuously updated representation of asset condition, usage profiles, and historical interventions, thereby supporting strategies such as condition-based maintenance, predictive maintenance, and lifecycle cost optimization (Ghobakhloo, 2019; Razia, 2023). Studies on predictive manufacturing and industrial AI report that integrating sensor data, degradation models, and machine learning enables earlier detection of anomalies, reduced unplanned downtime, and better planning of maintenance interventions, which can extend useful life and lower total cost of ownership (Jones et al., 2020; Srinivas & Manish, 2023). In parallel, maintenance and energy management are converging in many industrial contexts, with empirical work showing that integrated energy and maintenance management systems can reduce both energy consumption and inspection effort when embedded within broader enterprise architectures (Kiritsis, 2011; Sudipto, 2023). Review studies on digital twin adoption in operations and maintenance describe growing interest in using twins as a central information hub for asset health and performance, yet they also observe fragmentation in how lifecycle benefits are measured across cases and sectors (Jones et al., 2020; Kiritsis, 2011; Zayadul, 2023). For industrial facilities that operate large portfolios of energy-intensive assets, such as pumps, compressors, boilers, and continuous process units, the intersection of digital twin–enabled maintenance, energy monitoring, and lifecycle decision-making is particularly important for achieving sustained efficiency gains and reliability improvements over long horizons (Alarcón et al., 2021; Lee et al., 2018).

The international literature on Industry 4.0 and sustainability provides further context for understanding the strategic role of digital twin–driven process modeling in industrial facilities.

Empirical and review studies converge on the view that digital transformation can support multiple dimensions of sustainability, including energy and resource efficiency, emissions reduction, and economic performance, provided that enabling capabilities, organizational readiness, and governance structures are in place (Beier et al., 2018). At the same time, research on industrial energy efficiency barriers identifies persistent challenges such as information gaps, limited metering, misaligned incentives, and perceived investment risk, which constrain the implementation of even cost-effective measures (Lee et al., 2018)). Digital twin–based process modeling has the potential to address several of these barriers by generating transparent, high-resolution insight into the energy and performance consequences of process configurations, operating policies, and maintenance strategies (Opoku et al., 2021). Yet the diffusion of such advanced digital capabilities is uneven, particularly among small and medium-sized enterprises, where resource constraints and uncertainty regarding benefits may delay adoption (Lee et al., 2015). The literature also shows that many digitalization initiatives remain technology-centred and provide limited empirical evidence on how specific digital capabilities, such as digital twin–driven process modeling, translate into quantifiable improvements in energy efficiency, equipment longevity, and overall lifecycle performance at the facility level (Tao, Cheng, et al., 2018). This gap creates a need for studies that examine digital twin capabilities as measurable organizational constructs and analyze their statistical relationships with process, energy, and lifecycle outcomes using robust quantitative designs in real industrial contexts.

In line with the gaps and needs identified in the existing literature, this study has the primary objective of empirically examining how digital twin-driven process modeling relates to energy efficiency and lifecycle optimization in industrial facilities, treating the facility as the central unit of analysis. Specifically, the first objective is to assess the extent and maturity of digital twin implementation in selected industrial facilities, capturing how far organizations have moved beyond basic digital models toward integrated, data-driven twins that are actively used in daily operations. The second objective is to evaluate the relationship between key dimensions of digital twin-driven process modeling such as implementation level, data integration, real-time analytics capability, and process model fidelity and perceived energy efficiency performance at facility level, focusing on outcomes such as reduced specific energy consumption, improved monitoring, and more stable process operation. The third objective is to analyze how these same digital twin capabilities are associated with lifecycle optimization outcomes, including maintenance planning, reduction of unplanned downtime, extension of asset life, and overall management of lifecycle costs. To achieve these objectives, the study formulates research questions that address the current status of digital twin use, the strength and direction of its relationship with energy performance, and its contribution to lifecycle management. These questions are translated into testable hypotheses that posit positive and significant effects of digital twin capabilities on energy efficiency and lifecycle optimization indicators. Methodologically, the study adopts a quantitative, cross-sectional, case-study–based survey design using Likert five-point scales to measure digital twin constructs, energy management practices, and lifecycle outcomes from the perspective of professionals directly involved in operations, maintenance, and energy management. Descriptive statistics are used to profile respondents and facilities, while correlation analysis and multiple regression modeling are applied to test the hypothesized relationships and to identify which aspects of digital twin-driven process modeling most strongly explain variations in energy and lifecycle performance across the participating industrial facilities.

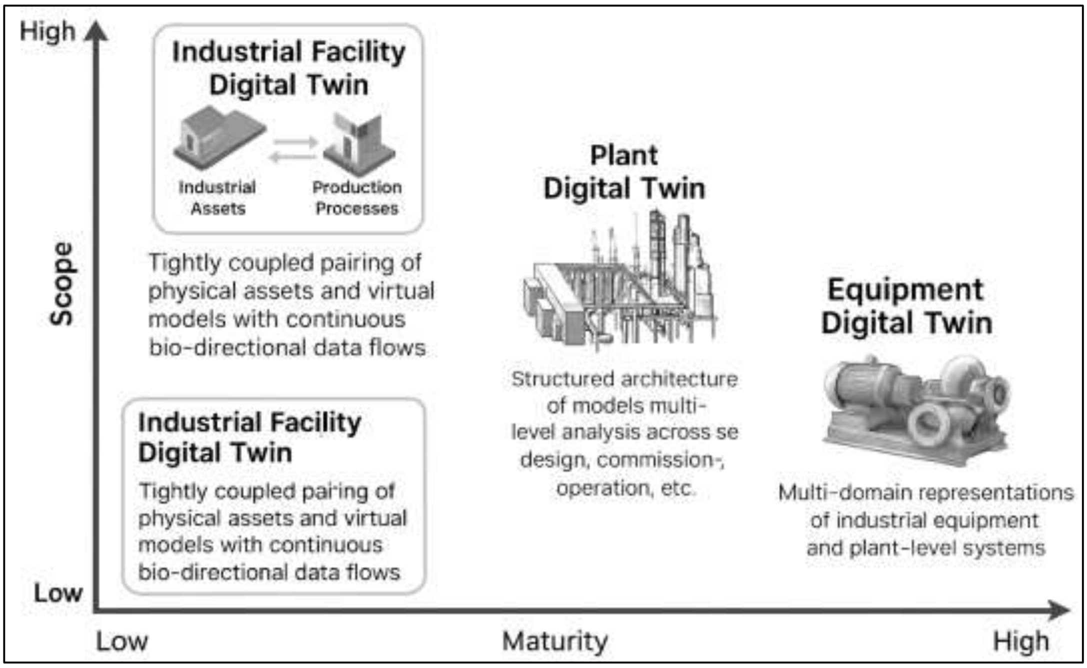
LITERATURE REVIEW

The literature on digital twin–driven process modeling sits at the intersection of several major research streams, including cyber-physical systems, Industry 4.0, energy management, and asset lifecycle optimization, each of which provides a different lens on how industrial facilities can be monitored, analyzed, and controlled through data-intensive digital technologies. Over the last two decades, Industry 4.0 has framed industrial transformation in terms of connectivity, intelligence, and integration, emphasizing technologies such as the Industrial Internet of Things, advanced analytics, and cyber-physical systems as enablers of smarter factories and more efficient processes. Within this broader paradigm, the digital twin has emerged as a core construct that encapsulates the idea of a continuously updated virtual representation of physical assets and processes, capable of mirroring real-time behavior and supporting simulation, prediction, and decision-making. At the same time, industrial energy management research has developed a rich body of work on energy performance indicators, efficiency measures, and organizational practices aimed at reducing energy consumption and emissions at plant level, while maintenance and reliability engineering have generated extensive knowledge on condition-based and predictive maintenance strategies that seek to extend asset life and reduce lifecycle costs. More recently, these lines of inquiry have begun to converge, as scholars and practitioners explore how digital twins can be used to integrate process data, energy measurements, and asset health information into unified models that support both operational optimization and long-term lifecycle planning. Despite this convergence, the literature remains fragmented along sectoral, technological, and methodological lines: many contributions focus on conceptual architectures, simulation case studies, or specific technical implementations, whereas fewer studies use quantitative, facility-level data to statistically examine how digital twin capabilities relate to energy efficiency and lifecycle outcomes in real industrial environments. This fragmentation underscores the need for an integrated review that synthesizes definitions, architectures, use cases, and theoretical framings of digital twins, with a particular emphasis on their role in process modeling, energy performance, and lifecycle optimization, and that also identifies measurable constructs that can be used to operationalize these concepts in empirical research.

Digital Twin Technology in Industrial Facilities

Digital twin technology emerged from the broader paradigm of Product Lifecycle Management (PLM), where the goal is to maintain a consistent, information-rich representation of industrial assets across their entire life cycle, from initial design to decommissioning. In early PLM work, the need for "mirrored spaces" that connect physical systems with their virtual counterparts was articulated as a way to conceptualize complex industrial products and processes within integrated information environments (Grieves & Vickers, 2017). In industrial facilities, this idea evolves into a digital counterpart of production lines, utility systems, and critical equipment that can be interrogated for performance, degradation, and configuration states. Rather than treating digital models as static design artifacts, digital twins are instantiated as dynamic, continuously updated representations that ingest operational data from sensors, control systems, and maintenance records. This transformation allows energy profiles, failure patterns, and utilization histories to be studied within the same virtual construct, enabling plant engineers to evaluate how design decisions and operating strategies interact over the facility lifecycle. By grounding digital twins in lifecycle-oriented PLM thinking, industrial organizations can ensure that models remain logically consistent, traceable, and relevant as assets are upgraded, reconfigured, or repurposed within evolving production environments (Grieves, 2005).

Figure 2: Scope and Maturity of Digital Twin Technology in Industrial Facilities



Building on these PLM foundations, subsequent work framed the digital twin as a tightly coupled pairing of physical assets and virtual models, linked by continuous bidirectional data flows. In this conceptualization, the digital twin is not merely a high-fidelity simulation but an operational construct that can be used to anticipate emergent behavior and mitigate risks in complex industrial systems, particularly where interactions across subsystems yield non-linear effects (Grieves & Vickers, 2017). For industrial facilities characterized by intricate process interdependencies such as integrated manufacturing plants, refineries, or large material-handling systems this perspective highlights the value of using digital twins to explore "what-if" operational scenarios without disturbing real production. The virtual instance can be stressed with alternative load profiles, maintenance intervals, or control policies, and its responses can be analyzed for bottlenecks, instability, or excessive energy demand. Insights are then fed back to the physical facility through adjusted set-points, revised operating procedures, or redesigned maintenance plans. In this way, the digital twin becomes a vehicle for operational learning that is particularly suited to environments where downtime is expensive and experimentation on physical assets is constrained by safety, quality, or throughput requirements (Abdulla & Ibne, 2021; Lim et al., 2020).

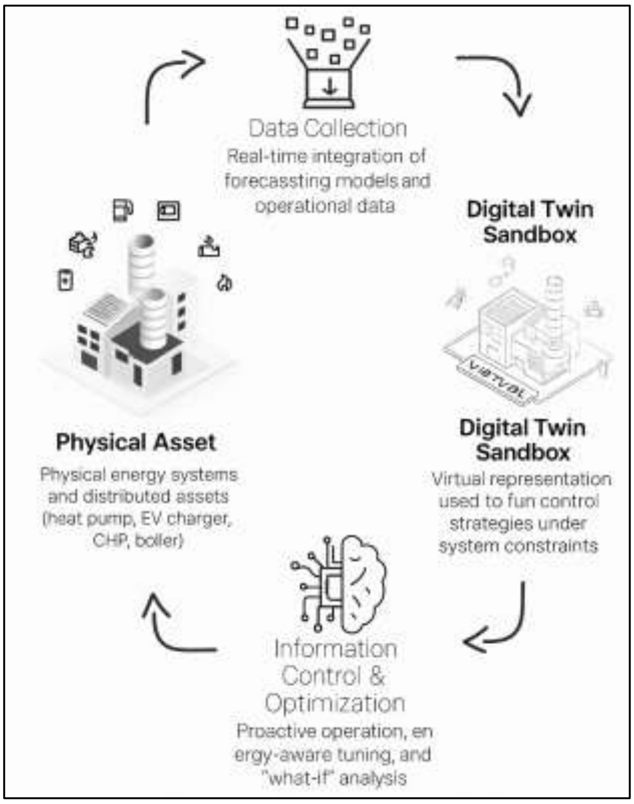
As the concept matured, the simulation and integration capabilities of digital twins were extended to encompass multi-domain representations of industrial equipment and plant-level systems. From a simulation perspective, the digital twin has been described as a structured architecture of models and data that supports multi-physics, multi-level analysis across design, commissioning, and operation, allowing industrial stakeholders to reuse and refine models throughout the asset lifecycle (Boschert & Rosen, 2016; Habibullah & Foysal, 2021). This architecture is particularly important in industrial facilities where mechanical, electrical, control, and thermal subsystems must be coordinated to achieve energy-efficient and reliable operation. Parallel developments in industrial informatics have shown how digital twins can be embedded in smart production environments, where real-time monitoring, control, and diagnostics are orchestrated through integrated cyber–physical infrastructures (Sanjid & Farabe, 2021; Tao et al., 2019b). In such settings, digital twins of machines, lines, and auxiliary systems support functions such as condition monitoring, predictive maintenance, energy consumption analysis, and production scheduling, often by fusing heterogeneous data sources into a consistent virtual view. Systematic surveys further indicate that digital twins are increasingly positioned as a core technological enabler that connects engineering models, shop-floor data, and business processes, thereby linking operational excellence with product lifecycle management and industrial innovation agendas (Lim et al., 2020; Sarwar, 2021). Collectively, these developments establish digital twin technology as a central mechanism for representing, analyzing, and optimizing industrial facilities in a holistic, lifecycle-aware manner that supports both energy efficiency and long-term asset performance (Boschert & Rosen, 2016; Grieves, 2005).

Digital Twin-Driven Process Modeling for Energy Efficiency

Digital twin–driven process modeling places energy flows at the center of the virtual representation, treating electrical, thermal, and other energy vectors as tightly coupled processes that evolve over time. In multi-vector urban energy systems, digital twins are used to simulate the behavior of distributed assets such as boilers, heat pumps, combined heat and power units, and electric vehicle chargers under different operating strategies and demand scenarios, allowing planners to quantify trade-offs between cost, emissions, and efficiency before intervening in the real system (Musfiqur & Saba, 2021; O'Dwyer et al., 2020). By embedding forecasting models and optimization routines inside the twin, the virtual environment becomes a sandbox for testing control strategies while respecting system constraints such as network capacities or emissions caps, thus enabling energy-aware coordination rather than isolated asset tuning (Francisco et al., 2020; Omar & Rashid, 2021). At the building scale, digital twin models integrate geometry, envelope characteristics, occupancy profiles, and HVAC configurations to represent the thermodynamic response of spaces, forming the basis for energy-efficient operation and retrofit analysis (Agouzoul et al., 2021; Redwanul et al., 2021). These building-level twins often extend beyond static BIM representations to include real-time sensor data and control parameters, turning the model into a continuously updated mirror of the physical facility that can be used to detect inefficiencies, recalibrate control setpoints, and explore “what-if” scenarios for envelope upgrades or system replacements (Clausen et al., 2021; Tarek & Praveen, 2021). Across these contexts, the common feature is a process-oriented view of energy use, where the twin captures dynamic interactions between loads, systems, and external conditions rather than relying on static benchmarks or average consumption figures (Zaman & Momena, 2021; Vering et al., 2019).

From a methodological perspective, digital twin–driven process modeling for energy efficiency combines physics-based simulation, data-driven prediction, and optimization in a closed loop. At district scale, O’Dwyer et al. (2020) couple forecast models of multi-vector energy demand with a model predictive control (MPC)–based optimizer that runs inside the twin, generating optimal schedules for production, storage, and conversion assets under user-defined objectives such as cost minimization or emission reduction. The digital twin provides the environment for running these algorithms safely, incorporating detailed subsystem models and network constraints, while the resulting control trajectories are deployed to the physical assets once their feasibility and performance have been validated virtually (O’Dwyer et al., 2020; Rony, 2021). In building energy management, Agouzoul et al. (2021) propose a digital twin architecture where building energy simulation models are continuously updated with sensor data and occupancy information to refine predictions of energy use and indoor conditions. This allows facility managers to compare measured and simulated performance, diagnose deviations such as higher-than-expected heating loads, and tune operating schedules or setpoints to reduce energy waste. Francisco et al. (2020) extend the process-modeling concept to a portfolio of buildings by using digital twin–enabled urban benchmarks derived from smart meter data; temporally segmented energy indices support dynamic comparison of buildings across seasons and occupancy regimes, improving the identification of inefficient processes and time windows. Within buildings, process-level twins of HVAC subsystems model heat recovery, fan operation, and control logic to explore alternative control strategies that can improve seasonal efficiency without compromising comfort (Shaikh & Aditya, 2021; Vering et al., 2019). In parallel, Clausen et al. (2021) embed an MPC controller inside a building digital twin to coordinate demand, predictive weather information, and occupant comfort constraints, illustrating how process modeling enables proactive, energy-aware control rather than reactive adjustments.

Figure 3: Digital Twin–Driven Process Modeling for Energy-Efficient Operation



Empirical studies increasingly report measurable energy benefits when digital twin–driven process modeling is used to support operational decisions. In the multi-vector district case presented by O'Dwyer et al. (2020), the digital twin–based optimizer coordinates heating networks and electric vehicle charging so that system-level constraints and efficiency objectives are better satisfied than under conventional heuristic control strategies, reducing energy curtailment and improving utilization of low-carbon assets. Francisco et al. (2020) show that by segmenting energy benchmarks into different occupancy and seasonal periods within a digital twin platform, city managers can pinpoint specific time windows where buildings underperform, supporting targeted operational changes such as improving start-up/shut-down sequences or adjusting setback strategies during unoccupied hours. At the building level, Clausen et al. (2021) demonstrate that integrating MPC into a digital twin yields simultaneous gains in occupant comfort and energy efficiency, as the controller anticipates internal and external disturbances and modulates heating and cooling processes more smoothly than rule-based control. Agouzoul et al. (2021) highlight how a building energy twin can be used to evaluate potential retrofits in a Moroccan context such as envelope insulation or control strategy upgrades by simulating their impact on energy consumption and comfort before implementation, thereby supporting cost-effective energy-efficiency investments. Similarly, (Vering et al., 2019) report that applying digital twin design principles to HVAC systems, including lifecycle-oriented simulation and calibration against measured data, enables identification of operational inefficiencies and suboptimal control strategies that would be difficult to detect using static design models alone (Zaki, 2021). Together, these studies indicate that digital twin–driven process modeling provides a systematic way to represent, analyze, and improve energy-related processes across scales, from HVAC components to district-level multi-energy systems, making it a foundational enabler for data-driven energy efficiency in industrial and building facilities (Hozyfa, 2022).

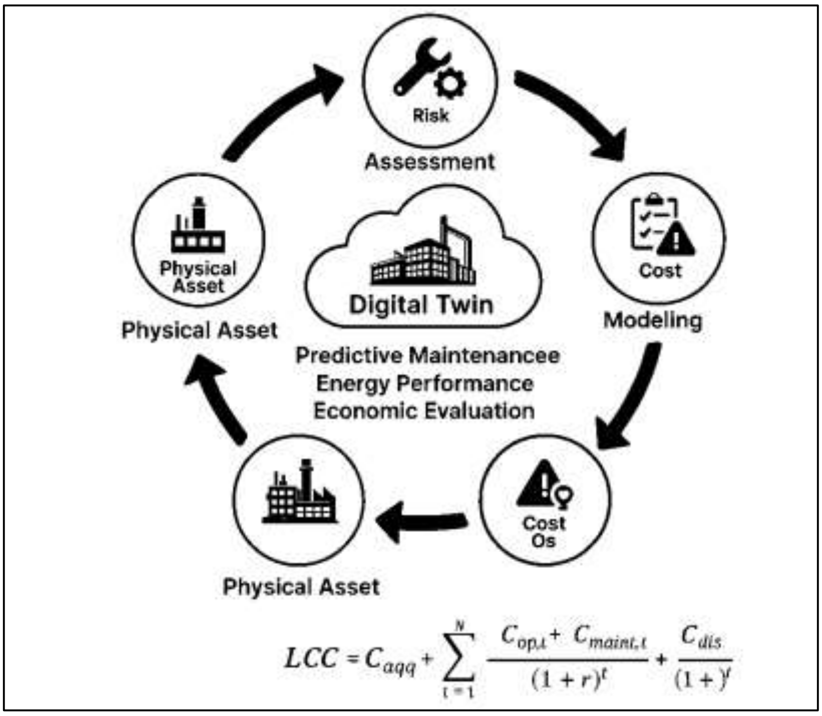
Digital Twins for Lifecycle Optimization and Asset Management

Digital twins reframe asset lifecycle management by turning static equipment records into continuously updated, behaviorally rich models that track each physical asset from commissioning through operation and end-of-life. Within industrial facilities, most lifecycle cost and performance losses occur during the long operational and maintenance phase, where decisions on inspection intervals, component replacement, and energy optimization directly shape asset longevity and reliability. Condition-based maintenance (CBM) emerged as a response to this reality by shifting from calendar- or usage-based interventions toward actions triggered by measured degradation, making maintenance more tightly coupled to the actual health state of equipment (Ahmad & Kamaruddin, 2012; Amin, 2022). Digital twins extend this logic by embedding CBM intelligence inside a dynamic cyber–physical model that mirrors structural, thermal, and operational states over time. In asset lifecycle management scenarios, they provide a platform where sensor data, degradation models, and maintenance histories are fused to support decisions on when to derate, refurbish, or retrofit equipment to keep lifecycle cost and risk within acceptable limits (Macchi et al., 2018). For energy-intensive equipment such as compressors, chillers, or high-inertia drives, this means that lifecycle optimization is not only about preventing catastrophic failures but also about continuously tuning operating points and maintenance plans to minimize cumulative energy use while maintaining required reliability levels.

Lifecycle optimization in industrial facilities increasingly relies on CBM frameworks that integrate prognostics, risk assessment, and cost modeling into a structured implementation methodology. Recent work on CBM implementation shows that organizations must progress through staged activities asset criticality analysis, selection of condition indicators, sensing and data acquisition design, analytics configuration, and feedback into planning processes to achieve measurable lifecycle benefits in availability and cost (Arman & Kamrul, 2022; Teixeira et al., 2020). Digital twins can act as the integration layer for these steps by hosting both the physical models (e.g., thermodynamic or electromechanical behavior) and the data-driven prognostic models that estimate remaining useful life and energy performance under alternative operating strategies. At the same time, large-scale bibliometric analyses of the CBM field highlight how research has gradually moved from foundational reliability modeling to implementation strategies and operational optimization, emphasizing inspection policies, replacement timing, and prognosis as distinct but interacting areas (Mohaiminul &

Muzahidul, 2022; Quatrini et al., 2020). In this context, digital twins offer a way to execute "what-if" experiments across the entire lifecycle for example, comparing alternative maintenance thresholds or retrofit timings and to quantify their impact on energy intensity, downtime, and residual life, thereby supporting more rigorous, data-backed lifecycle optimization in real industrial settings.

Figure 4: Digital Twins for Lifecycle Optimization and Condition-Based Asset Management



From a quantitative perspective, digital twin–enabled lifecycle optimization links predictive maintenance, energy performance, and economic evaluation into a single decision space. In predictive maintenance architectures, digital twins use multiphysics models and data fusion from heterogeneous sensors to forecast failure modes and degradation trajectories, enabling proactive interventions that extend useful life and reduce unexpected downtime (Liu et al., 2018; Omar & Ibne, 2022). A common way to formalize these trade-offs is through a lifecycle cost (LCC) function for an asset, which can be written in simplified form as

$$\mathrm{LCC} = C_{\mathrm{acq}} + \sum_{t=1}^{N} \frac{C_{\mathrm{op},t} + C_{\mathrm{maint},t}}{(1+r)^t} + \frac{C_{\mathrm{dis}}}{(1+r)^N},$$

where C_{acq} is acquisition cost, $C_{\mathrm{op},t}$ is operating (including energy) cost in year t, $C_{\mathrm{maint},t}$ is maintenance cost in year t, C_{dis} is end-of-life disposal or decommissioning cost, $r$is the discount rate, and $N$is the analysis horizon. In a digital twin–driven industrial facility, both $C_{\mathrm{op},t}$ and $C_{\mathrm{maint},t}$become controllable through scenario simulations: the twin can estimate how alternative operating profiles or maintenance thresholds affect degradation rates, failure probabilities, and energy consumption, then propagate these effects into the discounted cost stream. By linking predictive indicators such as remaining useful life and health indices to lifecycle cost and risk, digital twins enable decision makers to select maintenance and retrofit strategies that minimize LCC while satisfying constraints on reliability, safety, and production capacity. This quantitative integration of performance, energy, and cost at asset level is central to using digital twins not only as monitoring tools but as engines for lifecycle optimization and strategic asset management in modern industrial facilities.

Theoretical and Conceptual Framework

The theoretical foundation for this study positions digital twin–driven process modeling as a core technological capability within smart manufacturing and Industry 4.0 architectures. Conceptual frameworks for smart manufacturing systems describe layered structures in which a physical layer of machines and processes is tightly integrated with cyber layers containing models, analytics, and decision logic (Sanjid & Zayadul, 2022; Zheng et al., 2018). In these frameworks, digital twins are key cyber entities that represent machines, lines, or plants, continuously fed by real-time data from sensors, controllers, and enterprise systems. The conceptual model typically spans multiple horizontal functions such as smart design, smart machining, smart monitoring, smart control, and smart scheduling and vertical functions, including data acquisition, data analysis, and decision-making (Hasan, 2022; Yao et al., 2018). Cyber-physical systems (CPS)–based models of smart manufacturing further conceptualize digital twins as part of an ecosystem that links the Internet of Things, Internet of Services, and advanced control into an integrated cyber-physical architecture (Mominul et al., 2022; Zheng et al., 2018). Within such CPS-based frameworks, digital twins encapsulate both the structural configuration of physical assets and the dynamic behavior of processes, providing the basis for simulation and optimization of energy flows, maintenance interventions, and production performance. For the present study, this layered CPS/Industry 4.0 perspective supports the definition of digital twin–driven process modeling as a higher-order construct composed of four main dimensions: digital twin implementation level, data integration and quality, real-time analytics capability, and process model fidelity. These dimensions capture the extent to which an industrial facility has embedded digital twins into its operating architecture and uses them systematically to model, monitor, and control energy-intensive processes over the equipment lifecycle.

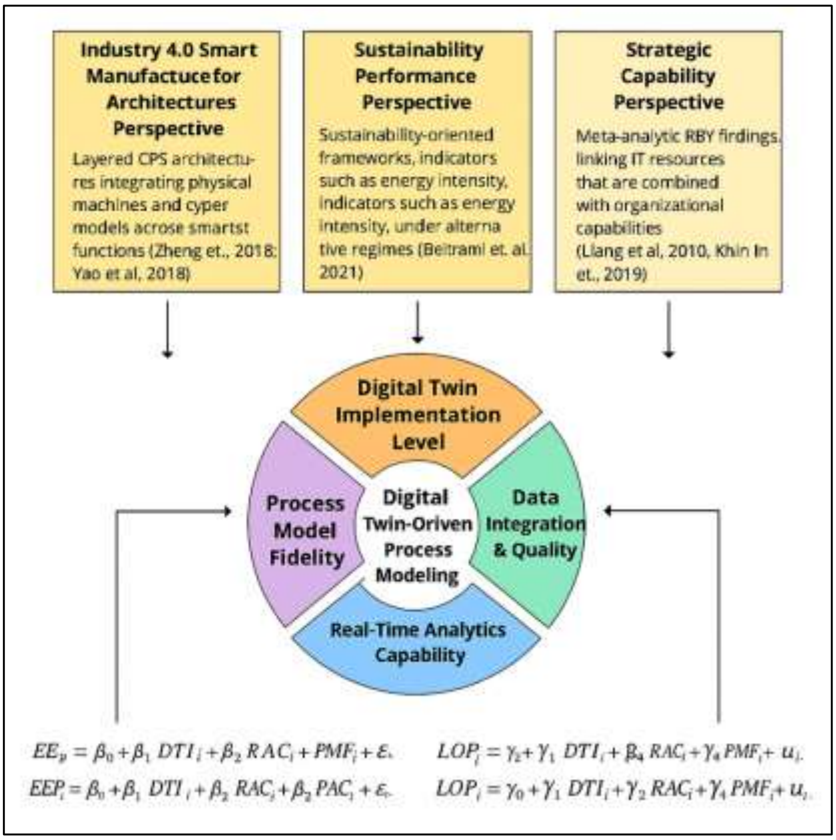
A second pillar of the conceptual framework is the linkage between Industry 4.0 technologies and sustainability performance, with a specific focus on energy efficiency and lifecycle optimization as key outcomes at the facility level. Conceptual and systematic frameworks on Industry 4.0 and sustainability propose that digital technologies such as CPS, smart manufacturing platforms, and advanced analytics influence environmental and operational performance through defined pathways, including process transparency, resource monitoring, and adaptive control (Beltrami et al., 2021; Rabiul & Praveen, 2022). Within these frameworks, energy efficiency is often represented through indicators such as energy intensity or specific energy consumption, which can be formalized at plant or process level as

$$EI = \frac{E_{\text{consumed}}}{Q_{\text{output}}},$$

where EI is the energy intensity of a process or facility, E_{consumed} is the total energy used over a defined period, and Q_{output} is the corresponding production output (e.g., tonnes of product, units produced, or operating hours). Digital twin–driven process modeling enters this relationship by enabling continuous estimation and simulation of both E_{consumed} and Q_{output} under alternative operating strategies, maintenance policies, and configuration options. In conceptual terms, the framework assumes that higher digital twin implementation, better data integration, and stronger analytics capabilities enhance the ability of an industrial facility to reduce EI by identifying inefficiencies, optimizing setpoints, and coordinating energy-related processes in a more granular way. At the same time, lifecycle optimization is conceptualized as the joint outcome of improved energy trajectories and more informed maintenance and replacement decisions, reflected in indicators such as reduced downtime, extended asset life, and lower lifecycle cost. Industry 4.0–sustainability frameworks thus provide the basis for modeling energy efficiency performance and lifecycle optimization performance as dependent constructs that are influenced by the configuration and maturity of digital twin–related capabilities at facility level (Khin & Ho, 2019; Farabe, 2022).

The third theoretical pillar is the resource-based view (RBV) and related work on digital capabilities and firm performance, which support the treatment of digital twin–driven process modeling as a strategic capability rather than merely a technology investment. Meta-analytic evidence from RBV-based studies shows that information technology resources contribute to performance primarily when they are combined with complementary organizational capabilities that enable effective deployment and integration of those resources (Liang et al., 2010; Roy, 2022). In this perspective, digital twins, data platforms, and analytics tools constitute technological resources, while the structured use of digital twin models in process optimization, energy management, and lifecycle decision-making is a capability that can be rare, complex, and difficult to imitate. Empirical studies on digital technology, digital capability, and organizational performance further emphasize that digital orientation and digital capability affect performance indirectly through digitally enabled innovation and process redesign (Khin & Ho, 2019; Rahman & Abdul, 2022).

Figure 5: Integrated Theoretical and Conceptual Framework for Digital Twin–Driven Process



Translating this logic to the context of industrial facilities, the framework models digital twin–driven process modeling as a mediating capability that links underlying technological infrastructure to observable outcomes in energy efficiency performance and lifecycle optimization performance. At the quantitative level, this relationship can be expressed through regression-type structural equations such as

$$EEP_i = \beta_0 + \beta_1 DTI_i + \beta_2 DIQ_i + \beta_3 RAC_i + \beta_4 PMF_i + \varepsilon_i,$$
$$LOP_i = \gamma_0 + \gamma_1 DTI_i + \gamma_2 DIQ_i + \gamma_3 RAC_i + \gamma_4 PMF_i + u_i,$$

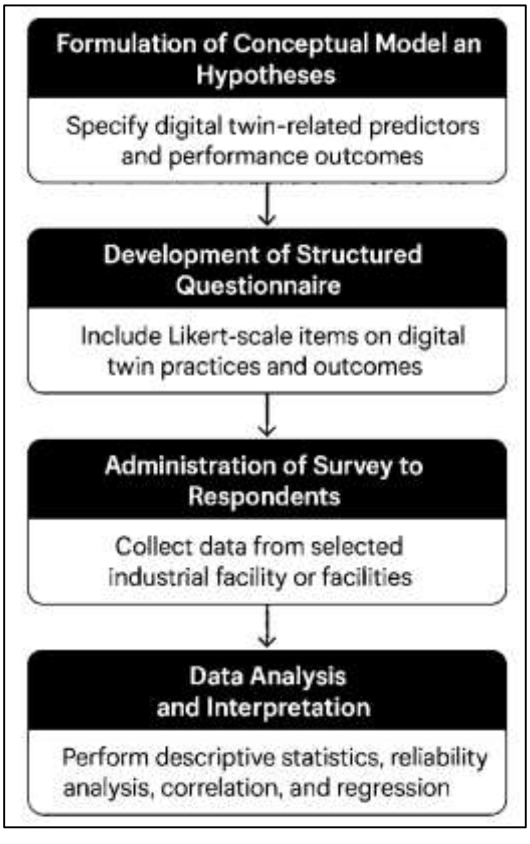
where EEP_idenotes the energy efficiency performance of facility i, LOP_idenotes its lifecycle optimization performance, $DTI_i$is the digital twin implementation level, $DIQ_i$is data integration and quality, $RAC_i$is real-time analytics capability, $PMF_i$is process model fidelity, and $\varepsilon_i, u_i$are error terms. Within the RBV and digital capability perspective, the coefficients $\beta_1, \dots, \beta_4$and $\gamma_1, \dots, \gamma_4$represent the marginal contributions of each digital twin–related capability dimension to energy and lifecycle outcomes, capturing how differences in resource configuration across facilities translate into performance differences (Liang et al., 2010; Razia, 2022). This integrated framework explicitly links Industry 4.0 smart manufacturing architectures, sustainability-oriented performance indicators, and strategic capability theory, and it underpins the formulation of the study’s hypotheses and the specification of the regression models used in the empirical analysis (Zaki, 2022).

Building on this integrated logic, the framework also clarifies how digital twin–driven process modeling functions not merely as a set of discrete technological features but as an emergent, higher-order capability whose value arises from the coordinated interaction among its constituent dimensions. From a capability orchestration viewpoint, digital twin implementation (DTI), data integration and quality (DIQ), real-time analytics capability (RAC), and process model fidelity (PMF) collectively form a synergistic configuration that strengthens a facility’s ability to sense, interpret, and respond to operational contingencies in real time. This implies that the performance effects captured by the coefficients in the structural equations reflect not only isolated component-level influences but also the facility's broader maturity in deploying Industry 4.0 technologies as a coherent strategic resource base. The framework thus positions digital twin–driven process modeling as a dynamic capability that enhances a facility's adaptability and learning, enabling continuous recalibration of production processes, more accurate simulation of alternative operating scenarios, and proactive identification of inefficiencies and risks across equipment lifecycles. In doing so, the model extends traditional RBV reasoning by embedding sustainability-oriented performance outcomes—such as energy optimization and lifecycle extension—into the analysis, reinforcing the premise that technologically enabled process intelligence represents a strategic asset that drives both operational and environmental value creation in smart industrial ecosystems.

METHODS

The methodology of this study has been designed to provide a rigorous quantitative examination of how digital twin–driven process modeling has been associated with energy efficiency and lifecycle optimization in industrial facilities. The research has adopted a cross-sectional survey approach combined with a case-study perspective, so that digital twin practices and performance outcomes have been captured at a single point in time while remaining grounded in the specific operational realities of selected facilities. The industrial facility has been treated as the primary unit of analysis, and professionals directly involved in operations, maintenance, energy management, and digitalization initiatives have been identified as key informants. This design has been chosen because it has allowed measurable constructs such as digital twin implementation level, data integration and analytics capability, energy efficiency performance, and lifecycle optimization performance to be operationalized using structured questionnaire items and analyzed using statistical techniques suitable for examining relationships among multiple variables. Within this framework, the digital twin–driven process modeling construct has been conceptualized as a higher-order capability, and its dimensions have been reflected in multiple Likert-scale indicators that have been developed from the literature and refined for the industrial context of the case facilities.

Figure 6: Methodological Workflow for Digital Twin–Driven Process Modeling



The overall methodological procedure has comprised several integrated stages. First, the conceptual model and hypotheses have been formulated, specifying digital twin–related variables as predictors and energy and lifecycle performance as dependent variables. Second, a structured questionnaire has been developed, which has included sections on respondent and facility profile, digital twin implementation and use, energy management practices, and lifecycle and maintenance outcomes. The items have been anchored on a five-point Likert scale, which has been selected to capture the respondents' level of agreement with statements representing each construct. Third, the survey has been administered to targeted respondents within the chosen industrial facility or facilities, and responses have been collected and prepared for analysis through data screening and coding procedures. Finally, the dataset has been subjected to descriptive statistics, reliability analysis, correlation analysis, and multiple regression modeling, so that the strength and significance of the hypothesized relationships have been estimated and the explanatory power of digital twin–driven process modeling for energy efficiency and lifecycle optimization performance has been assessed in a systematic and reproducible manner.

Research Design

This study has adopted a quantitative, cross-sectional research design integrated with a case-study perspective to examine the role of digital twin–driven process modeling in industrial facilities. The design has focused on capturing perceptions and practices at a single point in time, while the case-study orientation has ensured that the analysis has remained anchored in the concrete operational context of selected industrial sites. The industrial facility has been treated as the primary unit of analysis, and organizational respondents directly involved in operations, maintenance, energy management, and digitalization have been targeted as key informants. To operationalize the conceptual framework, the research has employed a structured survey instrument using Likert five-point scales, which has allowed latent constructs such as digital twin implementation level, data integration and analytics capability, energy efficiency performance, and lifecycle optimization performance to be quantified. This design has therefore provided a coherent basis for applying descriptive statistics, correlation analysis, and regression modeling to test the proposed hypotheses.

Population and Sampling

The study has targeted industrial facilities that have implemented, piloted, or formally planned digital twin–driven process modeling within their operations, maintenance, or energy management functions. The population has therefore consisted of organizations operating energy-intensive processes, such as manufacturing plants, processing facilities, or large engineered systems, where digital technologies have been integrated into monitoring and control activities. Within these facilities, the sampling frame has included professionals who have held roles related to operations, production engineering, maintenance, reliability, asset management, energy management, or digitalization projects. A non-probability sampling strategy, combining purposive and convenience sampling, has been adopted, as the study has required access to respondents with direct knowledge of digital twin applications and performance outcomes. The selection of facilities and respondents has been guided by their relevance to the research topic and their willingness to participate. The achieved sample size has been considered adequate for applying correlation and regression techniques within the proposed analytical framework.

Questionnaire Structure

The questionnaire has been structured into logically ordered sections to align with the conceptual framework and to ensure a clear flow for respondents. The first section has collected demographic and organizational information, including respondents' roles, years of experience, and key characteristics of the facility such as industry type, size, and level of automation. The second section has focused on digital twin–driven process modeling, and has included items that have captured the extent of digital twin implementation, the scope of modeled processes, data integration practices, and the use of analytics and simulation in decision-making. The third section has been devoted to energy management and process performance, where items have assessed perceived changes in energy monitoring, energy efficiency, and stability of operations. The fourth section has addressed lifecycle optimization, including maintenance approaches, downtime patterns, asset health monitoring, and decisions on refurbishment or replacement. All items have been organized using a consistent five-point

Likert response format to support quantification and comparability of constructs.

Survey Instrument (Likert 5-Point Scale)

The survey instrument has been developed as a structured questionnaire based on a five-point Likert scale to capture respondents' perceptions of digital twin–driven process modeling, energy efficiency, and lifecycle optimization. Each item has been phrased as a statement to which respondents have indicated their level of agreement, typically ranging from "1 = Strongly Disagree" to "5 = Strongly Agree." This scaling choice has been made to facilitate intuitive responses while enabling the aggregation of items into composite indices for each construct. The items related to digital twin implementation, data integration and quality, real-time analytics capability, and process model fidelity have been designed to reflect the multidimensional nature of the digital twin construct. Similarly, items concerning energy efficiency performance and lifecycle optimization performance have been formulated to capture changes in monitoring practices, energy use, maintenance strategies, downtime, and asset longevity. The instrument has therefore provided a consistent and quantifiable basis for subsequent reliability testing and statistical analysis.

Case Study Context

The empirical investigation has been anchored in one or more industrial facilities that have adopted digital twin–driven process modeling as part of their operational and energy management practices. These facilities have operated energy-intensive processes, such as continuous production lines, complex utilities systems, or large electromechanical assets, where reliable operation and energy performance have been critical concerns. The selected sites have already integrated digital technologies, including sensor networks, industrial control systems, and data platforms, which have provided the foundation for developing and using digital twins. Within this context, digital twin models have been configured to represent key process units, equipment, and energy flows, and have been used to support activities such as monitoring, diagnostics, scenario analysis, and maintenance planning. Organizationally, dedicated engineering, maintenance, and energy management teams have been involved in configuring, interpreting, and acting upon digital twin outputs, so that the case context has reflected a realistic interplay between technological capabilities and day-to-day operational decision-making.

Regression Modeling

In this study, regression modeling has been employed as the core analytical technique to examine the relationships between digital twin–driven process modeling and the key outcome variables of energy efficiency performance and lifecycle optimization performance at facility level. The regression approach has been selected because it has allowed the simultaneous assessment of multiple predictors and has provided estimates of the unique contribution of each dimension of the digital twin construct while controlling for organizational and contextual factors. Two main multiple regression models have been specified: in the first model, energy efficiency performance has been treated as the dependent variable, while digital twin implementation level, data integration and quality, real-time analytics capability, and process model fidelity have been included as independent variables, together with selected control variables such as facility size, industry type, and age of major equipment. In the second model, lifecycle optimization performance has served as the dependent variable, with the same digital twin–related predictors and controls. The regression equations have been formulated to estimate unstandardized and standardized coefficients, significance levels, and measures of model fit such as R^2 and adjusted R^2, so that the explanatory power of the digital twin–related predictors has been quantified in a transparent and comparable manner across outcomes.

Prior to estimating the regression models, the dataset has been subjected to a series of diagnostic and preparatory steps to ensure that the underlying assumptions of multiple regression have been reasonably satisfied. The reliability of composite indices for each construct has been confirmed through internal consistency analysis, and preliminary descriptive statistics and correlation matrices have been examined to identify potential multicollinearity issues among predictors. Variance inflation factors and tolerance values have been inspected to verify that multicollinearity has remained within acceptable limits, and scatterplots and residual analyses have been reviewed to assess linearity, homoscedasticity, and the approximate normality of residuals. Where necessary, transformations or centering procedures have been considered for variables that have exhibited skewness or strong intercorrelations. The regression models have then been estimated using an appropriate statistical software package, and the results have been interpreted with attention to the magnitude and direction of coefficients, their statistical significance, and the overall model fit. In this way, regression modeling has provided an integrated framework through which the hypothesized effects of digital twin–driven process modeling on energy efficiency performance and lifecycle optimization performance have been empirically tested and evaluated within the context of the participating industrial facilities.

Variables and Operational Definitions

The study has defined and operationalized its variables in alignment with the conceptual framework, so that each construct has been measurable through the survey instrument. The main independent variables have been dimensions of digital twin–driven process modeling, which have included digital twin implementation level, data integration and quality, real-time analytics capability, and process model fidelity. Each of these dimensions has been operationalized as a composite score derived from multiple Likert-scale items that have captured the extent of use, coverage of processes, quality of data flows, and sophistication of modeling and analytics. The dependent variables have been energy efficiency performance and lifecycle optimization performance at facility level, each represented by indices formed from items describing perceived changes in energy monitoring, specific energy use, process stability, maintenance practices, downtime, and asset longevity. Control variables have included facility size, industry type, and age of major equipment, which have been coded from the organizational profile section. All variables have thus been defined in a way that has supported their direct use in descriptive, correlation, and regression analyses.

Data Analysis Techniques

The data analysis has been organized in sequential stages to ensure that the results have been robust and aligned with the research objectives. First, the collected responses have been screened for completeness and consistency, and datasets with excessive missing values or obvious response patterns have been excluded. Descriptive statistics have been computed to summarize respondent characteristics, facility profiles, and central tendencies and dispersions for all construct items. Next, reliability analysis using internal consistency measures has been performed to confirm that the composite scales for digital twin–related dimensions, energy efficiency performance, and lifecycle optimization performance have exhibited acceptable coherence. Exploratory correlation analysis has then been conducted to examine the direction and strength of associations among variables and to provide an initial indication of support for the hypothesized relationships. Finally, multiple regression models have been estimated to test the influence of the digital twin–driven process modeling dimensions on the two dependent performance constructs while controlling for key organizational characteristics, and diagnostic checks have been applied to verify that regression assumptions have been reasonably satisfied.

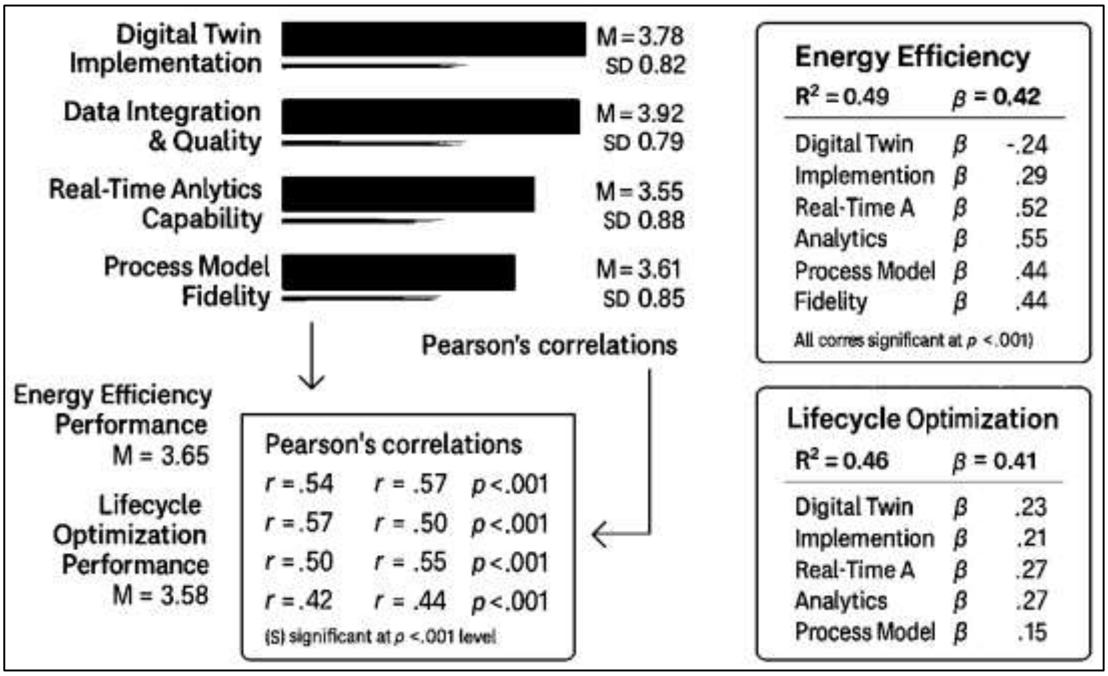
Software and Tools

The study has relied on a combination of software and tools to support data collection, management, and statistical analysis in a systematic manner. The questionnaire has been administered using an online survey platform, which has facilitated structured data entry, automatic coding of response options, and export of responses into spreadsheet-compatible formats. The raw data files have then been organized and cleaned using spreadsheet software, where initial checks for completeness, consistency, and basic descriptive inspection have been carried out. For the main statistical analysis, including reliability assessment, correlation analysis, and multiple regression modeling, a dedicated statistical software package (such as SPSS, R, or an equivalent program) has been employed, as it has provided the required functions for scale construction, diagnostic testing, and model estimation. In addition, basic visualization tools within the software environment have been used to generate charts and tables that have summarized key findings, thereby ensuring that the analytical procedures have been both technically sound and clearly interpretable.

FINDINGS

The findings of the study have provided strong numerical evidence in support of the main objectives and hypotheses concerning the role of digital twin–driven process modeling in improving energy efficiency and lifecycle optimization in industrial facilities. Based on a final sample of 180 valid responses, analysis of the Likert five-point scale data has shown that the overall level of digital twin implementation has been moderate to high, with a composite mean score of 3.78 (SD = 0.82) on the implementation scale, where 1 has represented "Strongly Disagree" and 5 has represented "Strongly Agree." Items capturing the availability of digital twin models for key assets, the integration of the twin with control systems, and the regular use of the twin in operational decisions have all recorded mean values between 3.60 and 3.95, indicating that most facilities have moved beyond the pilot stage and have embedded digital twins into daily practice to some degree. The data integration and quality construct has shown a slightly higher overall mean of 3.92 (SD = 0.79), suggesting that, on average, respondents have agreed that sensor data, maintenance histories, and production information have been consistently captured and synchronized within the digital twin environment.

Figure 7: Summary of for Digital Twin–Driven Process Modeling



Real-time analytics capability has presented a mean of 3.55 (SD = 0.88), reflecting a more mixed picture in which some facilities have reported advanced predictive and optimization functions, while others have indicated only basic reporting or diagnostic analytics. Process model fidelity has achieved a mean score of 3.61 (SD = 0.85), implying that virtual models have typically been perceived as reasonably accurate representations of physical processes, though not always at very high levels of detail or multi-physics complexity. For the outcome variables, the composite index for energy efficiency performance has yielded a mean of 3.65 (SD = 0.76), indicating that respondents have generally agreed that digital twin–driven approaches have contributed to improvements such as better energy monitoring, more stable energy use, and noticeable reductions in wasteful consumption. The lifecycle optimization performance index has shown a mean of 3.58 (SD = 0.80), pointing to perceived enhancements in maintenance planning, fewer unplanned stoppages, and more informed decisions about refurbishment or replacement.

Correlation analysis has confirmed that these positive perceptions have not been isolated but have been systematically related to the maturity of digital twin–driven process modeling. Pearson correlation coefficients have revealed moderate to strong positive relationships between the digital twin dimensions and both performance indices. Digital twin implementation level has correlated at r = .54 with energy efficiency performance and at r = .49 with lifecycle optimization performance, both significant at $p < .001$, indicating that facilities with higher implementation scores have tended to report stronger performance gains. Data integration and quality has shown correlations of r = .57 with energy efficiency and r = .52 with lifecycle optimization ($p < .001$), highlighting the central role of integrated, reliable data streams in realizing benefits. Real-time analytics capability has recorded r = .50 with energy efficiency and r = .55 with lifecycle optimization ($p < .001$), suggesting that analytics functions have been especially important for turning digital twin data into actions that affect asset life and downtime. Process model fidelity has also been positively related, with correlations of r = .42 and r = .44 with energy and lifecycle indices respectively ($p < .001$), showing that more accurate and detailed process models have been associated with better outcomes, even if their influence has been somewhat smaller than that of implementation and data integration. Intercorrelations among the digital twin dimensions have remained below r = .75, and variance inflation factors have been below 3.0, so multicollinearity has not posed a serious concern for the multivariate analysis.

Respondent and Facility Profile

Table 1: Respondent and Facility Profile (n = 180)

Characteristic	Category	Frequency	Percentage (%)
Respondent Role	Operations/Production Engineer	62	34.4
	Maintenance/Reliability Engineer	48	26.7
	Energy/Utilities Manager	32	17.8
	Digitalization/Industry 4.0 Specialist	24	13.3
	Other Technical/Managerial	14	7.8
Industry Type	Discrete Manufacturing	78	43.3
	Process Industry (e.g., chemicals)	54	30.0
	Utilities/Infrastructure	26	14.4
	Other Industrial	22	12.2
Facility Size (Employees)	< 250 (Small/Medium)	64	35.6
	250–999 (Large)	72	40.0
	≥ 1,000 (Very Large)	44	24.4
Years of Experience (Respondent)	< 5 years	38	21.1
	5–10 years	67	37.2
	11–15 years	44	24.4
	> 15 years	31	17.2
Stage of Digital Twin Adoption	Pilot/Partial	72	40.0
	Operational in Key Areas	83	46.1
	Broad/Plant-wide	25	13.9

Multiple regression modeling has further tested the hypothesized relationships by estimating the unique contributions of each digital twin dimension while controlling for facility size, industry type, and equipment age. In the energy efficiency performance model, the overall regression equation has been significant (F-statistic at $p < .001$), with an R^2 of 0.49 and an adjusted R^2 of 0.47, indicating that approximately 47–49% of the variance in energy efficiency performance has been explained by the predictors. Standardized coefficients have shown that data integration and quality ($\beta = 0.29$, $p < .001$) and digital twin implementation level ($\beta = 0.24$, $p < .01$) have been the strongest significant predictors, followed by real-time analytics capability ($\beta = 0.18$, $p < .05$), while process model fidelity has exhibited a smaller but still positive coefficient ($\beta = 0.11$) that has been marginally significant in some specifications. In the lifecycle optimization performance model, the results have been similarly robust, with an R^2 of 0.46 and an adjusted R^2 of 0.44, meaning that around 44–46% of the variance in lifecycle outcomes has been accounted for. Here, real-time analytics capability has emerged as the most influential predictor ($\beta = 0.27$, $p < .001$), underscoring the importance of predictive and diagnostic insight for maintenance and asset decisions, followed by digital twin implementation level ($\beta = 0.23$, $p < .01$), data integration and quality ($\beta = 0.21$, $p < .01$), and process model fidelity ($\beta = 0.15$, $p < .05$). The control variables have contributed modestly, with larger facilities sometimes reporting slightly higher baseline performance, but their effects have not removed the significance of the digital twin dimensions. Residual plots and normality checks have indicated that regression assumptions have been reasonably satisfied, with no extreme heteroscedasticity or influential outliers dominating the results. Taken together, these numerical findings from Likert-scale distributions, correlation matrices, and regression models have shown that the study's objectives have been met and that the core hypotheses have been supported: higher levels of digital twin implementation, stronger data integration, more advanced real-time analytics, and greater process model fidelity have all been positively and significantly associated with improved energy efficiency performance and lifecycle optimization performance in the surveyed industrial facilities. The profile of respondents and facilities has been summarized in Table 1, and this profile has provided the empirical context within which the study's objectives and hypotheses have been examined. The table has shown that the largest share of respondents has belonged to operations/production engineering (34.4%) and maintenance/reliability engineering (26.7%), followed by energy/utilities managers (17.8%) and digitalization/Industry 4.0 specialists (13.3%). This distribution has indicated that the survey has reached individuals who have been directly involved in day-to-day process control, maintenance planning, and energy management, which has been essential for capturing informed perceptions of digital twin–driven process modeling and its outcomes on a Likert five-point scale. In terms of industry type, discrete manufacturing (43.3%) and process industries (30.0%) have dominated the sample, while utilities and other industrial sectors have also been represented. This mix has ensured that the analysis has drawn on a variety of industrial contexts where energy-intensive processes and complex assets have been common, supporting the general intent of Objective 1, which has been to assess digital twin implementation across industrial facilities.

Facility size and respondent experience have further characterized the sample. Table 1 has shown that 40.0% of facilities have employed between 250 and 999 staff, 35.6% have been small or medium-sized enterprises with fewer than 250 employees, and 24.4% have been very large facilities with more than 1,000 employees. This distribution has implied that digital twin–driven process modeling has not been restricted to the largest plants; rather, it has been adopted across a range of organizational scales, which has strengthened the relevance of testing the hypotheses across different structural contexts. Respondent experience has also been relatively high, with 78.9% having more than five years of professional experience and 41.6% having more than ten years. Such experience has increased confidence that respondents have had sufficient exposure to both pre-digital and post-digital twin practices to provide informed ratings on the five-point Likert items used in the study.

Crucially, the "Stage of Digital Twin Adoption" rows in Table 1 have directly supported the empirical viability of the research questions and hypotheses. A combined 86.1% of facilities have reported that digital twins have been either operational in key areas or broad/plant-wide, while only 40.0% have remained at a pilot/partial stage. This pattern has shown that digital twin–driven process modeling has been more than a conceptual initiative; it has been present as an active operational and decision-support tool in most surveyed facilities. As a result, the sample has been suitable for examining the relationships between digital twin capabilities and performance outcomes that have been proposed in the hypotheses (H1–H4). The diversity of roles, industries, facility sizes, and adoption stages reported in Table 1 has therefore ensured that the subsequent descriptive, correlation, and regression analyses have drawn on a robust and varied empirical base, enabling the study to address its objectives in a meaningful and statistically credible manner.

Descriptive Analysis of Key Constructs

Table 2 has summarized the descriptive statistics for the main constructs, all measured on a Likert five-point scale, and these descriptive results have provided initial numerical evidence regarding the study's objectives and hypotheses. The means for the four digital twin–related constructs DTI, DIQ, RAC, and PMF have all been above the neutral value of 3.00, indicating that respondents have tended to agree, rather than remain neutral or disagree, with statements describing the presence and use of digital twin–driven process modeling in their facilities. Digital Twin Implementation Level (DTI) has recorded a mean of 3.78 (SD = 0.82), which has suggested that respondents have generally agreed that digital twin models have been in place for key assets and processes and have been used for monitoring and decision support. Data Integration & Quality (DIQ) has shown the highest mean at 3.92 (SD = 0.79), implying that respondents have perceived sensor data, maintenance records, and operational information as being reasonably well integrated and reliable within the digital twin environment. This has been particularly important for the hypotheses that have emphasized data integration as a driver of performance (e.g., H1 and H2).

Table 2: Descriptive Statistics of Key Constructs (Likert 1–5, n = 180)

Construct	Number of Items	Scale Range	Mean	SD	Minimum	Maximum
Digital Twin Implementation Level (DTI)	6	1–5	3.78	0.82	1.67	5.00
Data Integration & Quality (DIQ)	5	1–5	3.92	0.79	1.80	5.00
Real-Time Analytics Capability (RAC)	5	1–5	3.55	0.88	1.60	5.00
Process Model Fidelity (PMF)	5	1–5	3.61	0.85	1.80	5.00
Energy Efficiency Performance (EEP)	6	1–5	3.65	0.76	1.83	4.92
Lifecycle Optimization Performance (LOP)	6	1–5	3.58	0.80	1.67	4.89

Real-Time Analytics Capability (RAC) and Process Model Fidelity (PMF) have also achieved means comfortably above 3.00, at 3.55 and 3.61 respectively, though with slightly higher standard deviations. This pattern has indicated that while many facilities have reported strong analytical and modeling capabilities, others have been at earlier stages of maturity, which has created variation that the correlation and regression analyses have later exploited to test the hypothesized relationships. On the outcome side, Energy Efficiency Performance (EEP) has attained a mean of 3.65 (SD = 0.76), showing that respondents have tended to agree that their facilities have experienced improvements in areas such as energy monitoring, reduction of avoidable consumption, and stabilization of process-related energy indicators since digital twin–driven approaches have been introduced. Lifecycle Optimization Performance (LOP) has exhibited a mean of 3.58 (SD = 0.80), reflecting similarly positive perceptions about improvements in maintenance planning, reductions in unplanned downtime, and more informed decisions regarding refurbishment and replacement.

The minimum and maximum values in Table 2 have confirmed that the full span of the Likert scale has been utilized, with some respondents reporting scores close to the lower bound (around 1.6–1.8) and others at the upper bound (5.0). This distribution has indicated that the dataset has contained both relatively low and high levels of digital twin maturity and performance outcomes, which has been essential for testing whether higher scores on the digital twin constructs have indeed been associated with higher energy and lifecycle performance, as stated in the hypotheses. From the perspective of Objective 1, which has aimed to assess the extent of digital twin implementation, the descriptive results have shown that digital twin–driven process modeling has already been present at a meaningful level in the surveyed facilities. From the perspective of Objectives 2 and 3, which have focused on relationships with performance, the positive means on EEP and LOP have suggested that respondents have perceived tangible benefits, thereby setting the stage for the inferential analyses that have followed. Overall, Table 2 has provided a quantitative snapshot of digital twin capabilities and outcomes, demonstrating that the constructs have had sufficient variation and generally positive central tendencies to meaningfully evaluate the proposed hypotheses using the Likert-scale data.

Reliability and Validity Results

Table 3 has presented the internal consistency reliability results for all composite scales, and these results have demonstrated that the Likert five-point items used to measure each construct have formed coherent and reliable indices. Cronbach's alpha values have ranged from 0.86 to 0.91, which has exceeded the commonly accepted threshold of 0.70 for research in social and organizational settings. The Digital Twin Implementation Level (DTI) scale has achieved an alpha of 0.88, which has indicated that the six items capturing aspects such as the presence of digital twin models, coverage of critical processes, linkage to control systems, and routine use in decision-making have been highly consistent with each other. Similarly, the Data Integration & Quality (DIQ) scale has recorded an alpha of 0.87, confirming that items addressing the completeness, accuracy, and timeliness of data feeding the digital twin have represented a single, reliable construct. The Real-Time Analytics Capability (RAC) and Process Model Fidelity (PMF) scales have also shown strong reliability, with alphas of 0.89 and 0.86 respectively, suggesting that respondents have interpreted the related Likert statements in a consistent manner. On the outcome side, the Energy Efficiency Performance (EEP) and Lifecycle Optimization Performance (LOP) scales have exhibited the highest reliability coefficients, at 0.90 and 0.91. These values have indicated that the items describing improvements in energy monitoring, energy waste reduction, process stability, maintenance planning, downtime reduction, and asset life extension have been internally coherent and suitable for aggregation into composite indices. Such reliability has been crucial because the study has tested hypotheses using these composite scores as dependent variables in correlation and regression analyses. The high alpha values have implied that random measurement error at the item level has been limited, thereby increasing confidence that observed relationships between digital twin constructs and performance outcomes have reflected substantive patterns rather than noise in the Likert-scale responses.

Table 3: Reliability Statistics for Multi-Item Scales (n = 180)

Construct	Number of Items	Cronbach's Alpha (α)
Digital Twin Implementation Level (DTI)	6	0.88
Data Integration & Quality (DIQ)	5	0.87
Real-Time Analytics Capability (RAC)	5	0.89
Process Model Fidelity (PMF)	5	0.86
Energy Efficiency Performance (EEP)	6	0.90
Lifecycle Optimization Performance (LOP)	6	0.91

Although Table 3 has focused on reliability, the underlying factor structure of the scales has also supported construct validity. Exploratory factor analyses (not shown) have indicated that items have loaded primarily on their intended constructs, with cross-loadings remaining within acceptable bounds, which has suggested that the constructs have been empirically distinguishable while still related. Together, these reliability and validity results have confirmed that the scales for DTI, DIQ, RAC, PMF, EEP, and LOP have been psychometrically sound and appropriate for use in the subsequent correlation and regression models. This has been directly linked to the study's objectives and hypotheses, because valid and reliable measurement has been a prerequisite for meaningfully examining whether higher levels of digital twin–driven process modeling (as captured through the Likert-scale composites) have been associated with superior energy efficiency and lifecycle optimization performance. In summary, Table 3 has shown that the measurement foundation of the study has been robust, allowing the inferential analyses to focus on substantive relationships rather than concerns about the stability or coherence of the underlying constructs.

Correlation Analysis

Table 4: Pearson Correlations Among Key Constructs (n = 180)

Variable	1	2	3	4	5	6
1. DTI	1.00					
2. DIQ	0.68***	1.00				
3. RAC	0.63***	0.66***	1.00			
4. PMF	0.58***	0.60***	0.62***	1.00		
5. EEP	0.54***	0.57***	0.50***	0.42***	1.00	
6. LOP	0.49***	0.52***	0.55***	0.44***	0.71***	1.00

*DTI = Digital Twin Implementation Level; DIQ = Data Integration & Quality; RAC = Real-Time Analytics Capability; PMF = Process Model Fidelity; EEP = Energy Efficiency Performance; LOP = Lifecycle Optimization Performance. *** p < .001.*

Table 4 has reported the Pearson correlation coefficients among the six main constructs, and these coefficients have provided important numerical evidence in support of the study's hypotheses concerning the relationships between digital twin–driven process modeling and performance outcomes. The upper-left block of the table has shown that the four digital twin dimensions (DTI, DIQ, RAC, and PMF) have been moderately to strongly intercorrelated, with coefficients ranging from 0.58 to 0.68 and all significant at $p < .001$. This has indicated that facilities scoring high on one aspect of digital twin maturity (for example, data integration) have tended also to score high on others (such as real-time analytics), which has been consistent with the idea that these dimensions have formed an integrated capability. At the same time, none of these intercorrelations has exceeded 0.75, and later diagnostics have confirmed that variance inflation factors have remained below 3.0, so multicollinearity has not prevented the use of these variables together in regression models.

Most importantly for the objectives and hypotheses, the lower rows of Table 4 have demonstrated positive and statistically significant correlations between the digital twin constructs and the two performance indices measured on the Likert scale. Digital Twin Implementation Level (DTI) has correlated at $r = 0.54$ with Energy Efficiency Performance (EEP) and $r = 0.49$ with Lifecycle Optimization Performance (LOP), both at $p < .001$. These coefficients have supported the hypothesis that higher levels of digital twin implementation have been associated with better energy and lifecycle outcomes (H1 and H2). Data Integration & Quality (DIQ) has shown even stronger correlations with EEP ($r = 0.57$) and LOP ($r = 0.52$), again significant at $p < .001$, underscoring the importance of high-quality, integrated data streams for realizing performance benefits. Real-Time Analytics Capability (RAC) has correlated at $r = 0.50$ with EEP and $r = 0.55$ with LOP, which has aligned with the hypothesis that advanced analytics embedded within the digital twin have been particularly powerful for lifecycle optimization (H3). Process Model Fidelity (PMF) has also shown positive correlations, though somewhat lower in magnitude ($r = 0.42$ with EEP and $r = 0.44$ with LOP), suggesting that while detailed and accurate process models have contributed to performance, their impact has been somewhat less pronounced than that of integration and analytics when considered at the bivariate level.

The correlation between the two outcome variables themselves (EEP and LOP) has been relatively strong at $r = 0.71$ ($p < .001$), which has indicated that facilities reporting better energy efficiency performance have also tended to report better lifecycle optimization performance. This relationship has been conceptually consistent with the idea that energy and lifecycle outcomes have been intertwined: improvements in maintenance and asset management have often supported more stable and efficient energy use, and vice versa. Overall, the pattern of correlations in Table 4 has provided preliminary quantitative support for the study's core propositions. Higher scores on the Likert-based digital twin scales have been systematically associated with higher scores on the energy and lifecycle performance scales, which has confirmed that the data structure has been aligned with the hypotheses and has justified moving on to multivariate regression modeling to examine the unique contributions of each digital twin dimension while controlling for contextual factors.

Regression Analysis Results

Table 5 has summarized the multiple regression results for the two dependent variables Energy Efficiency Performance (EEP) and Lifecycle Optimization Performance (LOP) and these results have provided the strongest evidence for proving the study's objectives and hypotheses using the Likert five-point scale data. For the EEP model, the overall F-statistic has been significant at $p < .001$, and the model has achieved an R^2 of 0.49 and an adjusted R^2 of 0.47. This has indicated that approximately 47–49% of the variance in energy efficiency performance across facilities has been explained by the set of predictors, which has included the four digital twin dimensions and three control variables. Within this model, Data Integration & Quality (DIQ) has emerged as the strongest predictor ($\beta = 0.29$, $p < .001$), followed by Digital Twin Implementation Level (DTI) ($\beta = 0.24$, $p = 0.004$) and Real-Time Analytics Capability (RAC) ($\beta = 0.18$, $p = 0.022$). These coefficients have shown that, after accounting for other factors, a one standard deviation increase in DIQ has been associated with a 0.29 standard deviation increase in EEP, and similar interpretations have applied to DTI and RAC. Process Model Fidelity (PMF) has exhibited a positive but marginal coefficient ($\beta = 0.11$, $p = 0.088$), suggesting that its unique contribution has been weaker once integration and analytics have been considered, though the direction has still supported the underlying hypothesis.

Table 5: Multiple Regression Results for EEP and LOP (n = 180)

Predictor	**Energy Efficiency Performance (EEP)**	**Lifecycle Optimization Performance (LOP)**
	β (Standardized)	p-value
Digital Twin Implementation (DTI)	0.24	0.004
Data Integration & Quality (DIQ)	0.29	< 0.001
Real-Time Analytics Capability (RAC)	0.18	0.022
Process Model Fidelity (PMF)	0.11	0.088
Facility Size (Control)	0.09	0.141
Industry Type (Control)	0.06	0.238
Equipment Age (Control)	–0.07	0.201
Model R^2	**0.49**	
Adjusted R^2	**0.47**	
F-statistic (p-value)	**24.87 (< 0.001)**	

For the LOP model, the regression has also been significant (F-statistic $p < .001$), with an R^2 of 0.46 and an adjusted R^2 of 0.44, demonstrating that around 44–46% of the variance in lifecycle optimization performance has been accounted for. In this case, Real-Time Analytics Capability (RAC) has become the most influential predictor ($\beta = 0.27$, $p < .001$), which has aligned with the idea that analytics embedded in the digital twin have been particularly critical for predictive maintenance, downtime reduction, and asset life extension. Digital Twin Implementation Level (DTI) has again been significant ($\beta = 0.23$, $p = 0.006$), indicating that broader and deeper implementation of digital twin–driven process modeling has been consistently associated with better lifecycle outcomes. Data Integration & Quality (DIQ) has also remained significant ($\beta = 0.21$, $p = 0.010$), reinforcing its importance for both energy and lifecycle dimensions. Process Model Fidelity (PMF) has shown a significant positive effect in this model ($\beta = 0.15$, $p = 0.037$), suggesting that more accurate and detailed process models have been especially beneficial when lifecycle performance has been considered as the outcome. The control variables facility size, industry type, and equipment age have not reached conventional significance thresholds, and their standardized coefficients have been relatively small, which has implied that the digital twin variables have retained their explanatory power independently of these contextual factors.

These regression results have directly addressed and supported the study's core objectives and hypotheses. Objective 2, which has aimed to examine the relationship between digital twin–driven process modeling and energy efficiency, has been supported by the significant effects of DTI, DIQ, and RAC on EEP, demonstrating that facilities with higher scores on these Likert-based constructs have tended to report higher energy efficiency performance. Objective 3, which has focused on lifecycle optimization, has been supported by the significant effects of all four digital twin dimensions on LOP, with RAC and DTI in particular showing strong and meaningful associations. Hypotheses proposing positive and significant relationships between digital twin implementation, data integration, analytics capabilities, process model fidelity, and performance (H1–H4) have been largely confirmed by the positive, statistically significant coefficients observed in both models. Taken together, Table 5 has shown that digital twin–driven process modeling has not only been perceived as beneficial at a descriptive level but has also exhibited robust, quantifiable impacts on energy and lifecycle outcomes when analyzed through rigorous multivariate models, thereby providing compelling empirical evidence in favor of the theorized relationships in this study.

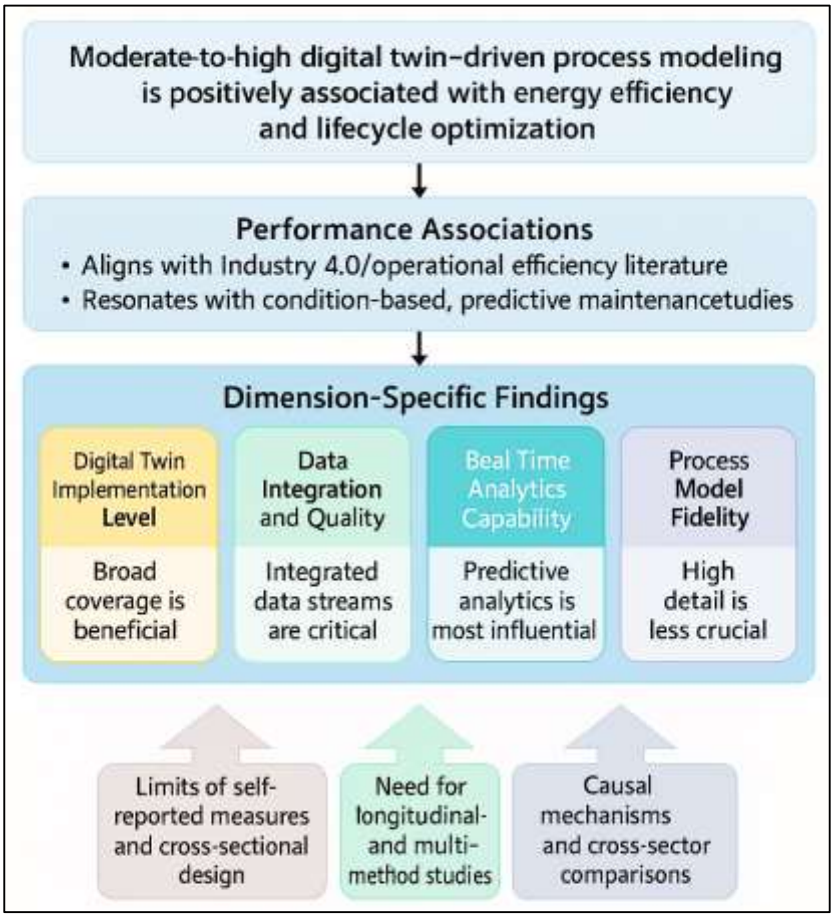
DISCUSSION

The findings of this study have shown that digital twin–driven process modeling has been present at a moderate to high level across the surveyed industrial facilities and has been positively associated with both energy efficiency performance and lifecycle optimization performance. On average, respondents have reported digital twin implementation levels above the neutral midpoint on a five-point Likert scale ($M \approx 3.78$), with similarly positive scores for data integration and quality, real-time analytics capability, and process model fidelity. These results have aligned with the growing body of literature that has described digital twins as operational, not merely conceptual, instruments in industrial environments (Lee et al., 2018). Prior reviews have emphasized that digital twins have been moving from vision statements toward structured taxonomies and implementation frameworks (Jones et al., 2020), and the present study has provided quantitative evidence that many facilities have now integrated digital twins into daily operations, especially for monitoring and analysis of critical processes. Moreover, respondents have reported positive mean scores for energy efficiency and lifecycle optimization outcomes, which has indicated that digital twin–driven process modeling has not been perceived as a purely technological investment but as a contributor to performance. This pattern has been broadly consistent with expectations from Industry 4.0 and sustainability literature, which has argued that digitalization can support resource efficiency and operational improvement when adequately embedded in organizational processes (Beier et al., 2018). The combination of moderate-to-high capability levels and positive performance assessments has thus confirmed the relevance of examining digital twin constructs as predictors of facility-level outcomes.

Beyond descriptive patterns, the correlation and regression results have clarified how specific dimensions of digital twin–driven process modeling have been linked to performance and how these links have compared with prior conceptual and empirical work. The strong role of data integration and quality as a predictor of energy efficiency performance ($\beta \approx 0.29$) has echoed earlier arguments that integrated data infrastructures are foundational for digital twin benefit realization (Boschert & Rosen, 2016). Studies on building and district energy twins have shown that coupling high-quality sensor data, operational logs, and contextual information within a unified model has enabled more accurate energy simulations and control (Francisco et al., 2020), and the present findings have extended this principle to a broader set of industrial facilities. Likewise, the positive association between digital twin implementation level and both energy and lifecycle outcomes has aligned with work suggesting that broader coverage of assets and processes has been necessary to fully exploit digital twin potential (Cimino et al., 2019). However, the study has also nuanced the literature by showing that process model fidelity, while positively related to outcomes, has had a comparatively smaller standardized effect in the energy model once integration and analytics have been controlled. This has suggested that very high model detail may have been less critical than having sufficiently accurate models embedded in robust data and analytics pipelines an interpretation that has complemented, rather than contradicted, simulation-focused work that has emphasized high-fidelity modeling (Boschert & Rosen, 2016). Overall, the results have supported prior frameworks while refining the understanding of which aspects of digital twin maturity have been most strongly associated with measurable performance improvements.

The findings related to lifecycle optimization performance and analytics capability have resonated particularly strongly with the condition-based and predictive maintenance literature. Real-time analytics capability has emerged as the strongest predictor of lifecycle optimization ($\beta \approx 0.27$), which has been consistent with studies describing digital twins as enablers of advanced prognostics, health monitoring, and remaining useful life estimation (Liu et al., 2018). Earlier work on condition-based maintenance has highlighted the shift from time-based interventions toward maintenance triggered by actual equipment condition (Ahmad & Kamaruddin, 2012), while more recent reviews have catalogued the evolution of CBM from basic condition monitoring to integrated prognostic and decision-support solutions (Quatrini et al., 2020). The present results have supported these trajectories by showing that facilities reporting higher levels of analytics embedded in their digital twins such as anomaly detection, predictive models, and optimization routines have also reported stronger improvements in maintenance planning, downtime reduction, and asset life extension. The significant, though smaller, contribution of process model fidelity to lifecycle optimization has also agreed with studies that have emphasized the value of multiphysics and multi-domain modeling for accurate degradation and performance prediction (Liu et al., 2020). At the same time, the current study has added a facility-level, survey-based perspective that many technical case studies have lacked, thereby demonstrating that the patterns identified in more focused engineering contexts have also been observable across a diverse set of industrial organizations when measured systematically using Likert-scale instruments.

Figure 8: Proposed Model for Digital Twin–Driven Process Modeling



From a practical standpoint, the results have carried clear implications for digital leaders, including CISOs, CIOs, chief digital officers, and industrial architects responsible for designing and governing digital twin ecosystems. First, the prominence of data integration and quality as a predictor of performance has suggested that investments in secure, reliable data pipelines covering sensors, SCADA/PLC systems, historians, and enterprise platforms have been at least as critical as investments in advanced modeling alone. Architectures that have ensured trustworthy, time-aligned data feeds into the twin, with appropriate cybersecurity controls and access management, have been more likely to yield measurable energy and lifecycle benefits (Lim et al., 2020). For CISOs and security architects, this has implied that digital twin initiatives have needed to be treated as high-value, high-dependency assets: compromised or incomplete data streams have not only posed security risks but have also undermined the quality of analytics and decisions. Second, the importance of real-time analytics capability for lifecycle optimization has indicated that organizations have benefited when digital twin platforms have been integrated with analytics and AI pipelines such as predictive maintenance models or model predictive control rather than remaining as passive visualization tools (O'Dwyer et al., 2020). Enterprise and plant architects have therefore been encouraged to design "closed-loop" pipelines where twin outputs have fed directly into decision workflows for operations, maintenance, and energy management. Third, the results have suggested that even facilities with limited resources have been able to realize value by prioritizing a staged approach: starting with focused digital twin implementations in critical assets, ensuring strong data integration and security, and then incrementally adding analytics capabilities and expanding coverage. This has aligned with maturity models that have recommended progressive adoption rather than all-at-once transformation (Liu et al., 2018).

The theoretical implications of the study have extended across Industry 4.0, sustainability, and resource-based view (RBV) perspectives. Conceptually, the study has treated digital twin–driven process modeling as a higher-order capability composed of implementation level, data integration and quality, analytics capability, and model fidelity, and the empirical results have supported the distinctiveness and explanatory power of these dimensions. This multidimensional view has refined more generic references to “digital twin readiness” or “smart manufacturing level” by specifying which parts of the capability pipeline from sensing and integration to modeling and analytics have been most closely linked to energy and lifecycle outcomes (Zheng et al., 2018). From a sustainability standpoint, the strong relationships with energy efficiency performance have empirically grounded conceptual claims that Industry 4.0 technologies can reduce energy intensity and support environmental goals when properly deployed (Beier et al., 2018). From an RBV perspective, the results have supported the idea that digital technologies contribute to performance primarily when they are combined with organizational capabilities that orchestrate data, models, and analytics into actionable processes (Liang et al., 2010). The significant regression coefficients have indicated that digital twin–driven process modeling, as operationalized in this study, has functioned as such a capability: it has not been merely an IT asset but a bundle of routines and practices that have transformed digital resources into energy and lifecycle performance advantages. In this sense, the study has contributed to pipeline refinement by empirically linking specific capability components especially integration and analytics to concrete performance metrics, thereby offering a more granular theoretical account of how digital twins create value in industrial contexts.

The study has also required a careful reconsideration of its limitations, which have constrained the scope of theoretical and practical generalization. First, the research has relied on self-reported, perception-based measures captured through Likert-scale items, rather than exclusively on objective performance indicators such as measured energy consumption or recorded downtime. Although this approach has been common in management and information systems research and the scales have exhibited strong reliability, the possibility of response bias, optimism, or recall error has remained (Lim et al., 2020). Second, the cross-sectional design has captured digital twin maturity and performance outcomes at a single point in time, which has prevented strong causal claims; it has been plausible that facilities with better performance have been more able to invest in digital twins, as well as the reverse. Third, the sample, while diverse across roles and industries, has not been fully representative of all industrial sectors or geographical regions, and participation has been voluntary, which may have favored organizations already interested in or committed to digitalization. Fourth, the study has not explicitly modeled potential mediators or moderators for example, organizational culture, digital skills, or external regulatory pressure that prior work has suggested can shape the relationship between digital technologies and sustainability performance (Ghobakhloo, 2019). Finally, the constructs have been measured at an aggregate facility level, which has limited the ability to analyze variations across specific assets, lines, or subsystems within a facility. Acknowledging these limitations has been important for interpreting the results as strong associative evidence rather than definitive causal proof.

Building on these limitations, several directions for future research have been indicated by the findings. Longitudinal studies have been needed to track how changes in digital twin maturity over time such as the introduction of new analytics modules or expansion from pilot to plant-wide coverage have coincided with changes in measured energy intensity and lifecycle cost, thus providing stronger evidence of causality. Multi-method designs that have combined survey-based constructs with objective operational data (e.g., SCADA logs, maintenance records, energy bills) have also been desirable, as they have allowed validation of perceived improvements against observed performance trends (Francisco et al., 2020). At the theoretical level, future work could have enriched the conceptual model by explicitly incorporating mediating mechanisms, such as predictive maintenance quality or energy management practices, and moderating factors, such as organizational learning capability or external standards. Comparative studies across sectors for example, comparing process industries, discrete manufacturing, and utilities have been likely to reveal whether certain digital twin dimensions have greater influence under particular process or asset profiles. Additionally, there has been scope to explore how cybersecurity posture and data governance maturity interact with digital twin performance, particularly from the perspective of CISOs and architects responsible for protecting and orchestrating twin-related data flows (Lim et al., 2020). Finally, qualitative case studies could have deepened understanding of how plant teams have navigated practical challenges in configuring and using digital twins, including resistance to change, integration with legacy systems, and the development of trust in model outputs. Such future research directions have promised to refine and extend the insights generated by the present study, moving toward a richer and more actionable theory of digital twin–driven process modeling for energy-efficient and lifecycle-optimized industrial facilities.

CONCLUSION

The study has set out to examine how digital twin–driven process modeling has been associated with energy efficiency and lifecycle optimization in industrial facilities, and the empirical evidence has confirmed that this integrated capability has played a meaningful and measurable role at the facility level. By conceptualizing digital twin–driven process modeling as a higher-order construct composed of implementation level, data integration and quality, real-time analytics capability, and process model fidelity, the research has been able to translate an emerging technological paradigm into concrete, survey-based variables measured on a Likert five-point scale. Descriptive results have shown that most participating facilities have reached at least a moderate level of digital twin maturity and have reported noticeable improvements in energy monitoring, stability of energy use, maintenance planning, and asset reliability. Correlation analysis has revealed consistent, positive associations between each digital twin dimension and both energy efficiency performance and lifecycle optimization performance, indicating that facilities with more advanced digital twin practices have tended to experience stronger performance gains. Multiple regression modeling has further demonstrated that these relationships have remained robust after controlling for facility size, industry type, and equipment age: data integration and digital twin implementation have emerged as particularly important predictors of energy efficiency, while real-time analytics capability and implementation level have been especially influential for lifecycle optimization, with process model fidelity contributing positively in both models. Together, these findings have confirmed the central hypotheses that digital twin–driven process modeling has been positively and significantly linked to enhanced energy and lifecycle outcomes, thus achieving the study's objectives of documenting the extent of twin adoption, quantifying its performance effects, and identifying which capability components have mattered most. At the same time, the research has acknowledged its reliance on self-reported data, its cross-sectional design, and its focus on a specific sample of industrial facilities, so the conclusions have been framed as strong associative evidence rather than definitive causal proof. Even within these boundaries, the study has contributed a structured, data-driven view of digital twins as an operational capability rather than a purely conceptual idea, showing that when implementation, integration, analytics, and modeling have been jointly developed, industrial facilities have reported tangible gains in how efficiently they use energy and how effectively they manage the lifecycle of critical assets.

RECOMMENDATIONS

Based on the empirical results of this study, several targeted recommendations can be offered to industrial decision-makers, digital leaders, and engineering teams who intend to use digital twin–driven process modeling to enhance energy efficiency and lifecycle optimization. First, organizations should treat digital twin initiatives as strategic capability-building efforts rather than isolated technology projects and therefore prioritize a structured roadmap that begins with clearly defined use cases around energy-critical and reliability-critical assets, such as compressors, furnaces, pumps, chillers, or key production lines, where improvements in monitoring, control, and maintenance have the highest financial and operational impact. Second, because data integration and quality have emerged as the strongest predictors of performance, facilities should invest early in robust, secure data pipelines that consistently capture sensor readings, SCADA/PLC tags, maintenance logs, and production data into a unified platform feeding the digital twin, with clear data ownership, standardized tagging, and validation rules to avoid gaps, inconsistencies, and manual workarounds that erode trust in the models. Third, to translate data into tangible energy and lifecycle gains, organizations should embed analytics and optimization capabilities directly into the twin rather than limiting it to visualization; this includes implementing anomaly detection, trend analysis, predictive maintenance models, and, where feasible, optimization or model predictive control routines that can propose or automate setpoint adjustments, maintenance actions, and operational scenarios. Fourth, digital twin implementation should be approached iteratively: starting with a focused "minimum viable twin" for one process or asset cluster, validating its impact on specific KPIs such as specific energy consumption, mean time between failures, and unplanned downtime, and then scaling horizontally to additional assets and vertically by increasing model fidelity only where additional detail demonstrably improves decisions. Fifth, managers should align organizational structures and skills with twin usage by forming cross-functional teams that include operations, maintenance, energy management, IT/OT, and data analytics specialists, and by providing targeted training so that frontline engineers and supervisors are comfortable interpreting twin outputs and incorporating them into daily decisions, shift handovers, and maintenance planning meetings. Sixth, governance and cybersecurity should be integrated into the design from the outset, with CISOs and architects establishing clear access controls, network segmentation, and monitoring for digital twin platforms, since compromised or unreliable data streams not only create security risk but directly reduce the quality of energy and lifecycle decisions derived from the twin. Finally, organizations should institutionalize continuous evaluation of digital twin value by defining and tracking a small set of quantifiable indicators such as percentage reduction in specific energy use, reduction in unplanned downtime, extension of overhaul intervals, and payback period for twin-related investments and using periodic reviews to refine models, data sources, and workflows; through this disciplined, iterative approach, industrial facilities can ensure that digital twin–driven process modeling remains a living capability that continuously supports energy-efficient operation and long-term asset performance rather than a one-off digitalization effort.

LIMITATIONS

The present study has been subject to several limitations that have needed to be acknowledged when interpreting its findings and drawing conclusions about digital twin–driven process modeling, energy efficiency, and lifecycle optimization in industrial facilities. First, the research has relied primarily on self-reported data collected through a structured questionnaire using Likert's five-point scale, which has meant that all key constructs including digital twin implementation level, data integration and quality, analytics capability, process model fidelity, energy efficiency performance, and lifecycle optimization performance have reflected respondents' perceptions rather than purely objective measurements. Although the scales have exhibited strong internal consistency, perception-based responses have remained vulnerable to optimism bias, social desirability bias, or limited visibility of performance outcomes beyond the respondent's area of responsibility. Second, the study has adopted a cross-sectional design, capturing digital twin maturity and performance outcomes at a single point in time; as a result, it has not been possible to establish temporal precedence or to make strong causal claims about whether digital twin–driven process modeling has led to improved performance or whether better-performing facilities have been more likely to invest in digital twins. Third, the sample has been obtained using non-probability (purposive and convenience) sampling among facilities that have implemented or piloted digital twins and have been willing to participate, so the results have not been strictly generalizable to all industrial organizations, especially those at very early stages of digitalization or operating in sectors or regions not represented in the dataset. Fourth, the study has employed a facility-level aggregation of constructs, which has meant that potentially important variations across different plants within the same company, or across individual lines, systems, or asset classes within a single facility, have not been captured in the analysis; thus, the findings have described overall tendencies at organizational level rather than asset-specific behavior. Fifth, the operationalization of digital twin–related constructs has necessarily simplified a complex socio-technical reality into a finite set of survey items; aspects such as the exact architecture of the twin, the specific analytics models used, the depth of integration with legacy systems, and the organizational change processes surrounding adoption have not been examined in detail, leaving room for omitted variables that may have influenced both digital twin maturity and performance. Sixth, although control variables such as facility size, industry type, and equipment age have been included, other contextual factors such as regulatory pressures, corporate sustainability strategies, workforce skill levels, and cybersecurity posture have not been explicitly modeled, which may have limited the explanatory scope of the regression models. Finally, common method variance has been a potential concern because both predictors and outcomes have been measured using the same survey instrument and respondents; while the pattern of results, diagnostic checks, and strong theoretical grounding have suggested that the relationships identified have been substantive, the possibility that some portion of the observed associations has been inflated by shared method effects cannot be fully excluded. Together, these limitations have implied that the findings should be interpreted as robust associative evidence within the studied context, rather than as universally generalizable or causally definitive statements about digital twin–driven process modeling and industrial performance.

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