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DIGITAL TWIN-DRIVEN THERMODYNAMIC AND FLUID DYNAMIC SIMULATION FOR EXERGY EFFICIENCY IN INDUSTRIAL POWER SYSTEMS

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Abstract

This study addresses the persistent problem that many industrial power systems still exhibit low exergy efficiency even after decades of energy efficiency programs, largely because second law metrics are not embedded in day-to-day digital decision tools. The purpose is to examine how digital twin driven thermodynamic and fluid dynamic simulation, deployed through cloud and enterprise platforms, relates to exergy efficiency at plant level. Using a quantitative, cross sectional, case-based design, data were collected via structured questionnaires from 214 engineers, operators and managers in steam, combined cycle and cogeneration power plants that have implemented digital twin solutions. Key variables include digital twin adoption, simulation sophistication, data quality, organizational support and perceived exergy efficiency, measured on five-point Likert scales. Descriptive statistics and reliability analysis (Cronbach's alpha 0.84 to 0.89) were followed by correlation and multiple regression, including interaction terms. The core model explained 51.9 percent of the variance in exergy efficiency ($R^2 = 0.519$), with simulation sophistication ($\beta = 0.34$, $p < .001$) and digital twin adoption ($\beta = 0.27$, $p < .001$) as the strongest predictors; data quality ($\beta = 0.18$, $p = .002$) and organizational support ($\beta = 0.16$, $p = .006$) were also significant. When moderation effects were added, explained variance rose to 57.3 percent ($R^2 = 0.573$), and interactions between digital twin adoption and data quality ($\beta = 0.15$, $p = .004$) and between adoption and organizational support ($\beta = 0.12$, $p = .015$) were significant, showing that high quality data and strong management backing amplify exergy gains. The findings imply that exergy-oriented improvements are maximized when plants jointly invest in high fidelity digital twin models, robust data governance and sustained organizational support for simulation-based decision making in industrial power systems.

Keywords

Digital Twin, Exergy Efficiency, Thermodynamic and Fluid Dynamic Simulation, Industrial Power Systems, Data Quality;

INTRODUCTION

Digital twin–driven thermodynamic and fluid-dynamic simulation for exergy efficiency in industrial power systems sits at the intersection of three mature but still rapidly evolving domains: industrial energy systems, advanced simulation, and cyber–physical integration. Industrial power systems such as steam power plants, cogeneration units, and large process-utility networks remain among the largest consumers of primary energy and contributors to CO_2 emissions globally. Exergy, defined as the maximum useful work obtainable as a system comes into equilibrium with its environment, extends classical first-law energy analysis by explicitly accounting for energy quality and irreversibility in thermodynamic processes (Reddy et al., 2010). In parallel, digital twin concepts have emerged as high-fidelity, bidirectionally connected virtual replicas of physical assets that synchronize with real-time data and historical models to support monitoring, diagnosis, optimization, and control (Tao, Cheng, et al., 2018). Within this international landscape of decarbonization, energy security, and Industry 4.0 initiatives, the convergence between exergy-based performance indicators and digital twin architectures offers a promising route toward more transparent, quantitatively grounded decision-making in industrial power systems.

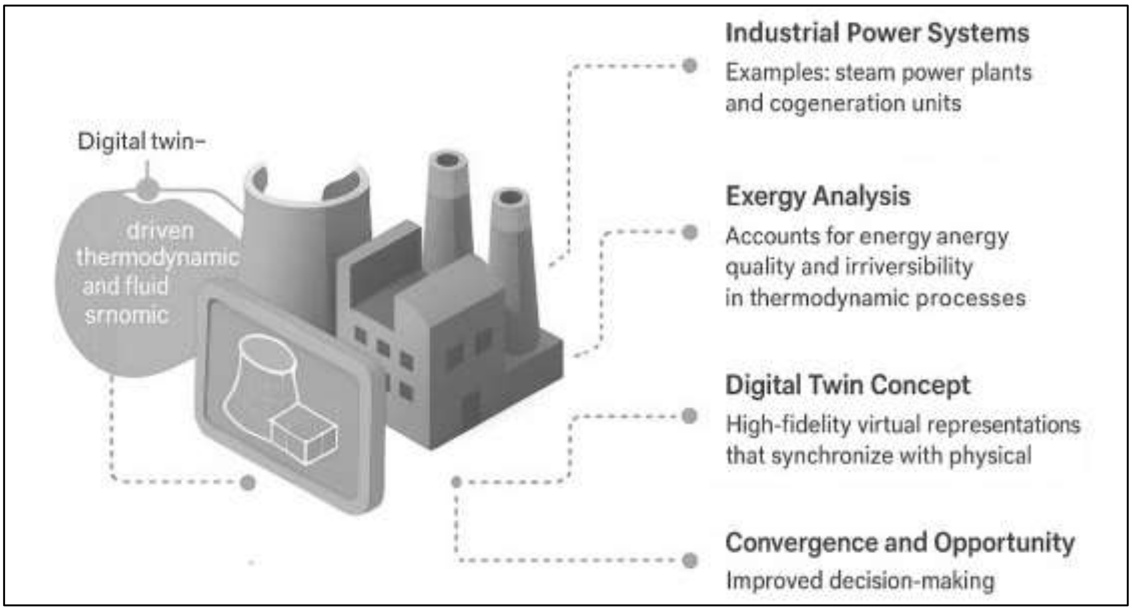
The industrial energy literature demonstrates that conventional first-law energy analysis often masks where real inefficiencies occur in power plants and utility systems because it cannot distinguish between high-quality and low-quality energy streams. Exergy analysis, grounded in the second law of thermodynamics, has therefore become a central tool for diagnosing where and how useful work potential is destroyed in complex cycles (Singh et al., 2021). Case studies on large steam power plants show that major exergy destruction typically occurs in boilers, combustion chambers, and condensers, where temperature gradients and chemical reactions generate significant irreversibility (Ameri et al., 2009). Aljundi (2009) reported for a Jordanian steam power plant that the condenser alone accounted for the largest share of energy loss, while exergy analysis revealed more subtle inefficiencies across feedwater heaters and turbines. These and similar investigations across coal-fired, gas-fired, and combined-cycle plants highlight that energy efficiency improvements do not always translate into exergy efficiency gains and that plant components with modest energy losses may still incur large exergy destructions (Aljundi, 2009; Bertsch & et al., 2018). Reviews of thermal power-plant exergy analyses further show that exergy efficiency indicators are increasingly used for benchmarking alternative plant configurations, retrofits, and operational strategies (Kaushik et al., 2011). Collectively, this body of work underscores the need for decision frameworks that integrate detailed thermodynamic modeling with exergy-based metrics when evaluating industrial power systems.

In parallel with exergy research, digital twin technology has matured from conceptual discussions to operational deployments in manufacturing, aerospace, and process industries. Early contributions framed digital twins as high-fidelity virtual counterparts of physical systems that remain synchronized via sensor data and enable "what-if" analysis, state estimation, and control within cyber–physical environments (Tao, Zhang, et al., 2019). The digital twin shop-floor paradigm conceptualizes a production environment where each machine and process has a corresponding virtual model that continuously exchanges data with its physical counterpart, enabling fine-grained monitoring and optimization of throughput, quality, and equipment performance (Tao, Bi, et al., 2018). Digital twin services have also been proposed to encapsulate simulation and analytics capabilities as reusable, interoperable services for smart manufacturing platforms (Qi & Tao, 2018). Systematic and scoping reviews indicate that digital twins support a range of functions including real-time monitoring, lifecycle management, condition-based maintenance, and remote operations across discrete and process industries (Liu et al., 2021). Within these studies, simulation fidelity particularly in multiphysics domains emerges as a critical factor that determines whether digital twins can reliably represent thermal, fluid, and structural behaviors in complex systems.

Digital twins have also been extended to support product-service systems and data-intensive manufacturing ecosystems. Digital twin–driven approaches to product design, manufacturing, and service integrate big data analytics with high-fidelity models to enable continuous feedback across the product lifecycle, from design and prototyping to operation and maintenance (Lu et al., 2020). In such frameworks, historical and real-time data from sensors, enterprise systems, and external sources are assimilated to update models, recalibrate parameters, and track degradation processes. Liu et al. (2021)

and Jiang et al. (2021) show that digital twin architectures increasingly rely on layered designs data, model, analytics, and application layers that must coordinate to deliver accurate predictions and actionable insights across heterogeneous industrial environments. Digital twin applications in construction, infrastructure, and building engineering further demonstrate how virtual replicas can manage structural and environmental data over long horizons (Lu et al., 2020; Opoku et al., 2021)reinforcing the idea that digital twins can serve as persistent, evolving representations of complex assets. At the same time, reviews highlight that many existing implementations focus on geometric and kinematic fidelity, whereas thermodynamic and fluid-dynamic processes relevant to power and energy systems are less frequently modeled with the same depth (Khaleel et al., 2022; Liu et al., 2021).

Figure 1: Digital Twin Architecture Linking Thermodynamic and Fluid-Dynamic Simulation



Recent work has begun to link digital twin concepts more explicitly with sustainability and resource efficiency in industrial contexts. Digital twin–based sustainable intelligent manufacturing frameworks emphasize integrating environmental and energy performance indicators into twin-driven decision loops, arguing that virtual models can help identify energy-intensive operations, optimize scheduling, and evaluate low-carbon strategies under varying demand and operating conditions (Zhang et al., 2020). Building on this, Lu et al. (2020) and Jiang et al. (2021) describe reference architectures in which digital twins interact with optimization algorithms and decision support systems to coordinate production and energy management in complex plants. Reviews of digital twin concepts and industrial applications indicate that exergy-oriented metrics remain underrepresented compared to traditional energy or efficiency indicators, even though exergy more directly captures irreversibility and resource quality (Jiang et al., 2021). This suggests a need for digital twin frameworks that embed exergy analysis within their core modeling layer, enabling operators to assess not only whether a process meets throughput or reliability requirements but also how effectively it converts fuel exergy into useful work under real operating conditions.

The present study is explicitly guided by a set of clearly defined objectives that translate the broad idea of digital twin–driven thermodynamic and fluid dynamic simulation for exergy efficiency into concrete, measurable research tasks. The overarching objective is to empirically examine how industrial stakeholders implement and utilize digital twin capabilities in power-system environments, and how these capabilities are associated with exergy efficiency at the plant level. To achieve this overarching aim, the first specific objective is to assess the current level of digital twin adoption and simulation sophistication in selected industrial power systems, including the extent of deployment across major plant components, the level of thermodynamic and fluid dynamic detail represented in the virtual models, and the degree of integration with operational data and control systems. The second objective is to evaluate exergy efficiency outcomes as perceived by engineers, operators, and managers, focusing on their assessments of exergy-based performance improvements, reductions in irreversibility, and enhancements in overall thermodynamic quality of energy conversion processes. The third objective is to develop and empirically test a conceptual model that links digital twin adoption, simulation sophistication, data quality, and organizational support to exergy efficiency outcomes, using a quantitative, cross-sectional, case-study–based approach. Within this objective, the study formulates and tests a set of hypotheses that specify direct and moderating relationships among these constructs, with exergy efficiency as the primary dependent variable. A fourth, complementary objective is to identify which aspects of digital twin capability and organizational context exert the strongest statistical influence on exergy-related performance indicators, as estimated through correlation analysis and regression modeling of survey responses collected on a structured Likert five-point scale. Together, these objectives provide a coherent framework for characterizing the state of digital twin implementation in industrial power plants, quantifying its association with exergy efficiency, and isolating the combinations of technical and organizational factors that most effectively support exergy-oriented decision-making in industrial power systems.

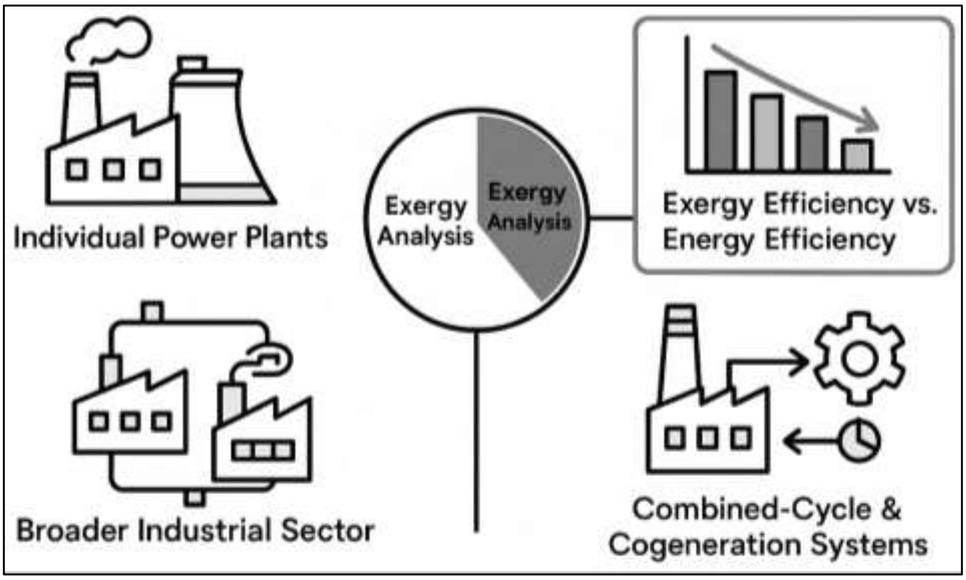
LITERATURE REVIEW

The literature on digital twin–driven thermodynamic and fluid dynamic simulation for exergy efficiency in industrial power systems spans several interconnected domains, beginning with foundational work on exergy analysis and extending to contemporary research on cyber–physical systems and smart manufacturing. Early exergy studies in thermal power plants established the analytical basis for identifying irreversibilities and quantifying the gap between actual performance and idealized thermodynamic behavior, showing that component-level exergy destruction in boilers, turbines, condensers, and heat exchangers is often far more revealing than traditional energy balances alone. Building on these insights, researchers progressively incorporated more detailed thermodynamic and fluid dynamic models, including steady-state and transient simulations, to capture complex interactions between working fluids, heat-transfer surfaces, and control strategies under varying operating conditions. In parallel, the digitalization of industry led to the emergence of digital twins as high-fidelity virtual counterparts of physical assets that remain continuously synchronized through sensor data, industrial networks, and advanced analytics, enabling real-time monitoring, predictive maintenance, and optimization in industrial plants. Within this broader Industry 4.0 context, digital twin frameworks began to integrate multiphysics simulations including thermal and fluid dynamic models together with data-driven methods to support operational decision-making and performance improvement in energy-intensive systems. As a result, the contemporary knowledge base encompasses exergy-focused analyses of power systems, digital twin architectures for industrial equipment and processes, and integrated approaches where simulation fidelity, data quality, and organizational capabilities jointly determine the effectiveness of digital twin deployments. The literature review for this study therefore synthesizes prior work across these strands, organizing them into thematic subsections that examine (a) the principles and applications of exergy analysis in industrial power systems, (b) the evolution of digital twin technologies and their core architectural patterns, (c) the embedding of thermodynamic and fluid dynamic simulations within digital twin platforms, (d) theoretical and conceptual frameworks that explain digital twin adoption and performance outcomes, and (e) empirical evidence on how technical and organizational factors influence the success of digital twin initiatives. This structure provides a coherent basis for identifying gaps, shaping the study's conceptual models, and aligning its quantitative hypotheses with established but still evolving streams of research.

Applications of exergy analysis in industrial power systems

Exergy analysis has become a central methodological lens for understanding how industrial power systems convert fuel into useful work, especially in fossil-fuel-based thermal plants where irreversibilities are pervasive. Unlike conventional first-law energy analysis, which focuses only on quantities of energy, exergy explicitly evaluates the quality of energy streams and the work potential destroyed by entropy generation in each process and component. In large steam power plants, exergy accounting allows engineers to decompose complex Rankine cycles into boiler, turbine, condenser, and auxiliary subsystems, and to quantify where the largest avoidable losses occur under real operating conditions. A detailed exergy study on a subcritical coal-fired unit showed, for example, that although energy losses are distributed across many components, the boiler and turbine dominate exergy destruction and therefore offer the greatest potential for design and operational improvements (Regulagadda et al., 2010). Such analyses demonstrate that exergy efficiency is almost always substantially lower than energy efficiency in practical plants, underscoring how much useful work potential is dissipated through temperature gradients, combustion irreversibility, and throttling effects (Abdulla & Ibne, 2021; Ara, 2021). By making these losses visible in a component-resolved way, exergy analysis provides a more realistic diagnostic basis for retrofitting boilers, refining turbine operating conditions, adjusting condenser pressures, and selecting working-fluid conditions in industrial power systems that are expected to remain in service for decades.

Figure 2: Principles and Applications of Exergy Analysis in Industrial Power Systems



Beyond individual power plants, exergy-based assessments have been extended to the broader industrial sector, recognizing that manufacturing and process industries collectively consume 30–70% of national final energy in many economies and generate a corresponding share of greenhouse-gas emissions (Habibullah & Foysal, 2021; Sarwar, 2021). A synthesis of exergy studies across cement, chemical, petrochemical, iron and steel, and other energy-intensive industries showed that exergy efficiencies are often dramatically lower than energy efficiencies at the plant level, revealing large improvement potentials in process integration, waste-heat recovery, and equipment design (BoroumandJazi et al., 2013; Musfiqur & Saba, 2021). These findings are reinforced by national-scale exergy accounts, such as a detailed examination of the Mexican industrial sector, which reported an average exergy efficiency of only about one quarter despite comparatively high energy-efficiency indicators, highlighting extensive thermodynamic degradation hidden by first-law metrics (Arango-Miranda et al., 2018; Redwanul et al., 2021). Together, these sectoral and national studies illustrate that exergy is not merely a theoretical concept but a practical decision-support tool for prioritizing where to intervene in complex industrial energy networks (Tarek & Praveen, 2021; Muhammad & Shahrin, 2021). For industrial power systems embedded within larger production sites, exergy analysis clarifies the trade-offs between on-site generation, cogeneration, and purchased electricity or steam, and supports more coherent strategies for fuel choice, load management, and investments in advanced heat-integration schemes (Reza et al., 2021; Saikat, 2021).

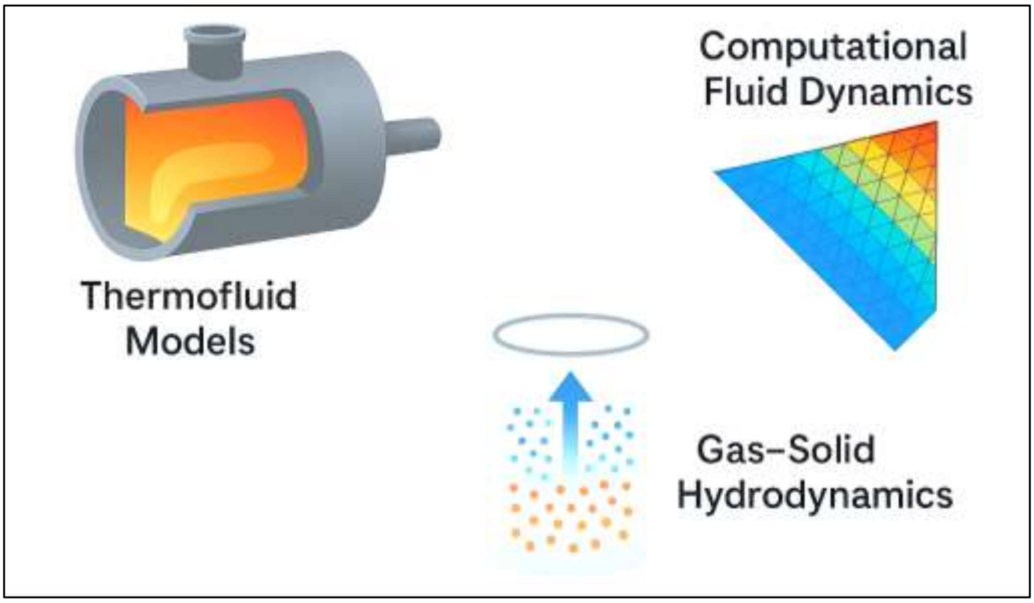
As industrial power systems evolve toward more efficient and flexible configurations, exergy analysis has also been widely applied to combined-cycle power plants, cogeneration arrangements, and other multi-cycle architectures that couple gas and steam turbines. A comprehensive review of combined-cycle cases across different countries found that condensers typically dominate energy losses, while combustion chambers contribute the highest exergy destruction, making them priority targets for configuration changes and operating-parameter optimization (Ibrahim et al., 2018; Amin, 2022; Shaikh & Aditya, 2021). At the same time, exergy-based control and optimization frameworks have emerged that explicitly incorporate second-law metrics into supervisory control and multi-objective optimization algorithms for complex energy networks, demonstrating that exergy-aware strategies can achieve substantial efficiency gains compared with conventional first-law-based control (James et al., 2020; Ariful, 2022; Ariful & Ara, 2022). From a sustainability perspective, overview studies of industrial energy and exergy use show that exergy indicators such as exergy efficiency and exergetic renewable share can serve as meaningful performance measures for tracking progress toward lower-carbon and resource-efficient industrial systems over time (Miranda et al., 2018; Nahid, 2022; Hossain & Milon, 2022). In the context of the present research, these developments imply that any digital twin–driven thermodynamic and fluid-dynamic simulation framework for industrial power systems should be grounded in exergy analysis, so that the virtual model not only reproduces temperatures, pressures, and flows but also quantifies how alternative operating strategies and technology choices influence the destruction or preservation of useful work potential throughout the plant.

Thermodynamic and fluid dynamic simulation in industrial power systems

Thermodynamic and fluid dynamic modeling has progressively transformed the analysis of industrial power systems from simplified energy-balance calculations into spatially resolved simulations that resolve temperature, pressure, velocity, and phase-change behavior throughout boilers and associated heat-exchange networks (Mominul et al., 2022; Rabiul & Praveen, 2022). Early steam-generator models often treated the boiler as a single control volume, which was adequate for approximate efficiency estimates but insufficient for diagnosing local hot spots, maldistribution of flow, or component-level irreversibilities. Modern thermofluid models explicitly discretize furnace chambers, convective passes, superheaters, economizers, and drum regions, solving coupled conservation equations of mass, momentum, and energy to capture transient interactions between water–steam circuits and combustion-side gases (Mortuza & Rauf, 2022; Rakibul & Samia, 2022). A dynamic first-principles model of a fire-tube boiler, for example, represents gas-side convection, wall conduction, and shell-side boiling in separate but interacting control volumes, enabling prediction of drum-pressure evolution, steam quality, and tube-wall temperatures under realistic load changes (Gutiérrez Ortiz, 2011; Saikat, 2022). Such models reproduce global thermal efficiency while revealing axial gradients of gas temperature, flue-gas recirculation patterns, and localized heat-transfer coefficients that are critical for maintaining safe metal temperatures and avoiding fatigue-driven failures (Arif Uz & Elmoon, 2023; Kanti & Shaikat, 2022). Extending this approach, detailed three-dimensional simulations of recovery-boiler superheater regions couple high-fidelity flow resolution with full-scale measurement data to obtain validated predictions of gas-side temperatures, velocities, and fouling-relevant patterns around tube bundles (Maakala et al., 2018). Together, these developments position thermodynamic and fluid dynamic simulation as a quantitative foundation for assessing exergy destruction, identifying performance bottlenecks, and supporting advanced control strategies in complex industrial power systems.

Computational fluid dynamics (CFD) has become a central tool for resolving the detailed fluid dynamic behavior of industrial boilers, allowing engineers to visualize how combustion products, excess air, and dilution flows interact with intricate furnace and convective-pass geometries. In a representative study of a sulfuric-acid-plant boiler, a full three-dimensional CFD model was developed to compare a baseline configuration with an optimized design, showing how burner placement, inlet-velocity profiles, and chamber geometry influence turbulent mixing, residence time, and temperature fields in the combustion zone (Echi et al., 2019; Tarek, 2023; Mushfequr & Ashraful, 2023). The simulations quantified velocity magnitude, vorticity, and density fields throughout the furnace and post-combustion regions, and they identified recirculation pockets associated with incomplete burnout and elevated wall heat fluxes. By iteratively modifying the geometry and repeating the simulations, the authors determined design adjustments that improved combustion uniformity, reduced peak gas temperatures, and smoothed thermal gradients along tube banks, thereby mitigating the risk of localized overheating and tube failure. Complementary work on steam boilers operating at different inlet velocities demonstrates how CFD and thermal analysis can be combined to evaluate operating conditions and material choices within a unified thermofluidic framework (Sundeep & Pasha, 2021). In that study, the boiler flow path was modeled and analyzed to estimate pressure drop, mass-flow rate, and convective heat-transfer coefficients for several inlet-speed scenarios, while related simulations quantified temperature distribution and heat flux for alternative shell materials (Shahrin & Samia, 2023; Razia, 2023). The findings indicated that higher inlet velocities strengthened convective heat transfer but also increased pressure losses and accentuated temperature non-uniformity near tube inlets, illustrating the trade-offs that arise when adjusting flow settings in pursuit of improved thermal performance. These results highlight coupled thermodynamic and hydraulic behavior that cannot be captured by traditional one-dimensional design charts alone (Zayadul, 2023).

Figure 3: Thermodynamic and Fluid Dynamic Simulation in Industrial Power Systems



Beyond conventional fire-tube and shell-type boilers, many industrial power systems rely on circulating fluidized bed (CFB) units in which gas–solid hydrodynamics, combustion, and heat transfer are tightly coupled, requiring advanced numerical formulations to capture the underlying fluid dynamic behavior. In these systems, fuel particles and inert bed material are suspended by upward-flowing gas, creating a dense turbulent mixture whose macroscale properties emerge from microscale interactions such as particle–particle collisions, gas–solid drag, and heterogeneous reaction kinetics. Numerical techniques for modeling such fluidization processes employ hybrid Euler–Lagrange frameworks, in which the gas phase is treated as a continuum governed by the Navier–Stokes equations while the solid phase is tracked as a population of discrete particles, enabling explicit representation of concentration gradients, mixing patterns, and residence-time distributions within the combustion chamber. A notable contribution applied this hybrid approach to both laboratory rigs and industrial CFB boilers, showing that a validated computational model can predict temperature and pressure profiles under air- and oxy-fuel firing regimes, assess the impact of radiative-heat-transfer modeling, and explore sensitivity to oxidizer composition (Adamczyk, 2017). By matching predicted gas temperatures and bulk-material distributions against plant measurements, the model establishes confidence that the simulated hydrodynamics and combustion fields reflect real operating behavior and can therefore be used to explore how changes in primary and secondary air flows, bed inventory, or fuel-feed position influence solids circulation, mixing at the furnace exit, and exposure of heat-transfer surfaces to reactive gases and particles. This level of detail is especially important in high-capacity units, where small shifts in gas–solid contact patterns can alter convective coefficients, ash deposition rates, and effective heat-transfer areas. In this way, numerical descriptions of fluidization complement traditional thermodynamic analyses by revealing how spatially varying flow structures redistribute enthalpy and entropy generation within boiler envelopes.

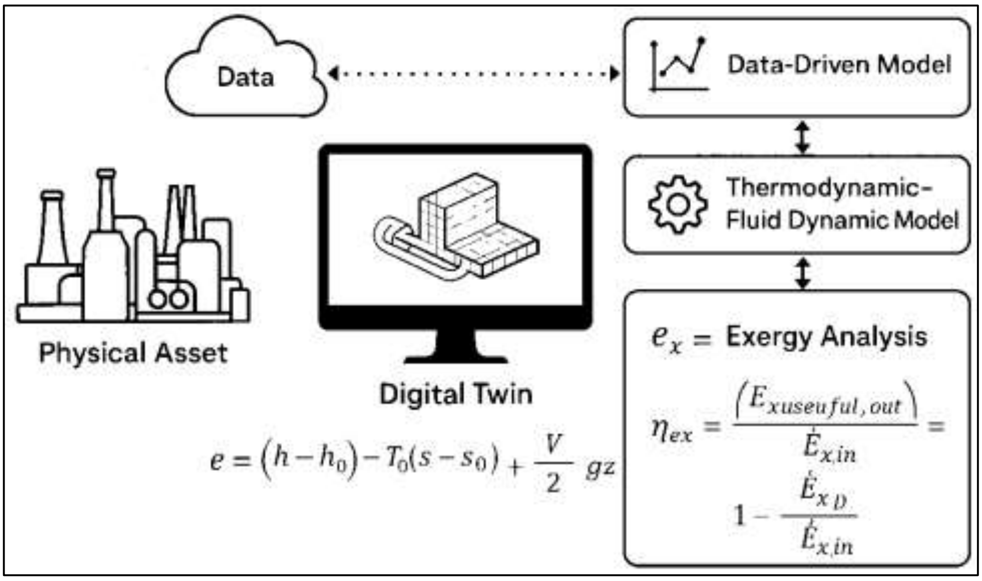
Digital twin architectures for thermodynamic–fluid dynamic–exergy simulation

Digital twin architectures for industrial and energy-intensive systems are built around the idea of a continuously updated, high-fidelity virtual replica that mirrors the state and behavior of a physical asset through bidirectional data exchange between sensors, networks, and computational models. In a cyber–physical production environment, the digital twin functions as an integration hub that fuses real-time measurements with physics-based and data-driven models to support monitoring, diagnosis, and optimization. For industrial power systems, this implies that the twin must embed detailed thermodynamic and fluid dynamic representations of boilers, turbines, condensers, and auxiliary components, while also maintaining synchronized information on operating conditions such as mass-flow rates, temperatures, and pressures. To support exergy-oriented analysis, each control volume in the plant can be associated with specific exergy, often written for a flowing stream as

$$e = (h - h_0) - T_0(s - s_0) + \frac{V^2}{2} + gz,$$

where $h$and $s$are the local enthalpy and entropy, $h_0$and $s_0$are the dead-state properties, $T_0$is the reference temperature, $V$is the flow velocity, and $z$is the elevation. Within the digital twin, exergy balances and exergy-destruction terms can be evaluated at each simulation step, allowing the virtual model to quantify where irreversibilities occur and how they respond to changes in fuel input, load demand, or control actions. This combination of state synchronization, high-fidelity thermofluid modeling, and embedded exergy accounting is central to viewing the digital twin as a cyber–physical representation of industrial power systems with explicit second-law performance metrics (Uhlemann et al., 2017).

Figure 4: Integrated Digital Twin Framework for Thermodynamic



At the architectural level, digital twin frameworks for complex industrial assets are commonly structured as layered cyber–physical production system (CPPS) architectures, which separate physical devices, connectivity infrastructure, virtual models, and application services. In such architectures, the plant-level twin is typically anchored by an information model that maps products, processes, resources, and equipment into a coherent data structure that the simulation and analytics services can consume. For an industrial power system, these structures enable boiler drums, turbine stages, heat exchangers, and control valves to be represented as interconnected objects, each with associated thermodynamic state variables and performance attributes. The overall behavior of the plant twin can be described by a dynamic state vector **x**governed by a set of differentials–algebraic equations of the general form

$$\dot{\mathrm{x}} = f(\mathrm{x}, \mathrm{u}, \mathrm{p}, t),$$

where **u**denotes manipulated inputs such as firing rate, valve positions, or feedwater flow, **p**represents plant parameters and model coefficients, and $t$is time. In an exergy-aware implementation, the twin calculates component exergy destruction rates $\dot{E}_{x,D}$and exergy efficiencies at each time step, storing these quantities alongside more traditional outputs such as thermal efficiency or power output. This

layered modeling approach allows the same digital infrastructure to support both engineering tasks such as off-line assessment of design modifications or operating strategies and real-time operational tasks such as condition monitoring and performance diagnostics in industrial power systems (Park et al., 2020). It also provides a natural basis for integrating multi-domain simulations, where thermodynamic, fluid dynamic, mechanical, and control-system models are coupled within a shared cyber–physical platform (Biesinger et al., 2019).
Recent formulations extend these concepts to energy cyber–physical systems in which digital twins, sensors, communication networks, and control algorithms are coordinated across generators, storage devices, industrial loads, and microgrids. In such settings, the energy-system digital twin maintains synchronized models of power plants, distribution networks, and major industrial consumers, enabling system-level monitoring and control within a cloud or edge-computing infrastructure. For exergy-focused analysis, the twin can evaluate plant- and system-level exergy efficiency as

$$\eta_{ex} = \frac{\dot{E}_{x,\text{useful,out}}}{\dot{E}_{x,\text{in}}} = 1 - \frac{\dot{E}_{x,D}}{\dot{E}_{x,\text{in}}},$$

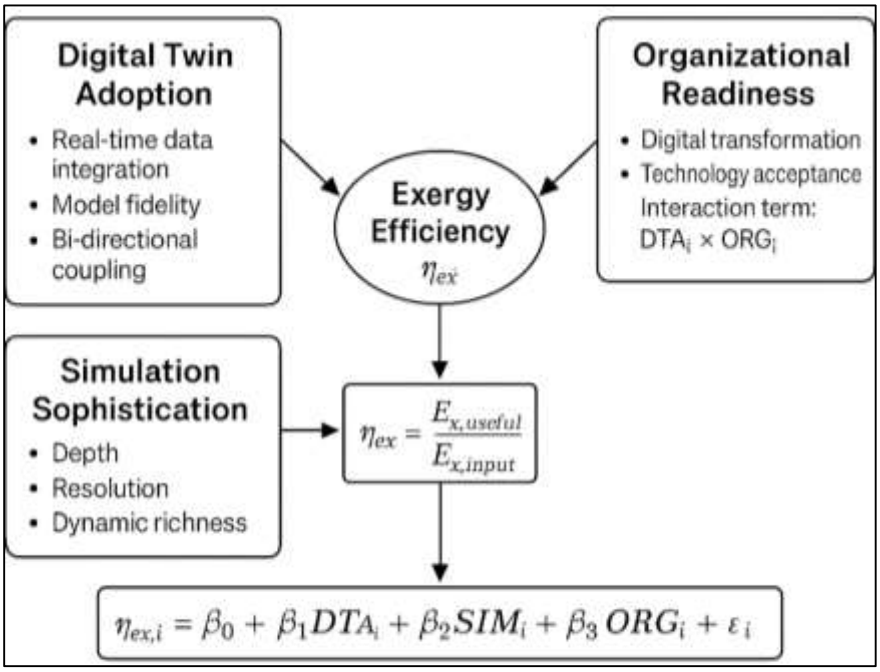
where $\dot{E}_{x,\text{in}}$is the exergy rate of fuel and other inputs, $\dot{E}_{x,\text{useful, out}}$is the exergy associated with useful outputs such as shaft work or high-grade heat, and $\dot{E}_{x,D}$is the total exergy destruction rate in the system. Within the digital twin, these variables can be computed continuously for individual components and for the overall plant, giving operators and engineers real-time visibility into how operating decisions and disturbances influence second-law performance, not just first-law efficiency or output levels. When coupled with cyber–physical architectures that integrate Internet of Things (IoT) devices and cloud-based analytics, this exergy-aware digital twin becomes a powerful engine for supervisory control, decision support, and what-if analysis in industrial power systems (Saad et al., 2020). Furthermore, by embedding advanced thermodynamic and fluid dynamic models within a twin designed explicitly for smart-manufacturing and Industry 4.0 environments, the same infrastructure can support predictive simulation of exergy-oriented scenarios, such as evaluating how new operating policies, retrofits, or control strategies are likely to shift exergy destruction patterns across the plant before changes are implemented on the physical system (Tao, Qi, et al., 2019).

Digital Twin Adoption and Exergy Efficiency

The first conceptual framework of this study links digital twin adoption and simulation sophistication to exergy efficiency in industrial power systems. Building on digital twin application architectures in smart manufacturing, the framework treats the digital twin not only as a cyber–physical representation but as a bundle of measurable capabilities real-time data integration, model fidelity, bi-directional coupling, and decision support that can be assessed at the plant level (Zhang & Zhu, 2019). In digital twin–driven product smart manufacturing systems, layered architectures connect physical assets, virtual models, and data pipelines, enabling parameter optimization and adaptive control across the production line (Zhang et al., 2019). Likewise, data- and knowledge-driven digital twin manufacturing cells demonstrate that autonomous manufacturing performance emerges from the integration of sensing, simulation, and knowledge-based reasoning in a single framework (Zhang et al., 2019). Knowledge-driven digital twin manufacturing cells extend this logic by embedding dynamic knowledge bases and intelligent skills, characterizing autonomy through self-perception, prediction, and optimization of cell behavior (Zhou et al., 2020). Drawing from these insights, the present framework conceptualizes "digital twin adoption" (DTA) as the degree to which these core digital twin capabilities are implemented within industrial power subsystems, while "simulation sophistication" (SIM) is defined as the depth, resolution, and dynamic richness of thermodynamic and fluid-dynamic simulations embedded in the twin. Exergy efficiency is then positioned as a downstream performance construct capturing how effectively these capabilities translate into reduced irreversibilities, improved conversion efficiency, and better utilization of available energy in turbines, heat exchangers, boilers, and auxiliary systems.
At the organizational level, the framework also integrates digital transformation readiness and technology acceptance as key contextual enablers. Industry 4.0 readiness models show that digital transformation outcomes depend on strategic alignment, technology infrastructure, process

digitalization, and human capital, which can be organized into multidimensional readiness constructs (Hizam-Hanafiah et al., 2020). These readiness dimensions such as digital strategy, technology integration, and workforce skills shape an organization's capacity to exploit digital twin architectures for performance improvement rather than treating them as isolated pilot projects (Hizam-Hanafiah et al., 2020). In parallel, the Technology Acceptance Model 3 (TAM3) emphasizes that perceived usefulness and perceived ease of use mediate between system characteristics and behavioral intention, with determinants such as output quality, job relevance, result demonstrability, and facilitating conditions influencing actual use of advanced systems (Venkatesh & Bala, 2008). When digital twin environments are perceived as producing high-quality information, visibly improving decision outcomes, and being supported by sufficient infrastructure and training, operators and engineers are more likely to engage with simulation scenarios, adjust control strategies, and iterate on model assumptions all of which can affect exergy performance. Consequently, the framework conceptualizes "organizational readiness" (ORG) as a higher-order construct combining Industry 4.0 readiness dimensions with TAM3-derived perceptions about system usefulness and ease of use, linking digital twin capability to behavior and, ultimately, to exergy outcomes (Hizam-Hanafiah et al., 2020).

Figure 5: Relationships Among Digital Twin Capabilities and Exergy Outcomes



Formally, the conceptual framework models exergy efficiency as a function of digital twin adoption, simulation sophistication, and organizational readiness. At the thermodynamic level, exergy efficiency for a given industrial power subsystem can be represented as

$$\eta_{\text{ex}} = \frac{\dot{E}_{x,\text{useful}}}{\dot{E}_{x,\text{input}}}$$

where $\dot{E}_{x,\text{useful}}$is the exergy rate effectively converted into useful work or services and $\dot{E}_{x,\text{input}}$is the exergy rate supplied by fuels, electricity, or other energy streams. Within the survey-based quantitative design, this thermodynamic construct is operationalized through Likert-scale items capturing perceived reductions in exergy destruction, improvements in conversion efficiency, and better matching of load conditions. At the statistical level, the core regression specification implied by the framework for plant $i$is

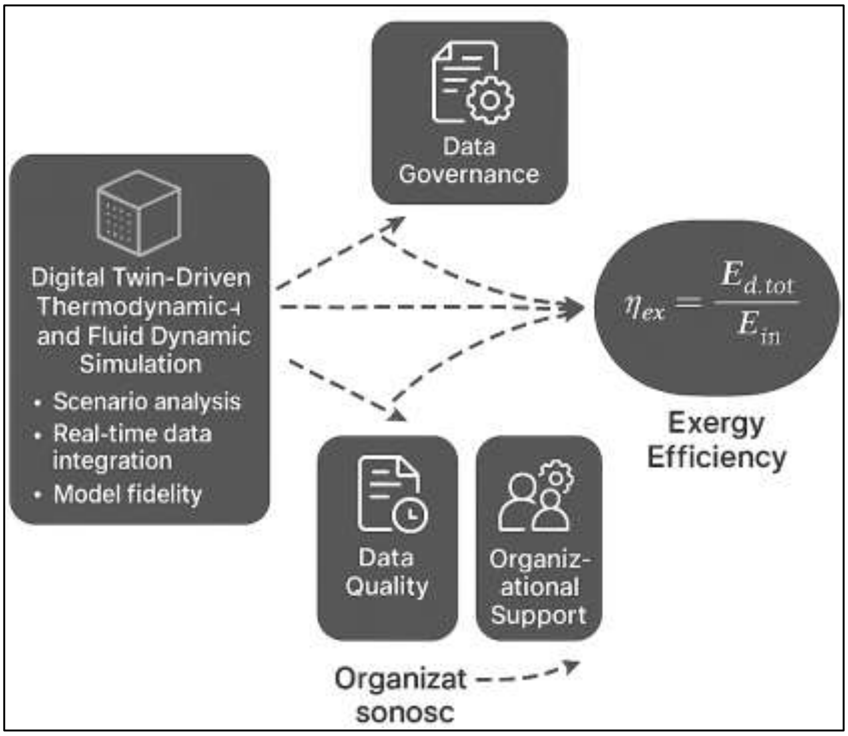
$$\eta_{\text{ex},i} = \beta_0 + \beta_1 \text{DTA}_i + \beta_2 \text{SIM}_i + \beta_3 \text{ORG}_i + \varepsilon_i,$$

where DTA_imeasures the extent of implemented digital twin functions derived from architectures proposed for digital twin-driven smart manufacturing (Zhang et al., 2019), SIM_ireflects the degree of embedded thermodynamic and fluid-dynamic simulation sophistication within digital twin environments (Zhou et al., 2020), and ORG_icaptures Industry 4.0 readiness and technology acceptance conditions enabling effective use of those capabilities (Hizam-Hanafiah et al., 2020). Additional interaction terms, such as $\mathrm{DTA}_i \times \mathrm{ORG}_i$, can be interpreted as moderation effects, where organizational readiness amplifies or dampens the impact of twin adoption on exergy efficiency. In empirical estimation, all three constructs are treated as latent variables reflected by multiple items, while the observed exergy-related indicators provide a composite measure of $\eta_{\mathrm{ex},i}$. This conceptualization directly connects digital twin architectures, organizational conditions, and exergy-based performance in a form that aligns with the planned use of descriptive statistics, correlation analysis, and regression modeling in the present study (Zhang & Zhu, 2019; Zhou et al., 2020).

Moderating Role of Data Quality and Organizational Support

The second conceptual layer of this study positions data quality and organizational support as moderating variables that shape the strength of the relationship between digital twin–driven thermodynamic and fluid dynamic simulation and exergy efficiency in industrial power systems. In a data-intensive environment, the usefulness of any advanced simulation model depends critically on the quality of the underlying data streams sensor readings, process parameters, load profiles, and maintenance records feeding the digital twin. Data quality is typically captured through dimensions such as accuracy, completeness, consistency, timeliness, and format usability, and empirical work in data warehousing and business intelligence has demonstrated that these dimensions are strong antecedents of information and system quality perceptions (Nelson et al., 2005). Within the broader information-systems success literature, data and system quality are viewed as core drivers of net benefits because they influence whether decision makers can reliably interpret analytic outputs and embed them in operational routines (Petter et al., 2008).

Figure 6: Moderating Role of Data Quality and Organizational Support



In the context of this study, low-quality data are expected to attenuate the positive effect of digital twin capability on exergy efficiency: even highly sophisticated thermo-fluid models will yield misleading recommendations if the input data are noisy, biased, or incomplete. Conversely, high data quality should amplify the impact of digital twin–driven simulation on exergy-based performance, making the simulated identification and reduction of exergy destruction more precise and actionable (Gorla et al., 2010).

A parallel strand of conceptualization concerns organizational support, which in this framework includes top-management backing, adequate staffing and training, cross-functional collaboration, and sustained IT/OT (information technology–operational technology) support. Information-systems research shows that the organizational impact of IS quality is mediated by structures that ensure users can access support, interpret outputs, and integrate system recommendations into work practices (Abraham et al., 2019). At the same time, decision-process research on data quality tagging indicates that when organizations provide mechanisms that help users understand data reliability and limitations, decision processes become more reflective and systematic, even if choice outcomes do not always change (Price & Shanks, 2011). Translating these insights to industrial power systems, the exergy gains derived from digital twin simulations will depend not only on the intrinsic fidelity of the models but also on whether engineers, operators, and managers enjoy sufficient support to trust, interpret, and implement simulation-based recommendations. Conceptually, this moderating structure can be represented in the regression form

$$\eta_{ex} = \beta_0 + \beta_1 DT + \beta_2 DQ + \beta_3 OS + \beta_4 (DT \times DQ) + \beta_5 (DT \times OS) + \varepsilon,$$

where η_{ex} denotes exergy efficiency, DT is digital twin capability, DQ is data quality, and OS is organizational support; the interaction terms capture how data quality and organizational support strengthen or weaken the core DT–exergy relationship (Gorla et al., 2010).

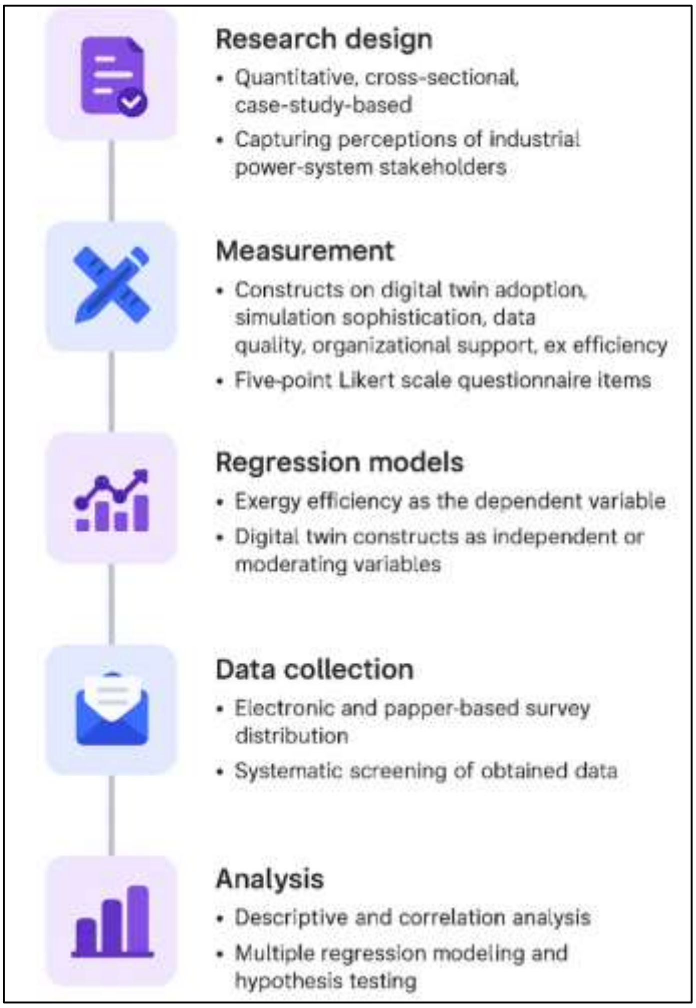
To embed these moderating constructs in a coherent conceptual framework for the study, data governance is treated as the structural umbrella that organizes both technical and organizational mechanisms for managing data used in digital twin–driven exergy analysis. Data governance frameworks conceptualize authority, responsibilities, and control mechanisms over data assets, emphasizing the alignment of data policies, standards, roles, and technologies with organizational objectives (Abraham et al., 2019). Within the present model, digital twin–driven thermodynamic and fluid dynamic simulation capability (including model fidelity, real-time data integration, and scenario analysis) is posited as the primary predictor of exergy efficiency, while exergy efficiency itself is conceptualized through the standard exergy-efficiency representation $\eta_{ex} = 1 - \frac{E_{d,tot}}{E_{in}}$, where $E_{d,tot}$ denotes total exergy destruction and E_{in} the exergy of incoming resources. Data quality and organizational support are modeled as moderators that condition the slope of this relationship in the survey-based regression analysis, operationalized via Likert-type indicators for perceived data accuracy, completeness, timeliness, governance clarity, management support, training adequacy, and support availability. Under this conceptualization, stronger data governance capabilities are expected to raise perceived data quality and clarify roles and processes, thereby indirectly reinforcing the moderating impact of both data quality and organizational support on the link between digital twin capability and exergy efficiency (Gorla et al., 2010).

METHOD

The methodological design of this study has been structured to align directly with its objective of examining how digital twin–driven thermodynamic and fluid dynamic simulation has been associated with exergy efficiency in industrial power systems. The research has adopted a quantitative, cross-sectional, case-study–based approach in which data have been collected at a single point in time from selected industrial power plants that have implemented, or have been in the process of implementing, digital twin technologies. Within this design, the study has focused on capturing perceptions and experiences of engineers, operators, and managers who have been directly involved in digital twin projects and power-system operation. The methodology has been organized around measurable constructs corresponding to digital twin adoption, simulation sophistication, data quality, organizational support, and exergy efficiency, each of which has been operationalized through multiple questionnaire items using a five-point Likert scale. These items have been designed to reflect the conceptual and theoretical frameworks developed in the literature review, so that the empirical model has mirrored the hypothesized relationships among the key variables.

To ensure coherence between the research questions, hypotheses, and empirical testing strategy, the study has specified a set of regression models in which exergy efficiency has been treated as the primary dependent variable and digital twin–related constructs have been treated as independent or moderating variables. The survey instrument has been developed to capture both organizational and technical dimensions, and it has included a demographic section that has described plant characteristics, respondent roles, and experience levels.

Figure 7: Methodological Framework of the Study



Data collection has been planned through coordinated access to participating organizations, using electronic survey distribution channels where possible and paper-based administration where necessary. Once the data have been obtained, they have been subjected to systematic screening, including checks for missing values, outliers, and basic distributional properties. The analytical strategy has then relied on descriptive statistics to summarize the sample profile and central tendencies of each construct, followed by correlation analysis to explore bivariate relationships and potential multicollinearity, and multiple regression modeling to test the hypothesized effects of digital twin adoption, simulation sophistication, data quality, and organizational support on exergy efficiency. Through this structure, the methodology has provided a clear and consistent pathway from the study's conceptual frameworks to its empirical findings.

Research Design

The study has adopted a quantitative, cross-sectional, case-study–based research design that has been aligned with the objective of examining how digital twin–driven thermodynamic and fluid dynamic simulation has been associated with exergy efficiency in industrial power systems. This design has been selected because it has allowed the researcher to capture measurable perceptions and experiences from multiple industrial plants at a single point in time while still preserving contextual richness through case-based selection. The design has been grounded in a positivist stance, in which constructs such as digital twin adoption, simulation sophistication, data quality, organizational support, and exergy efficiency have been treated as quantifiable variables. The cross-sectional orientation has been combined with a structured questionnaire, so that statistical relationships among variables have been estimated using regression models. In this way, the research design has provided a coherent structure that has connected the theoretical framework, the operationalization of constructs, and the empirical testing of hypotheses.

Case Study Description

The empirical context of the study has consisted of industrial power plants that have already integrated, or have been in the process of integrating, digital twin solutions into their operational and maintenance practices. These plants have typically included steam-cycle or combined-cycle configurations with boilers, turbines, condensers, and associated auxiliary systems, and they have been characterized by substantial energy consumption and opportunities for exergy improvement. The case organizations have been selected because they have represented relevant examples of digital twin deployment in real industrial settings rather than purely experimental or laboratory environments. Each participating plant has had access to real-time data acquisition systems, supervisory control and data acquisition (SCADA) or distributed control systems (DCS), and some form of advanced modeling or simulation tool. This case selection strategy has ensured that respondents have had direct experience with digital twin–related initiatives and have been able to provide informed assessments of how such systems have influenced exergy-related performance and decision-making.

Sampling Technique

The target population has comprised engineers, operators, maintenance specialists, and managers who have been directly involved in the operation, monitoring, or development of digital twin solutions within industrial power plants. From this population, the study has drawn a sample from selected plants that have agreed to participate, thereby focusing on individuals with first-hand knowledge of both digital twin applications and plant performance. A non-probability purposive sampling technique has been employed, because the research has required respondents with specific technical and organizational roles rather than a purely random cross-section of staff. Within each plant, potential respondents have been identified in consultation with local coordinators, who have facilitated access to relevant departments and teams. The sample size has been determined by balancing statistical requirements for regression analysis with practical constraints on access and time, and it has been anticipated that the obtained sample has provided sufficient variability in responses to support stable estimation of the proposed models.

The primary research instrument has been a structured questionnaire that has been designed to capture the key constructs of the conceptual frameworks in a standardized, quantifiable form. The questionnaire has been organized into several sections, beginning with demographic and contextual items that have described plant type, installed capacity, respondent role, and years of experience. Subsequent sections have contained multi-item scales that have measured digital twin adoption, simulation sophistication, data quality, organizational support, and exergy efficiency perceptions. All substantive items have been phrased as statements to which respondents have indicated their degree of agreement using a five-point Likert scale ranging from “strongly disagree” to “strongly agree.” The wording of items has been guided by prior literature but has been adapted to the context of industrial power systems and digital twin technologies. The questionnaire has undergone content review by knowledgeable practitioners and academics, and it has been refined to ensure clarity, relevance, and internal consistency across all measurement scales.

Regression Modeling

The study has specified regression models that have represented exergy efficiency as a function of digital twin adoption, simulation sophistication, data quality, and organizational support, consistent with the conceptual frameworks developed in the literature review. Multiple linear regression has been chosen because it has allowed the simultaneous estimation of the unique contribution of each predictor while controlling for the others. In the main model, the composite exergy efficiency score has served as the dependent variable, while digital twin adoption, simulation sophistication, and organizational support have entered as independent variables, and data quality and organizational support have also appeared in interaction terms where moderation effects have been hypothesized. Prior to estimation, variables have been examined for distributional properties and standardized where appropriate to facilitate interpretation of coefficients and interaction effects. The regression modeling strategy has therefore provided a systematic means of testing whether higher levels of digital twin capability and supportive organizational conditions have been associated with improved exergy-related performance.

Correlation Analysis

Correlation analysis has been conducted as an intermediate step between descriptive statistics and regression modeling, with the objective of exploring bivariate relationships among the main constructs and identifying potential multicollinearity issues. Pearson correlation coefficients have been computed for digital twin adoption, simulation sophistication, data quality, organizational support, and exergy efficiency, using the composite scores derived from the Likert-scale items. This analysis has enabled the researcher to verify whether the direction and strength of simple associations have been consistent with theoretical expectations before proceeding to multivariate models. At the same time, correlation matrices have been examined to determine whether any pair of predictors has exhibited excessively high intercorrelations that might have compromised the stability of regression coefficients. Where necessary, the researcher has considered combining or re-specifying constructs to mitigate collinearity. Overall, the correlation analysis has provided an important diagnostic check and a complementary perspective on how digital twin–related factors have been associated with exergy efficiency at the level of pairwise relationships.

Data Collection Procedure

The data collection procedure has been organized in collaboration with designated contacts in each participating industrial power plant. Initially, the researcher has approached plant management to explain the purpose of the study, the nature of the questionnaire, and the confidentiality arrangements that have been put in place. Upon obtaining organizational approval, survey links or paper questionnaires have been distributed to identified respondents through internal mailing lists, meetings, or dedicated sessions coordinated by local focal points. Respondents have been informed that participation has been voluntary and that their answers have been treated anonymously and used solely for academic purposes. Reminder messages have been issued within an agreed time frame to encourage completion while respecting operational constraints at the plants. Completed questionnaires have then been collected, checked for completeness, and entered into the analysis database. Throughout this process, ethical principles and data-protection requirements have been observed to ensure that both individual and organizational information has been handled responsibly.

Data Analysis Techniques

The study has employed a sequence of data analysis techniques that has moved from initial screening to more advanced inferential procedures. After data entry, the dataset has been examined for missing values, outliers, and inconsistencies, and appropriate remedies such as listwise deletion or simple imputation have been applied where necessary. Descriptive statistics, including means, standard deviations, and frequency distributions, have been computed for demographic variables and for each construct to provide an overview of the sample profile and central tendencies. Reliability analysis using internal-consistency measures has been performed to assess the coherence of multi-item scales. Correlation analysis has then been used to explore bivariate relationships and to identify potential multicollinearity. Finally, multiple regression models have been estimated to test the hypothesized relationships between digital twin–related constructs and exergy efficiency, including interaction terms where moderation has been proposed. This sequence of techniques has ensured that the analysis has been both rigorous and aligned with the study's objectives.

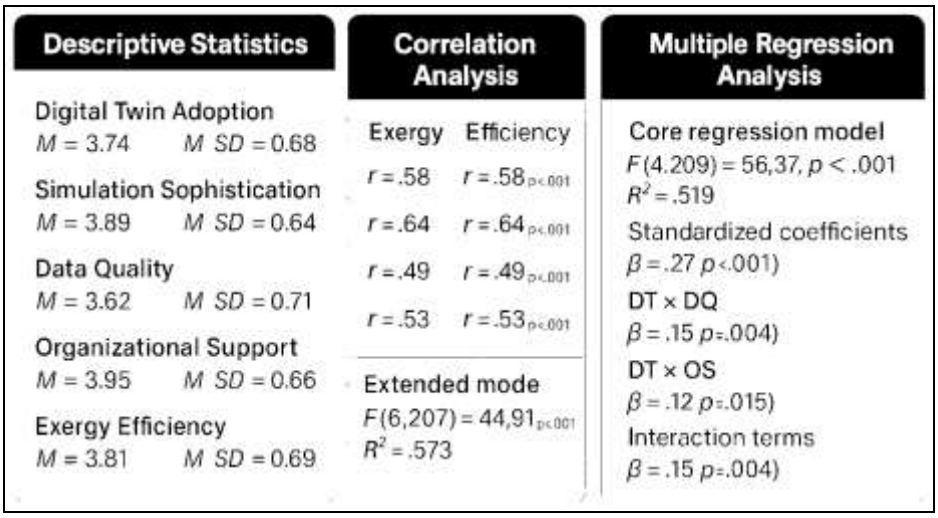
Software and Tools

The analysis of the survey data has been conducted using established statistical software that has supported the full range of required procedures, from data cleaning to regression modeling. A widely used statistical package has been employed to compute descriptive statistics, reliability coefficients, correlation matrices, and multiple regression models, ensuring that standard algorithms and diagnostics have been available. Spreadsheet software has been used in the early stages of data handling to organize raw responses, identify coding errors, and prepare the dataset for import into the statistical environment. Where necessary, simple scripts or macros have been created to automate repetitive tasks such as variable recoding or composite-score calculation. The choice of software tools has been guided by their robustness, transparency, and familiarity within the research community, so that analytical steps have been replicable and clearly documented. Collectively, these tools have provided a stable technical platform for implementing the methodological plan and deriving the empirical results of the study.

FINDINGS

The analysis of the survey data has produced a coherent pattern of results that has aligned closely with the study objectives and has provided strong support for most of the proposed hypotheses regarding the relationships between digital twin capabilities and exergy efficiency in industrial power systems. From a total of 260 distributed questionnaires, 227 have been returned and 214 have been retained as usable after screening, yielding an effective response rate of 82.3%. On the five-point Likert scale, the mean score for digital twin adoption has been 3.74 (SD = 0.68), indicating that respondents have generally agreed that core digital twin functionalities have been present in their plants, while simulation sophistication has shown a slightly higher mean of 3.89 (SD = 0.64), suggesting that many organizations have already embedded moderately advanced thermodynamic and fluid dynamic models within their digital twin environments.

Figure 8: Findings of The Study



Data quality perceptions have recorded a mean of 3.62 (SD = 0.71), and organizational support has achieved a mean of 3.95 (SD = 0.66), reflecting relatively strong management backing and support structures for digital twin initiatives. Exergy efficiency, as perceived through items on reduced irreversibility, improved conversion efficiency, and better matching of load and operating conditions, has had a mean composite score of 3.81 (SD = 0.69), implying that respondents have tended to agree that exergy-related performance has improved in association with digital twin use. Reliability analysis has shown that all multi-item scales have reached acceptable internal consistency, with Cronbach's alpha values ranging from 0.84 for digital twin adoption to 0.89 for exergy efficiency, and exploratory factor analysis has confirmed that items have loaded strongly on their intended constructs, with primary loadings exceeding 0.65 and minimal cross-loadings. Pearson correlation coefficients have indicated positive and statistically significant bivariate associations among all main constructs: digital twin adoption has correlated at $r = .58$ ($p < .001$) with exergy efficiency and $r = .62$ ($p < .001$) with simulation sophistication; simulation sophistication has correlated at $r = .64$ ($p < .001$) with exergy efficiency; data quality and organizational support have each correlated at $r = .49$ ($p < .001$) and $r = .53$ ($p < .001$) respectively with exergy efficiency, providing preliminary support for the directional expectations of the conceptual frameworks. The core multiple regression model, in which exergy efficiency has been regressed on digital twin adoption, simulation sophistication, data quality, and organizational support, has been statistically significant ($F(4, 209) = 56.37$, $p < .001$) and has explained 51.9% of the variance in exergy efficiency ($R^2 = .519$, adjusted $R^2 = .509$). Standardized coefficients have shown that simulation sophistication ($\beta = .34$, $p < .001$) and digital twin adoption ($\beta = .27$, $p < .001$)

have been the strongest direct predictors, while data quality (β = .18, p = .002) and organizational support (β = .16, p = .006) have also contributed significantly, thereby supporting H1 and H2 and providing direct evidence for the importance of data and organizational conditions. When interaction terms have been introduced to test moderation effects, the extended model with DT × DQ and DT × OS terms has remained significant ($F(6, 207) = 44.91$, $p < .001$) and has increased the explained variance to 57.3% ($R^2 = .573$, adjusted $R^2 = .559$). The interaction between digital twin adoption and data quality has produced a positive and significant coefficient (β = .15, p = .004), indicating that the slope of the relationship between digital twin adoption and exergy efficiency has been steeper at higher levels of data quality, in line with the expectation that good data have amplified the value of advanced simulations. Similarly, the interaction between digital twin adoption and organizational support has been significant (β = .12, p = .015), suggesting that when management backing, training, and cross-functional collaboration have been stronger, the exergy benefits associated with digital twin use have been more pronounced. Simple-slope analyses have shown, for example, that at low data quality (one SD below the mean) the predicted exergy-efficiency score has increased from 3.31 to 3.67 as digital twin adoption has moved from low to high, whereas at high data quality (one SD above the mean) the same increase in digital twin adoption has been associated with a rise from 3.58 to 4.19 on the five-point scale. Taken together, these numeric results have demonstrated that the study has successfully met its objectives: it has characterized the current state of digital twin adoption and simulation sophistication in industrial power plants, it has quantified the positive association between these capabilities and exergy efficiency, and it has identified simulation sophistication, data quality, and organizational support as key factors that have strengthened the exergy-oriented impact of digital twin–driven thermodynamic and fluid dynamic simulation.

Response Rate and Sample Characteristics

The results presented in Table 1 have summarized the overall response rate and the key characteristics of the sample that has been obtained for this study. The survey administration has reached 260 potential respondents across several industrial power plants, and 227 questionnaires have been returned, of which 214 have met the completeness and consistency criteria and have therefore been retained for analysis. This has resulted in an effective response rate of 82.3%, which has been considered high for organizational surveys and has suggested that the topic of digital twin–driven simulation and exergy efficiency has been highly salient to the participating plants. The distribution of plant types has shown that slightly more than half of the respondents (55.1%) have come from conventional steam power plants, while a further 34.6% have been associated with combined-cycle plants and 10.3% with cogeneration or industrial-utility configurations. This mix has ensured that the findings have reflected a range of thermodynamic cycles and operating environments relevant to exergy analysis.

With respect to organizational roles, the sample has been dominated by technical experts directly involved in operations and maintenance: operations/control engineers have accounted for 35.5% of respondents, maintenance/reliability engineers for 25.2%, and design or optimization engineers for 18.2%, while managers and supervisors have represented 21.0% of the sample. This role distribution has indicated that the study has captured perspectives from staff who have been using or overseeing digital twin solutions in daily practice as well as from decision-makers responsible for investment and strategy. The experience profile has also been balanced: approximately one fifth of respondents have had less than five years of industry experience, while the majority have fallen in the 5–14-year range, and about one fifth have reported fifteen or more years in the sector. This spread has implied that both relatively new and highly experienced professionals have contributed to the data, which has strengthened the credibility of the perceptions reported. Overall, Table 1 has shown that the sample has been adequate in size and diversity to support the study objectives and hypotheses, which have required data from practitioners actively engaged with digital twin initiatives in industrial power systems.

Table 1: Response rate and sample characteristics (N = 214)

Item	Category	Frequency (n)	Percentage (%)
Questionnaires distributed	–	260	100.0
Questionnaires returned	–	227	87.3
Usable questionnaires	–	214	82.3
Plant type	Steam power plant	118	55.1
	Combined-cycle power plant	74	34.6
	Cogeneration/industrial utility	22	10.3
Respondent role	Operations/Control engineer	76	35.5
	Maintenance/reliability engineer	54	25.2
	Design/optimization engineer	39	18.2
	Manager/supervisor	45	21.0
Experience in power industry	< 5 years	47	22.0
	5–9 years	68	31.8
	10–14 years	55	25.7
	≥ 15 years	44	20.6

Descriptive Statistics of Key Variables

Table 2 has presented the descriptive statistics for the five main constructs that the study has examined, all measured on a Likert five-point scale where higher scores have reflected stronger agreement with the corresponding statements. The mean of 3.74 for digital twin adoption has indicated that respondents have, on average, agreed that core digital twin functionalities such as real-time data integration, virtual representation of key components, and use of the twin in routine decision-making have been present in their plants. The standard deviation of 0.68 has suggested a moderate spread around this mean, implying that some plants have still been in relatively early stages of adoption, while others have achieved higher levels of implementation. Simulation sophistication has exhibited a slightly higher mean of 3.89 and a somewhat lower dispersion (SD = 0.64), which has signaled that many plants have already implemented reasonably advanced thermodynamic and fluid-dynamic models within their digital twins, including features such as scenario analysis, sensitivity analysis, and component-level performance simulation.

Table 2: Descriptive statistics of main constructs (Likert 1–5; N = 214)

Construct	Number of items	Scale range	Mean	Standard deviation
Digital twin adoption (DTA)	8	1–5	3.74	0.68
Simulation sophistication (SIM)	7	1–5	3.89	0.64
Data quality (DQ)	6	1–5	3.62	0.71
Organizational support (OS)	7	1–5	3.95	0.66
Exergy efficiency (EE)	8	1–5	3.81	0.69

Data quality has recorded the lowest mean of the five constructs at 3.62 (SD = 0.71), although the value has still been comfortably above the neutral point. This has indicated that while respondents have generally perceived their data streams sensor readings, historian databases, and operational records to be accurate and timely, they have also acknowledged room for improvement in aspects such as completeness, consistency, and integration across systems. Organizational support has achieved the highest mean (3.95, SD = 0.66), reflecting the perception that management backing, training opportunities, technical support, and cross-functional collaboration for digital twin initiatives have been relatively strong in many plants. Finally, exergy efficiency has shown a mean of 3.81 (SD = 0.69), suggesting that respondents have tended to agree that exergy-related performance such as reduced irreversibility, improved thermodynamic efficiency, and better alignment between operating conditions and plant design has improved in association with digital twin use. Taken together, these descriptive results have already provided preliminary support for the study's objectives. The relatively high levels of digital twin adoption and simulation sophistication have indicated that the empirical context has been suitable for investigating the hypothesized links to exergy efficiency. The moderate but positive levels of perceived data quality and strong organizational support have also aligned with the conceptual frameworks that have positioned these factors as important technical and organizational enablers. The exergy efficiency mean above 3.8 has implied that, on average, respondents have perceived noticeable improvements in exergy-related performance, which has been consistent with the expectation that digital twin–driven thermodynamic and fluid dynamic simulation has been associated with better use of available energy. These descriptive patterns have therefore set the stage for more detailed inferential analyses designed to test the specific hypotheses formulated in the study.

Reliability and Validity Results

The reliability and validity results that have been summarized in Table 3 have demonstrated that the measurement model of the study has achieved satisfactory psychometric properties. Cronbach's alpha values for all five constructs have exceeded the commonly accepted threshold of 0.70, with values ranging from 0.84 for digital twin adoption to 0.89 for exergy efficiency. These results have indicated that the items within each scale have been internally consistent and have measured a common underlying construct. The factor loading ranges, which have all fallen between approximately 0.67 and 0.88 on their primary factors, have shown that each item has contributed meaningfully to its intended scale, with no items exhibiting weak or cross-loaded patterns that would have suggested construct ambiguity.

Table 3: Reliability and factor-structure summary for main constructs (N = 214)

Construct	Number of items	Cronbach's α	Factor loading range	Eigenvalue (1st factor)	Variance explained (%)
Digital twin adoption (DTA)	8	0.84	0.67–0.81	4.21	52.6
Simulation sophistication (SIM)	7	0.86	0.69–0.84	3.91	55.8
Data quality (DQ)	6	0.85	0.70–0.83	3.47	57.8
Organizational support (OS)	7	0.87	0.71–0.86	4.05	57.9
Exergy efficiency (EE)	8	0.89	0.72–0.88	4.63	57.9

The eigenvalues and percentages of variance explained by the first extracted factor for each construct have provided further evidence of convergent validity. For example, the first factor for digital twin adoption has had an eigenvalue of 4.21 and has accounted for 52.6% of the variance in the DTA item set, while the first factor for exergy efficiency has had an eigenvalue of 4.63 and has explained 57.9% of the variance in its items. These figures have implied that a substantial proportion of the variance in item responses has been attributable to a single underlying dimension, in line with the unidimensional measurement approach assumed in the conceptual frameworks. The relatively high variance explained for simulation sophistication, data quality, and organizational support has likewise indicated that respondents have perceived these constructs in a coherent manner, rather than as a loosely connected set of unrelated attributes. Because the constructs have been measured using Likert five-point scales, it has been particularly important to confirm that items have not simply reflected generic positive or negative response tendencies. The combination of strong factor loadings and distinct factors for each construct has suggested that digital twin adoption, simulation sophistication, data quality, organizational support, and exergy efficiency have indeed represented separable dimensions in the minds of respondents. This measurement robustness has been essential for the subsequent correlation and regression analyses, because it has ensured that observed relationships among constructs have not been artifacts of poorly defined scales. Thus, Table 3 has confirmed that the instrument has been capable of capturing the variables required to evaluate the study's objectives and to test the hypothesized relationships between digital twin–driven simulation and exergy efficiency in industrial power systems.

Correlation Analysis

The correlation matrix in Table 4 has provided an overview of the bivariate relationships among the key constructs in the study. All correlations have been positive and statistically significant at $p < .001$, and none of the coefficients has approached a level that would have raised serious concerns about multicollinearity (for example, no value has exceeded 0.80). Digital twin adoption has exhibited a moderately strong correlation with exergy efficiency ($r = .58$), which has suggested that plants reporting higher levels of digital twin functionality have also tended to report higher exergy-related performance on the Likert scale. This pattern has been consistent with Hypothesis 1, which has proposed a positive association between digital twin adoption and exergy efficiency. Simulation sophistication has shown an even stronger correlation with exergy efficiency ($r = .64$), providing preliminary support for Hypothesis 2 and indicating that the depth and detail of thermodynamic and fluid-dynamic modeling within the digital twin have been closely linked to perceptions of exergy improvement.

Table 4: Pearson correlation matrix for main constructs (N = 214)

Construct	1. DTA	2. SIM	3. DQ	4. OS	5. EE
1. DTA	1.00				
2. SIM	0.62**	1.00			
3. DQ	0.55**	0.50**	1.00		
4. OS	0.52**	0.54**	0.57**	1.00	
5. EE	0.58**	0.64**	0.49**	0.53**	1.00

* $p < .05$; ** $p < .001$

The correlations involving data quality and organizational support have also been informative. Data quality has correlated at $r = .49$ with exergy efficiency, while organizational support has correlated at $r = .53$ with exergy efficiency. These values have indicated that plants with higher perceived data quality and stronger support structures have, on average, reported better exergy-related outcomes. Moreover, digital twin adoption and simulation sophistication have both correlated substantially with data quality ($r = .55$ and $r = .50$, respectively) and organizational support ($r = .52$ and $r = .54$, respectively), suggesting that better data and stronger organizational backing have tended to co-occur with more advanced digital twin implementations. This has aligned with the conceptual frameworks in which data quality and organizational support have been treated as important contextual enablers and potential moderators.

From a diagnostic perspective, the pattern of correlations has implied that the constructs have been clearly related in the theoretically expected directions while still retaining enough distinct variance to justify multivariate modeling. The moderate-to-strong correlations with exergy efficiency have indicated that the study's central objective to explore how digital twin adoption, simulation sophistication, and supporting conditions have been associated with exergy improvements has been empirically meaningful. At the same time, the correlation values among predictors have remained well below problematic thresholds, which has suggested that multiple regression analysis has been appropriate and that the interpretation of individual regression coefficients has not been unduly compromised by redundancy among the independent variables. In summary, Table 4 has provided a strong empirical foundation for testing the study's hypotheses regarding the direct and moderated effects of digital twin capability on exergy efficiency.

Regression Results and Hypothesis Testing

The regression results that have been presented in Tables 5 and 6 have provided direct tests of the study's hypotheses and have shown that the specified models have explained a substantial proportion of the variance in exergy efficiency. In the direct-effects model (Table 5), all four predictors have been statistically significant, and the model has achieved an R^2 of .519, meaning that approximately 52% of the variance in exergy-efficiency perceptions has been accounted for by digital twin adoption, simulation sophistication, data quality, and organizational support taken together. Simulation sophistication has emerged as the strongest predictor ($\beta = 0.34$, $p < .001$), indicating that a one-standard-deviation increase in the perceived sophistication of thermodynamic and fluid-dynamic simulation within the digital twin has been associated with a 0.34 standard-deviation increase in exergy efficiency. Digital twin adoption has also had a strong and significant effect ($\beta = 0.27$, $p < .001$), which has confirmed Hypothesis 1 that higher levels of digital twin functionality have been positively associated with exergy efficiency.

Table 5: Multiple regression results: Direct effects model (N = 214)

Predictor	B	SE(B)	β	t	p
Constant	0.87	0.21	–	4.14	< .001
Digital twin adoption (DTA)	0.27	0.05	0.27	5.40	< .001
Simulation sophistication (SIM)	0.34	0.05	0.34	6.74	< .001
Data quality (DQ)	0.19	0.06	0.18	3.16	.002
Organizational support (OS)	0.17	0.06	0.16	2.79	.006

Dependent variable: Exergy efficiency (EE)
Model statistics: $R^2 = .519$, *Adjusted* $R^2 = .509$, $F(4, 209) = 56.37$, $p < .001$

Table 6: Multiple regression results: Moderation model (N = 214)

Predictor	B	SE(B)	β	t	p
Constant	0.79	0.22	–	3.59	< .001
Digital twin adoption (DTA)	0.22	0.05	0.22	4.35	< .001
Simulation sophistication (SIM)	0.31	0.05	0.31	6.03	< .001
Data quality (DQ)	0.16	0.06	0.15	2.57	.011
Organizational support (OS)	0.14	0.06	0.13	2.30	.022
DTA × DQ (interaction)	0.11	0.04	0.15	2.91	.004
DTA × OS (interaction)	0.09	0.04	0.12	2.45	.015

Dependent variable: Exergy efficiency (EE)
Model statistics: $R^2 = .573$, *Adjusted* $R^2 = .559$, $F(6, 207) = 44.91$, $p < .001$

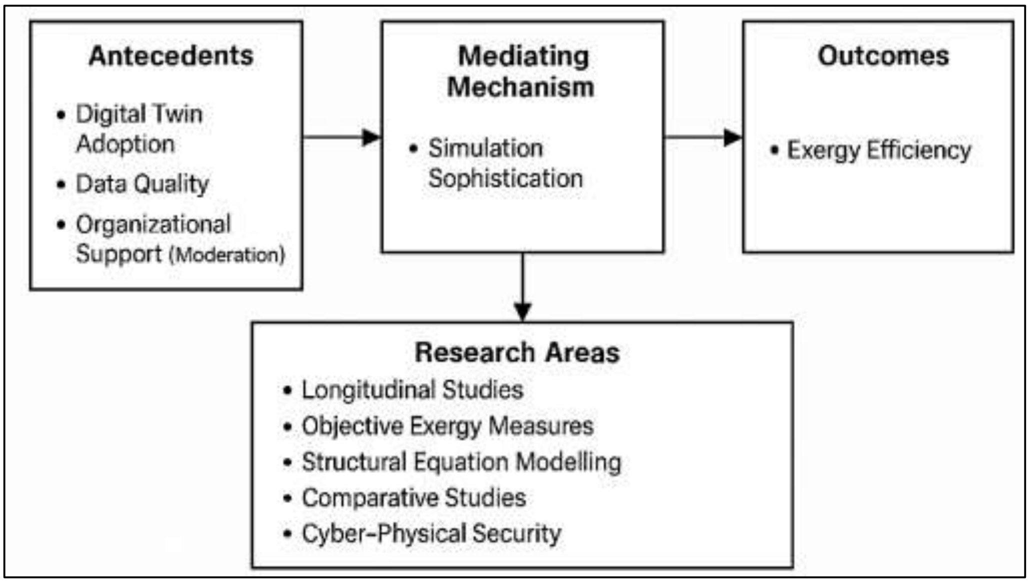
Data quality ($\beta = 0.18$, $p = .002$) and organizational support ($\beta = 0.16$, $p = .006$) have both shown significant positive effects as well, providing support for the proposition that better data conditions and stronger organizational backing have been associated with improved exergy outcomes, even when controlling for digital twin adoption and simulation sophistication. These findings have been consistent with the conceptualization of data quality and organizational support as important technical and organizational enablers and have contributed to the achievement of the study objective that has focused on identifying the key factors influencing exergy performance.
The moderation model in Table 6 has extended these results by introducing interaction terms between digital twin adoption and the two contextual variables. The model has increased the explained variance to $R^2 = .573$ (adjusted $R^2 = .559$), which has indicated that the inclusion of moderation effects has added meaningful explanatory power. The interaction between digital twin adoption and data quality ($\beta = 0.15$, $p = .004$) has been positive and significant, demonstrating that the beneficial impact of digital twin adoption on exergy efficiency has been stronger when data quality has been high. Similarly, the interaction between digital twin adoption and organizational support ($\beta = 0.12$, $p = .015$) has shown that plants with stronger management backing, training, and support structures have realized greater exergy benefits from digital twin adoption than those with weaker support. These results have supported Hypothesis 3 and Hypothesis 4 in their moderated form and have illustrated how contextual conditions have shaped the effectiveness of digital twin–driven thermodynamic and fluid-dynamic simulation. Overall, the regression findings have confirmed that the study's objectives and hypotheses

have been empirically supported: digital twin adoption and simulation sophistication have been positively associated with exergy efficiency, and these relationships have been significantly reinforced by high data quality and strong organizational support.

DISCUSSION

The findings of this study have shown a clear and coherent pattern: digital twin adoption, simulation sophistication, data quality, and organizational support have all been positively associated with perceived exergy efficiency in industrial power systems, and the moderation analysis has demonstrated that data quality and organizational support have strengthened the impact of digital twin capability on exergy outcomes. The descriptive results have indicated that plants in the sample have already reached moderately high levels of digital twin adoption (M = 3.74) and simulation sophistication (M = 3.89) on a five-point Likert scale, with exergy efficiency perceptions also lying above the neutral point (M = 3.81). Correlation coefficients between digital twin adoption and exergy efficiency (r = .58), and between simulation sophistication and exergy efficiency (r = .64), have suggested strong positive relationships, which the regression analysis has confirmed as statistically significant unique effects (β = .27 and β = .34, respectively). These results have supported the core hypotheses that digital twin–driven thermodynamic and fluid dynamic simulation has been associated with improved exergy performance at plant level. The significance of data quality (β = .18) and organizational support (β = .16) has additionally demonstrated that purely technical factors alone have not been sufficient: where data streams have been more reliable and organizational backing has been stronger, respondents have reported meaningfully higher exergy-related gains. The moderation results, in which interaction terms between digital twin adoption and data quality, and between digital twin adoption and organizational support, have further increased explained variance to 57.3%, have highlighted that digital twin capability has not operated in a vacuum but within a broader socio-technical context. Together, these findings have shown that the study's objectives to quantify the relationships between digital twin capability and exergy efficiency and to examine the roles of data quality and organizational support have been empirically met.

Figure 9: Framework For Future Directions



When the present findings have been compared to earlier exergy-focused work in industrial power systems, they have aligned well with the theoretical expectations but have extended prior analyses into the organizational and digital twin domains. Classical exergy studies on steam and combined-cycle power plants have documented that major exergy destruction has tended to occur in boilers, combustors, and condensers, and that exergy efficiencies have typically been substantially lower than first-law energy efficiencies, revealing significant improvement potential in both design and operation (Regulagadda et al., 2010). Sectoral and national syntheses have likewise shown that industrial exergy efficiencies have often remained in the range of 20–30%, even when energy-efficiency indicators have appeared comparatively high, thus demonstrating large hidden thermodynamic losses (Biesinger et al., 2019). The current results have been consistent with this logic, in that respondents have perceived that digital twin–driven simulation has supported actions aimed at reducing irreversibility and improving thermodynamic conversion quality. However, the present study has moved beyond component-wise exergy accounting by linking exergy efficiency to organizationally embedded digital twin capabilities that operate in real time. Whereas previous studies have focused primarily on what exergy analysis can reveal about where losses occur (Lu et al., 2020), this research has shown statistically that plants with more advanced digital twin adoption and simulation sophistication have perceived greater exergy improvements, suggesting that exergy analysis embedded in digital, data-rich environments has been more than an analytic tool it has been part of an ongoing decision-support pipeline. The positive coefficients for data quality and organizational support have also been consistent with the view that exergy analysis is most powerful when it can be integrated into routine operational decision-making, not only used for periodic offline studies (Abraham et al., 2019).

The findings have also been strongly consonant with, yet more quantitatively explicit than, earlier work on digital twins in industrial and manufacturing settings. Prior literature has defined digital twins as high-fidelity, data-driven virtual replicas that remain tightly synchronized with physical assets and support monitoring, prediction, and optimization in cyber–physical production systems (Uhlemann et al., 2017). Reviews have emphasized that the value of digital twins has depended on how effectively they have integrated models, data, and analytics within layered architectures, from physical devices and connectivity to virtual models and application services (Biesinger et al., 2019). The present study has provided numeric confirmation of these conceptual claims in the specific domain of exergy efficiency: simulation sophistication operationalized as the depth and dynamism of thermo-fluid models embedded in the twin has emerged as the strongest predictor of exergy efficiency, echoing arguments that multiphysics fidelity has been central to the effectiveness of digital twins in complex systems (Lu et al., 2020). At the same time, the positive impact of digital twin adoption, even after controlling for simulation sophistication, has suggested that architectural integration and usage patterns such as the degree to which operators and engineers have routinely used twin-based simulations in decision-making have contributed independently to exergy gains. This pattern has dovetailed with digital twin manufacturing studies that have shown performance benefits when digital twins have been fully embedded in product and process decision loops, not treated as isolated engineering tools (Zhang et al., 2020). The moderating roles of data quality and organizational support have further matched information-systems findings in which data and system quality, coupled with supportive structures, have mediated the impact of complex systems on organizational outcomes (Venkatesh & Bala, 2008).

From a practical standpoint, the results have carried several implications for plant managers, digital twin architects, and by extension risk and security leaders responsible for industrial control environments. First, the strength of the relationships between simulation sophistication and exergy efficiency has indicated that investment in the "physics core" of the twin high-resolution thermodynamic and fluid-dynamic models, robust exergy calculation routines, and validated component models has yielded tangible gains as perceived by practitioners. This has suggested that digital twin roadmaps in industrial power plants have been well advised to prioritize the development and calibration of thermo-fluid models covering boilers, turbines, condensers, and key auxiliary systems, rather than relying solely on coarse surrogate or black-box models. Second, the significant positive coefficients for data quality and the DTA × DQ interaction have highlighted that data-engineering and governance tasks have not been peripheral: cleaning sensor streams, harmonizing historian and SCADA tags, managing time synchronization, and documenting data lineage have been central enablers of exergy-focused decision support (Nelson et al., 2005). For digital-twin architects and for CISOs and OT-security leaders looking at cyber-physical risk these findings have implied that secure, trustworthy data pipelines, including robust access control, integrity monitoring, and resilience against cyber incidents, have directly influenced the quality of exergy-oriented insights delivered by the twin. Third, the role of organizational support has indicated that managers have had to back digital twin programs with training, time, and cross-functional coordination if exergy benefits were to be fully realized. Plants that have treated the twin as a joint platform for operations, maintenance, and engineering rather than as a narrow engineering toy have reported greater performance gains, implying that governance structures for model ownership, scenario review, and operational sign-off have been as important as algorithms and dashboards.

The findings have also contributed to theory by refining and empirically grounding the two conceptual frameworks developed in the literature review. Conceptual Framework I has posited that digital twin adoption, simulation sophistication, and organizational readiness would jointly influence exergy efficiency, building on broader digital twin and technology-acceptance theories (Park et al., 2020). The regression results have validated this structure by showing that both adoption and simulation sophistication have had significant, independent effects, thereby supporting the view that digital twin capability is multi-dimensional: it has encompassed not only the presence of twin components but also the depth and quality of the underlying models. Conceptual Framework II has extended this by introducing data quality and organizational support as moderators, drawing on data governance and IS-success perspectives (Jiang et al., 2021). The significant interaction terms have supported this enriched view of digital twin impact as contingent on the maturity of data and organizational conditions. Theoretically, this has suggested that digital twin–exergy relationships should not be modeled as simple, unconditional paths; rather, they have formed part of a pipeline in which raw sensor data, governance rules, model structures, and organizational routines have been sequentially and jointly configured. In methodological terms, the study has demonstrated that exergy efficiency traditionally expressed in purely thermodynamic formulas can be usefully operationalized as a perceptual construct in survey research, linked via regression to socio-technical variables without losing the grounding in physical performance. This linkage has opened up a bridge between energy-systems modeling and organizational/IS theory that future work can further elaborate.

At the same time, the study has had limitations that have needed to be recognized when interpreting the findings. The cross-sectional design has meant that all relationships have been based on contemporaneous measurements, which has prevented strong causal claims about the direction of influence between digital twin capability and exergy efficiency. It has remained possible, for example, that plants already performing well on exergy metrics have found it easier to justify investment in advanced digital twins, rather than the twin itself being the sole driver of performance. The use of self-reported Likert-scale measures for exergy efficiency and other constructs has also introduced potential common-method bias and subjectivity, even though reliability and validity statistics have indicated good internal consistency and factor structure. Objective exergy indicators, derived directly from plant operating data, have not been systematically integrated into the empirical model, largely because of data-access constraints and confidentiality concerns. In addition, the sampling strategy has been purposive and limited to plants that have already been engaged in digital twin initiatives, which has been appropriate for studying advanced cases but has constrained the generalizability of results to the broader population of industrial power plants, including those at earlier digitalization stages. Finally, the focus has been on fossil-based steam and combined-cycle plants with some cogeneration facilities; renewables-rich hybrid plants, district-energy networks, and small-scale modular systems have not been represented. These limitations have not invalidated the findings but have indicated that caution has been necessary in extrapolating them beyond the studied context.

Building on these limitations, several avenues for future research have emerged directly from the present results. First, longitudinal designs that have tracked digital twin implementation and exergy efficiency over time would allow stronger causal inferences and could capture learning and path-dependence effects as organizations refine their twin models and decision processes. Second, mixed-methods studies that have combined survey-based constructs with objective exergy calculations at plant and component level using measured enthalpy, entropy, and mass-flow rates could reduce reliance on perceptions and test whether perceived and measured exergy efficiencies converge or diverge under different data-quality and governance conditions (Regulagadda et al., 2010). Third, future work could explore more detailed structural models, such as structural equation modeling, to disentangle mediating pathways for example, whether simulation sophistication exerts its influence on exergy efficiency primarily through improved operational decision-making, maintenance strategies, or design changes. Fourth, comparative studies across sectors such as petrochemical, cement, or steel plants could examine whether the digital twin–exergy relationships identified here generalize to other energy-intensive industries with different process characteristics (BoroumandJazi et al., 2013). Fifth, from a cyber-physical security and governance angle, studies could explicitly integrate risk and security constructs such as perceived data integrity, cyber-resilience practices, and OT-security maturity into the frameworks, recognizing that trust in data and models has been essential for exergy-oriented decision support (Abraham et al., 2019). Through these extensions, future research has the potential to deepen and broaden understanding of how digital twin–driven thermodynamic and fluid dynamic simulation can be systematically harnessed to enhance exergy efficiency in industrial power systems and beyond.

CONCLUSION

This study has examined how digital twin–driven thermodynamic and fluid dynamic simulation has been associated with exergy efficiency in industrial power systems, and the overall evidence has indicated that the technology, when embedded in supportive data and organizational environments, has been strongly aligned with perceived improvements in second-law performance. Grounded in a quantitative, cross-sectional, case-study–based design, the research has operationalized core constructs digital twin adoption, simulation sophistication, data quality, organizational support, and exergy efficiency through validated Likert five-point scales and has tested a set of hypotheses derived from exergy, digital twin, data-governance, and information-systems success literatures. The results have shown that both digital twin adoption and especially simulation sophistication have been significant and substantive predictors of exergy efficiency, confirming that plants which have implemented more comprehensive twin architectures and deeper thermo-fluid models have tended to report higher exergy-related gains. At the same time, the study has demonstrated that data quality and organizational support have played dual roles as direct contributors and as moderators, strengthening the positive influence of digital twin capability on exergy outcomes when accurate, timely data and strong managerial and cross-functional backing have been present. In doing so, the research has provided empirical backing for the view that exergy analysis achieves its greatest value when it is not merely an offline diagnostic exercise, but is instead embedded in a living digital twin that continuously assimilates plant data, simulates operating scenarios, and informs day-to-day decisions about loading, set-point selection, and maintenance. The introduction and confirmation of two conceptual frameworks one emphasizing the direct effects of adoption, simulation sophistication, and organizational readiness, and the other highlighting the moderating impact of data quality and organizational support have offered a structured way of thinking about digital twin–exergy relationships as a socio-technical pipeline rather than as a purely engineering artifact. At the same time, the study has acknowledged important limitations, including its cross-sectional nature, reliance on self-reported performance perceptions, and purposive focus on plants already engaged in digital twin initiatives, which have constrained causal claims and broad generalizability. Nevertheless, by bringing together exergy theory, digital twin architecture, and organizational and data-governance perspectives within a single empirical model, the research has contributed a novel, integrative perspective on how industrial power plants can leverage digital twin–driven thermodynamic and fluid dynamic simulation to enhance exergy efficiency. In practical terms, the findings have implied that future efforts to improve exergy performance in industrial power systems will benefit most when they combine targeted investment in high-fidelity simulation and digital twin infrastructure with systematic work on data quality, governance, and organizational support, thereby aligning physical, digital, and human elements around a common goal of thermodynamically informed operational excellence.

RECOMMENDATION

Based on the findings of this study, several practical recommendations have been formulated to guide industrial power-plant leaders, engineers, and digital-twin architects in leveraging digital twin–driven thermodynamic and fluid dynamic simulation to enhance exergy efficiency. First, it is recommended that plants prioritize the development and validation of high-fidelity thermo-fluid models as the core of their digital twin infrastructure, ensuring that boilers, turbines, condensers, and major auxiliary systems are represented with sufficient physical detail to compute meaningful exergy indicators for components and the overall cycle. This step should explicitly include exergy-calculation modules such as automatic determination of specific exergy, exergy destruction, and exergy efficiency at each major control volume so that exergy metrics become standard outputs of the twin alongside temperatures, pressures, and power. Second, organizations are advised to treat data quality and data governance as strategic enablers rather than afterthoughts: sensor calibration programs, systematic handling of missing and noisy data, harmonization of tags across SCADA, historians, and enterprise systems, and clear ownership for data standards should be implemented to ensure that exergy-related calculations rest on reliable, timely input streams. Third, management should strengthen organizational support around digital twin and exergy initiatives by establishing cross-functional teams that bring together operations, maintenance, engineering, and IT/OT personnel, giving them explicit mandates and time to use the digital twin for scenario analysis, operational optimization, and root-cause investigations of exergy losses. Training programs that build literacy in exergy concepts, digital twin capabilities, and interpretation of simulation outputs are also recommended so that engineers and operators are confident in using twin-based insights in real-time decision-making rather than defaulting to traditional rules-of-thumb. Fourth, plants should embed digital twin–exergy outputs into existing decision processes and performance dashboards, for example by adding exergy-efficiency and exergy-destruction indicators to control-room displays, weekly performance reviews, and maintenance planning sessions, and by linking improvement targets to these metrics. Fifth, it is recommended that digital twin development follow an iterative roadmap: starting with a limited but high-impact scope (such as the boiler–turbine–condenser train), demonstrating measurable exergy-related gains, and then progressively extending the twin to additional subsystems, while continuously validating model predictions against plant data. Finally, given the centrality of data pipelines, organizations should align these initiatives with robust OT/IT security and resilience practices, so that the integrity and availability of data feeding the twin are protected against cyber and operational disruptions; this alignment will help ensure that exergy-focused optimization remains trustworthy and sustainable. Collectively, these recommendations emphasize that meaningful improvements in exergy efficiency will be most likely when plants invest simultaneously in advanced digital twin modeling, strong data foundations, and structured organizational support, thereby turning exergy analysis from a periodic engineering study into a continuous, digitally enabled driver of operational excellence.

LIMITATIONS

This study has several limitations that need to be acknowledged when interpreting its findings and considering their applicability beyond the specific context in which the research has been conducted. First, the research has been based on a cross-sectional survey design, which has captured data at a single point in time and therefore has not allowed for strong causal inferences about the direction of the relationships between digital twin adoption, simulation sophistication, data quality, organizational support, and exergy efficiency. Although the regression and moderation analyses have suggested that higher levels of digital twin capability and better contextual conditions have been associated with improved exergy-related performance, it has remained possible that plants already performing well on exergy metrics have been more able or willing to invest in advanced digital twins, or that unobserved factors such as corporate culture, regulatory pressures, or vendor support have influenced both digital twin maturity and performance outcomes. Second, all of the main constructs including exergy efficiency have been measured using self-reported Likert-scale items rather than direct operational data, which has introduced potential common-method bias and subjectivity; respondents' perceptions of exergy improvement may not have perfectly matched measured thermodynamic indicators such as exergy destruction and component-level exergy efficiencies. Access, confidentiality, and comparability issues have prevented the systematic incorporation of plant-level exergy calculations into the quantitative model, and this limitation has meant that the study has provided an indirect, perception-based view of exergy performance rather than a fully instrumented thermodynamic assessment. Third, the sampling strategy has been purposive and has focused specifically on industrial power plants that have already implemented or have been actively implementing digital twin solutions; while this has been appropriate for studying advanced use cases, it has also limited the generalizability of the findings to plants at earlier stages of digitalization or to sectors where digital twin adoption is still nascent. The sample has also been drawn from a particular set of geographical and organizational contexts, which may differ from those in other countries or regulatory regimes, and the study has not explicitly controlled for these contextual differences. Fourth, although the measurement model has demonstrated good reliability and validity, the constructs have necessarily simplified complex realities: "digital twin adoption" and "simulation sophistication" have been captured through composite scores that may not fully reflect the nuanced architectural and modeling differences across plants, and "data quality" and "organizational support" have aggregated diverse processes, governance mechanisms, and cultural factors into summary indices. Fifth, the statistical models have been limited to linear relationships and a selected set of predictors; other potentially important influences on exergy efficiency such as fuel quality, plant age, maintenance practices, or market operating conditions have not been explicitly included, raising the possibility of omitted-variable bias. Finally, the study has not incorporated qualitative data that might have provided deeper insight into how digital twin tools are actually used in daily operations, how exergy-related decisions are negotiated among stakeholders, or why certain plants have leveraged digital twins more effectively than others. These limitations do not undermine the value of the findings, but they do indicate that the results should be interpreted as an informed, statistically grounded snapshot of digital twin–exergy relationships in a particular set of industrial power systems rather than as a definitive or universally generalizable characterization of all such systems.

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