THE IMPACT OF DIGITAL TWIN ADOPTION ON STRATEGIC PERFORMANCE IN COAL-FIRED POWER PLANTS: THE MEDIATING ROLE OF DATA-DRIVEN DECISION-MAKING AND THE MODERATING EFFECT OF ORGANIZATIONAL IT READINESS

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Abstract: This study investigates the strategic impact of digital twin adoption in coal-fired power plants, with particular emphasis on the mediating role of data-driven decision-making and the moderating effect of organizational IT readiness. Grounded in the Resource-Based View (RBV), Technology-Organization-Environment (TOE) framework, and Dynamic Capabilities Theory, a comprehensive structural model was developed and tested using data from 402 respondents across the energy sector. Structural equation modeling (SEM), mediation and moderation analyses were employed using the R language. The findings confirm that digital twin adoption significantly enhances strategic performance; however, this effect is fully mediated by data-driven decision-making. In other words, the value of digital twins is only realized when organizations possess the capability to transform data into actionable decisions. Moreover, organizational IT readiness positively moderates the relationship between digital twin usage and strategic performance, implying that infrastructure, human capability, and digital culture are essential enablers of successful technology integration.

This research contributes to digital transformation literature by offering an empirically validated, theory-integrated model that bridges technology adoption with strategic outcomes. It also provides practical guidance for energy executives, IT managers, and policy makers in driving intelligent modernization in legacy sectors. The study concludes that digital transformation is not only a technological endeavor but an organizational challenge that demands readiness, capability, and strategic alignment.

Keywords: Digital Twin, Strategic Performance, Data-Driven Decision-Making, Organizational IT Readiness

Introduction

Currently, the global energy sector is undergoing a profound structural transformation driven by sustainability, digitalization, and decarbonization demands. Despite sustained growth in renewable energy investments, coal continues to play a significant role in the global power mix, accounting for over one-third of global electricity generation as of 2022 (International Energy Agency [IEA], 2023). In regions with rapidly growing energy demand, such as South Asia and Southeast Asia, coal's dominant role is particularly pronounced due to the slow pace of infrastructure transformation (Zhang et al., 2023). Meanwhile, international policies such as the Paris Agreement have intensified pressure on traditional energy sectors to reduce emissions and improve efficiency. Therefore, for coal-based power companies, leveraging advanced technologies to upgrade outdated infrastructure has become an inevitable path for survival and transformation (Akhator & Oboirien, 2025).

Coal-fired power plants, as the most complex and carbon-intensive component of global energy infrastructure, face multiple challenges. These challenges include not only environmental issues such as high CO_2 and particulate matter emissions but also operational difficulties such as aging equipment and low operational efficiency (Ismail et al., 2024). In many developing countries, coal-fired power plants often suffer from inadequate maintenance mechanisms, low combustion efficiency, and weak responsiveness to grid demand fluctuations. Additionally, increasingly stringent regulatory policies and public opposition to pollution are forcing companies to reduce their environmental footprint while maintaining profitability (Cui et al., 2023). Due to the lack of real-time monitoring systems and modern control measures, these facilities often struggle to achieve performance optimization and predictive maintenance. In this context, the introduction of digital solutions has become particularly necessary.

The Fourth Industrial Revolution (Industry 4.0) has brought about a series of disruptive technologies, including the Internet of Things (IoT), artificial intelligence (AI), machine learning, and digital twins. These technologies are reshaping traditional energy systems, driving their transformation toward automation, intelligence, and virtualized management (Yu et al., 2022). Among these, digital twins, as a key Industry 4.0 technology, enable the creation of virtual replicas of physical assets, facilitating real-time monitoring, predictive analysis, and remote diagnostics—particularly suited for highly complex facilities like coal-fired power plants (Ranawaka et al., 2024). Digital twin systems integrate sensor data, historical operational records, and simulation models to help managers make more precise and scientific decisions and maintenance schedules. Although the application of this technology in the energy sector is still in its early stages, existing research indicates that it holds significant potential for improving energy efficiency, reducing unplanned downtime, and optimizing resource utilization (Xu et al., 2024).

In many emerging economies, coal remains the core energy source for power generation, making the promotion of digital innovation in these regions of strategic importance. Take India, Indonesia, and Vietnam as examples. These countries need to meet rapidly growing energy demands while also fulfilling increasingly stringent environmental sustainability targets (Akhator & Oboirien, 2025). Technologies such as digital twins offer low-cost, scalable solutions to help coal-fired power plants achieve performance monitoring and operational optimization. Additionally, the deployment of these technologies enables emerging economies to bypass traditional transition barriers to some extent and directly align with global best practices in energy management (Cui et al., 2023). With infrastructure investment continuing to flow into the Global South, technology transfer and digital capacity building have become important components of national energy strategies and policies (Ismail et al., 2024). Therefore, exploring the role of digital twin technology in the strategic performance of coal-fired power plants in emerging economies has significant theoretical value and practical significance.

Research Objectives

1. Explore the direct impact of digital twin adoption on strategic performance.
2. Analyze the impact of digital twin adoption on data-driven decision-making.
3. Assess the impact of data-driven decision-making on strategic performance.
4. Analyze the mediating role of data-driven decision-making in the relationship between digital twin adoption and strategic performance.
5. Assess the mediating role of organizational IT readiness in the relationship between digital twin adoption and strategic performance.

Literature Review

The Resource-Based View (RBV) is a foundational theory in strategic management, emphasizing how a firm's unique resources contribute to sustainable competitive advantage (Barney, 1991). These resources must meet the following criteria: valuable, scarce, inimitable, and non-substitutable (often referred to as VRIN attributes).

In the context of digital transformation, the RBV has been extended to encompass intangible assets such as IT infrastructure, digital culture, and knowledge-based capabilities (Wade & Hulland, 2004). Digital twins—cyber-physical systems capable of real-time mapping of operational processes—are positioned within this framework as technically complex and knowledge-intensive resources.

When these resources are appropriately embedded into systems, they can generate operational intelligence, reduce downtime, and enable predictive maintenance. In coal-fired power plants, these functions are particularly critical due to the capital-intensive and mission-critical nature of the infrastructure (Kabir, Halder, & Ray, 2024).

Additionally, RBV posits that technical resources alone are insufficient to produce outstanding outcomes unless supported by organizational enabling factors such as employee capabilities, leadership vision, and integration with legacy systems (Zheng, Zhang, & Du, 2022). This implies that digital twin systems only generate strategic value when organizations can effectively leverage their outputs through data governance, analytical capabilities, and decision-making processes (Yu et al., 2022). Therefore, RBV provides a solid theoretical foundation for understanding why some coal-fired power plants can derive greater performance benefits from the same digital innovations.

The TOE framework proposed by Tornatzky and Fleischer (1990) provides a systematic approach to understanding how innovation adoption decisions are influenced by three core domains:

Technological context (e.g., compatibility, complexity, perceived benefits)

Organizational context (e.g., size, IT readiness, top management support)

Environmental context (e.g., regulatory requirements, competitive pressure, stakeholder expectations)

The TOE framework is particularly relevant for studying the adoption of complex enterprise technologies in highly regulated, infrastructure-intensive industries such as energy (Baker, 2012).

In this study, TOE is used to explain the moderating role of organizational IT readiness, which includes factors such as the availability of a scalable IT backbone, employee proficiency with analytical tools, and a culture that supports innovation (Ismail, Hasini, and Al-Bazi, 2024).

Digital twin technology relies heavily on real-time data, artificial intelligence modeling, and IoT integration, requiring strong IT capabilities and organizational commitment. The TOE framework posits that if organizations lack the readiness to absorb and adapt such technologies, adoption efforts may result in cost overruns or underutilization of functionality. Additionally, the external environment—particularly in the context of global decarbonization agendas, emissions regulations, and energy price volatility—plays a critical role in shaping the urgency and direction of digital investments (Akhator & Oboirien, 2025).

The TOE framework is particularly valuable in emerging economies due to its emphasis on contextual heterogeneity: the same technology may yield different outcomes depending on an organization's internal capabilities and the institutional pressures it faces. This enables more nuanced interpretations of adoption success across firms with differing resource and policy constraints.

While the Resource-Based View (RBV) explains the role of valuable assets, and the Technology-Organization Environment (TOE) emphasizes contextual conditions, Dynamic Capabilities Theory explores how organizations continuously adjust their resources in rapidly changing environments (Teece, Pisano, & Shuen, 1997). Dynamic capabilities are defined as an organization's ability to integrate, build, and reconfigure internal and external capabilities to respond to environmental fluctuations and seize emerging opportunities.

In the coal-fired power generation sector, dynamic capabilities are critical due to the dynamic nature of regulatory environments, fuel costs, and public oversight. Digital twin systems serve as strategic enablers for achieving such capabilities by providing simulation platforms, real-time diagnostic tools, and predictive tools to support proactive decision-making and continuous organizational learning (Ranawaka et al., 2024).

From a strategic management perspective, dynamic capabilities encompass three core activities: (1) perceiving environmental changes and opportunities;(2) Seizing these opportunities through resource allocation; (3) Transforming the organizational resource base to maintain competitiveness (Teece, 2007). Digital twin technology enhances these three core activities: it enables coal-fired power plants to detect process anomalies, test corrective measures, and implement process improvements based on simulation feedback. The result is the formation of a more adaptive and responsive organizational model.

In addition, digital twin systems facilitate data-driven decision-making, which is a critical process for dynamic capabilities. By integrating analytical insights into planning and operations, organizations cultivate a culture of evidence-based strategy, cross-functional integration, and agility. This is consistent with findings that companies with strong dynamic capabilities are better able to cope with turbulent industry transformations, such as the current shift toward cleaner energy solutions (Xu et al., 2024). Digital twin technology was first proposed by Michael Grieves in the early 21st century and initially applied to product lifecycle management (PLM) (Grieves, 2014). As technology has evolved, the concept has transitioned from a “static digital copy” to an intelligent system with real-time sensing, behavioral simulation, and performance optimization capabilities (Tao et al., 2019). Currently, digital twins are defined as “a complex system model that integrates multi-physics, multi-scale, and probability-based simulation, which uses real-time data to accurately reflect the operating status of physical entities.”

The core of digital twin technology includes four major components:

Physical entities: such as boilers, turbines, condensers, and other equipment;

Virtual models: high-fidelity simulation systems built based on physical models, statistical models, or machine learning algorithms;

Real-time connectivity: real-time two-way data flow through sensors and IoT devices;

Data analysis and intelligent functions: prediction, optimization, and intelligent decision-making based on AI and big data platforms.

The development of digital twins has benefited from a series of breakthroughs in underlying technologies, such as improved computing power, the popularization of edge computing, the maturity of cloud platforms, and improved sensor accuracy.

In recent years, this technology has gradually extended from the engineering design level to strategic decision support systems and has been widely applied in operation and maintenance management, risk assessment, and sustainable development strategies (Fuller et al., 2020; Söderberg et al., 2022). Digital twin technology provides an effective solution for this by constructing detailed models that can be combined with data analysis to achieve real-time monitoring of equipment operating status and fault prediction, thereby reducing downtime and maintenance costs.

The application of digital twins has developed rapidly in recent years, not only because of its own merits, but also because other new technologies have emerged during this period. Digital twins are generally used in combination with the Internet of Things (IoT) and deep learning. Digital twins share the same characteristics as IoT in connecting physical entities with their virtual components, while deep learning is often used to assist digital twins in detection and diagnosis.

There are many definitions of digital twins, and experts and scholars in different fields have given it different definitions. At the time, digital twins were divided into three parts: the physical part, the virtual part, and the connection part. The physical part and the virtual part interact with each other through the connection part to exchange data and information. Since then, digital twins have entered the stage. More and more scholars have begun to define digital twins in various fields.

Tao et al. divided digital twins into five parts based on smart manufacturing workshops: physical part, virtual part, connection, data, and services. Different fields have different understandings and definitions of digital twins, but with the development of digital twins, the definitions of digital twins in various fields are becoming more mature and specific. Digital twin technology has now become a technology that complements intelligent diagnosis.

The main feature of digital twins is their high-precision mapping of the entire life cycle of equipment. They integrate physical and virtual data throughout the entire life cycle, which is then processed and analyzed for equipment monitoring and diagnosis. Previous simulation technologies were unable to achieve high-precision mapping of the entire life cycle, but the emergence of digital twins has made this possible, providing support for the intelligent fault diagnosis of complex electromechanical equipment such as ball mills.

Digital twin models serve as the foundation and container for digital twin functionality, while digital twin modeling forms the basis for digital twin model-driven methods. Multi-coupled digital twin high-precision modeling involves integrating multiple physical phenomena of different dimensions on the foundation of digital twin technology to establish high-precision, comprehensive, and realistic multi-physics field models, thereby enabling a comprehensive description and prediction of complex systems. By integrating knowledge from relevant disciplines corresponding to specific dimensions, digital twin models can be precisely constructed from four model dimensions: geometry, physics, behavior, and rules. To more effectively advance ball mill model construction research, previous studies on model construction will be analyzed and summarized from these four model dimensions.

Geometric model construction encompasses the description of various characteristics of physical entities, such as shape, size, and position. During the preparation of geometric models, particular emphasis is placed on model accuracy and simplification, both of which are of great significance. The value of geometric models extends far beyond their role in shape modeling. In fact, the completeness and data accuracy of geometric models provide a foundation for multiple fields, including but not limited to motion analysis, design optimization, and virtual interaction. Therefore, accuracy and precision have become key focuses in geometric model construction. For example, Zhang et al. successfully applied high-quality virtual visualization technology to predict tool wear conditions, thereby enhancing the predictability of tool performance. Zhao Haoran et al. proposed a three-dimensional visualization monitoring method for real-time monitoring of production workshops. Dong Qing et al. established a digital twin model through rigid-flexible coupling analysis to assess the load-bearing capacity of crane structures during operation. To achieve fast geometric model transfer, loading, and browsing across various applications, appropriate model simplification methods must be adopted. Geometric model simplification aims to reduce data volume, thereby generating relatively small transfer files while maintaining high physical accuracy. Additionally, this simplification method offers the advantage of high compatibility across different platforms. For example, Li and Nan proposed a generic model simplification method that optimizes mesh structures to enhance model analysis efficiency. Liu Xiaochi et al. addressed issues such as low efficiency in virtual-physical data interaction and poor virtual debugging effects during the production process of digital twin models. After successfully constructing the model, they performed mesh processing and applied a half-face folding algorithm to lightweight complex digital twin models. These improvements provide a deeper understanding of the key role of geometric models in digital twin technology and how to effectively apply them in different fields to achieve more accurate and efficient engineering and scientific research.

Strategic performance is the achievement and effect of a company's implementation of its strategy. It considers the company's strategy as an organic whole and comprehensively analyzes the impact of the implementation of the company's strategy on its performance (Sheng Hong, 2011).One of the important measures of a company's success is the implementation of its strategy. In order to comprehensively guarantee the benefits brought about by the implementation of corporate strategy, it is necessary to build a strategic performance evaluation system that emphasizes the integrity of the strategy system. This system should deeply analyze the wide-ranging impact that strategy implementation may have, accurately measure the level of corporate performance, and select appropriate evaluation indicators to dynamically track strategy execution. In addition, it is necessary to conduct a detailed assessment of the soundness of the company's overall strategy and continuously supervise the execution of management behavior to promote the flexibility and adaptability of the company's strategy.

In the early 20th century, a prevailing view held that the core of corporate strategy lay in gaining competitive advantage, which primarily stemmed from the attractiveness of the industry in which the company operated and the relative competitive position it held within that industry. In exploring the evaluation of business organization effectiveness, the research field initially focused on micro-level internal environmental factors; in contrast, the consideration of external environmental influences was relatively neglected. At the same time, the DuPont analysis method gradually became the core evaluation system for measuring corporate performance. Although this analysis method provides a relatively comprehensive evaluation framework for characterizing corporate management efficiency and profitability, its excessive reliance on financial data limits the breadth and depth of its reflection of the actual operating conditions of enterprises, and it has significant limitations. With the passage of time, the concept of economic value added (EVA) emerged. The core principle of EVA is to define corporate profits from the perspective of shareholders' economic interests, using residual income as the measurement standard and incorporating comprehensive capital costs, thereby ensuring a high degree of consistency between corporate operations and shareholder returns. This concept also promotes management's emphasis on capital operation efficiency and long-term returns. However, the EVA concept, which is highly dependent on financial indicators, has significant shortcomings. These are mainly manifested in its calculation method, which fails to consider differences in the industry, development stage, and size of the enterprise, resulting in an inability to comprehensively assess the operational efficiency and effectiveness of the enterprise. In addition, the relative lack of comparability is another important limitation.

At the end of the 20th century, as a new performance evaluation method, the balanced scorecard was widely introduced and applied. It not only significantly broke through the limitations of traditional methods in terms of effectiveness but also gained widespread verification and recognition in practice. In the field of corporate performance evaluation, the balanced scorecard, with its unique analytical indicator system, has become a core tool for evaluating corporate performance and is widely applied in actual performance management operations. Academics Du Dubin (2012) and Zahirul Hoque (2014) used this indicator system to construct a systematic enterprise performance evaluation model that integrates four dimensions: finance, customers, internal processes, and learning and growth. This model deeply integrates the elements of enterprise strategy and performance management, aiming to promote the achievement of established strategic evaluation and management goals by optimizing human resource management and enhancing market competitiveness. This achievement has had a profound impact on the field of corporate strategic effectiveness evaluation and has given rise to a number of innovative theories and practices. Wu Senfu (2002) and Zhang Jide (2014) explained that the balanced scorecard for measuring corporate performance is not simply the sum of the four dimensions, but rather a comprehensive corporate performance evaluation system based on the overall strategic planning of the enterprise. As an important tool in strategic control management, the balanced scorecard's functions go far beyond performance evaluation. In order to integrate enterprise performance and strategy throughout the entire process, promote the transformation of management concepts and ways of thinking, and achieve scientific performance management, researchers Ruan Pingnan, Shao Ya (2010) and Sun Yush (2013) jointly proposed a theoretical framework for the balanced scorecard. This framework mainly aligns corporate strategy and performance by building a core organizational structure for enterprise management, providing a forward-looking perspective and standardized template for enterprise performance management that is difficult to quantify. Its theoretical core lies in viewing strategy as a core element, focusing on balanced development, continuously improving practice, and treating cause-and-effect relationships as an important link in performance evaluation.

Performance management, as an important means for companies to achieve sustainable and stable development and implement their strategic vision, has always been widely recognized by academia and industry. Against this backdrop, the use of balanced scorecards has become a key issue. Li Jie (2013) and Wan Xin (2016) have emphasized the necessity of the proper application of balanced scorecards. Furthermore, Hu Yuanlin and Li Hang (2017) proposed that in the specific implementation of the Balanced Scorecard, the fundamental challenge for the performance management system is to establish a causal logic framework and, based on this, develop a Balanced Scorecard scheme tailored to the company's characteristics to achieve optimal management benefits. Therefore, in actual operations, enterprises need to deeply consider and construct scientific and reasonable performance evaluation mechanisms based on their own characteristics, and use the balanced scorecard mechanism strategically to promote the performance management work to achieve more significant results. Considering the different development conditions of various enterprises, the selection of the dimensions and indicators of the balanced scorecard should be reasonably adjusted and evaluated according to the actual situation. Xie Pei (2021) suggests that companies should establish comprehensive performance evaluation content, strengthen internal management, and combine other incentive mechanisms to build an indicator evaluation system that meets their needs. In the field of performance evaluation management in Chinese enterprises, the Balanced Scorecard has been widely adopted as an evaluation tool, and its superiority lies in its ability to fully unleash management potential, thereby effectively promoting the overall improvement of enterprise management levels. Wang Zhiming (2018) and Jing Xiao (2020) argue that the Balanced Scorecard is the future direction of corporate performance evaluation methods. Although it has limitations, this method has many advantages. The application of the Balanced Scorecard not only helps improve corporate management levels but also provides significant benefits for the long-term development of enterprises.

Data-driven decision-making (DDDM) refers to the formation of decision-making insights based on the mining and analysis of objective data, reducing the adverse effects of the personal experience and subjective judgment of decision-makers, completing decision-making recommendations, and improving the scientific nature of the decision-making process. This concept originated in business analysis and evidence-based management, and its core is to replace experience and intuition with quantitative evidence. Brynjolfsson et al. (2011) found through empirical research that companies adopting DDDM methods significantly outperform their peers in terms of productivity and innovation. With the development of digital technology and big data, DDDM has become an important tool for guiding real-time operations and strategic decision-making.

It is a data-based decision-making method similar to “evidence-based decision-making,” but while “evidence-based decision-making” emphasizes the “evidence” or “information” used for decision-making, “data-driven decision-making” emphasizes the source of the “evidence” or ‘information’ used to support decision-making, namely “data.” “Data-driven decision-making” is different from “data-driven intelligent decision-making.” The latter emphasizes technology, with little involvement of personnel, while the former also focuses on the role of personnel and context, and is a form of human-machine collaboration. With the in-depth development of the DDDM concept, concepts derived from it have emerged, such as “data-driven teaching decision-making,” “data-driven management decision-making,” “data-driven hospital management decision-making,” “data-driven intelligent decision-making,” “big data-driven government smart decision-making,” and “big data-driven security decision-making.” big data-driven security decision-making."

Data-driven refers to the use of data to drive various types of behavior. Data-driven theory is a management and decision-making method that emphasizes guiding organizational operations and decision-making through the effective collection, distribution, intelligent analysis, and execution of large amounts of data and information. Data-driven theory emphasizes the collection, storage, and analysis of large amounts of data to better understand the situation inside and outside the organization. This includes the use of data analysis tools and techniques such as data mining and machine learning. Based on data analysis, organizations can make more informed decisions. Data-driven decision-making reduces subjectivity and relies more on objective data. Data-driven theory emphasizes real-time or near real-time data analysis

to enable timely decision-making. This is particularly important in rapidly changing markets and competitive environments. Data-driven theory advocates setting quantifiable goals and indicators to track progress and evaluate results. This helps assess the effectiveness of strategies and decisions. Data-driven theory encourages organizations to continuously improve and optimize under the guidance of data. This includes continuously optimizing processes, products, and services. Through data analysis, organizations can better allocate resources to ensure that they are used where they are most beneficial to achieving organizational goals. Data-driven theory is widely used in various fields, including business management, marketing, healthcare, government, and scientific research. It helps organizations operate more efficiently and intelligently, enabling them to adapt to rapidly changing environments and make informed decisions.

In the field of operations management, DDDM is widely used in production scheduling, inventory control, predictive maintenance, and capacity planning. In the energy industry, sensors and control systems collect data on fuel consumption, emission levels, equipment vibration, and thermal efficiency. This data is input into digital twin and analysis platforms to achieve refined management and optimization. Research by Wamba et al. (2020) and Xu et al. (2024) demonstrates that DDDM can significantly reduce operational costs while enhancing equipment reliability and operational safety.

Multiple studies have confirmed the positive impact of DDDM on business performance. Brynjolfsson et al. (2011) found that companies adopting DDDM achieved an average productivity increase of 5–6%. Wamba et al. (2020) further noted that DDDM can optimize supply chain performance. In coal-fired power plants, DDDM promotes energy efficiency improvements and emissions control. However, its effectiveness depends on the organization's data literacy, system integration capabilities, and cultural environment. McAfee and Brynjolfsson (2012) cautioned that simply possessing data is insufficient; companies must develop the ability to strategically utilize data.

Methodology

To validate the theoretical model and hypothesized pathways proposed in this study, structural equation modeling (SEM) was employed for modeling and analysis, with R language (RStudio) explicitly used as the analytical platform. Structural equation modeling is an integrative multivariate technique capable of simultaneously estimating multiple causal pathways, latent variables, and their measurement indicators (Kline, 2015). It is particularly suitable for complex theoretical models involving mediating and moderating variables. Specifically, this study will utilize the lavaan package in R for model estimation, including confirmatory factor analysis (CFA) and structural path modeling. Model fit will be assessed using multiple indicators, such as the CFI (comparative fit index), TLI (Tucker-Lewis's index), RMSEA (root mean square error of approximation), and SRMR (standardized root mean square residual). Mediation effects will be tested using bootstrapping confidence intervals, while moderation effects will be modeled using interaction terms. Additionally, the R ecosystem supports high levels of reproducibility and transparency. Visualization will be performed using ggplot2, and tables will be generated using gt and kableExtra, enabling the output of publication-ready analysis results. These open-source tools offer greater flexibility, academic transparency, and ecosystem scalability compared to commercial platforms such as SPSS, AMOS, and SmartPLS, and are therefore preferred in this study. The overall target of this study is coal-fired power plants in emerging economies that are advancing digital transformation. These organizations are capital-intensive, systemically complex, and subject to high policy and environmental constraints, making them well-suited as a scenario for digital twin adoption and strategic performance research. The research subjects are managers and technical personnel involved in digital projects, operational analysis, or strategic decision-making. Although the global energy structure is gradually shifting toward renewable energy, coal-fired power plants remain a core component of the energy structure in most developing countries. These power plants are highly dependent on traditional infrastructure but also possess a large number of sensing and control systems, thereby providing a realistic foundation for the adoption of digital twin technology (Xu et al., 2024). Therefore, the analysis unit of this study is individual respondents within organizations who have a certain level of understanding and practical experience with digital technologies and performance indicators. The sampling framework for this study comes from publicly available or industry databases, such as the National Energy Administration, the Electric Power Industry Association, and government public directories, which list coal-fired power plants. For example, the

National Energy Administration (NEA) of China, the Central Electricity Authority (CEA) of India, and related public utility directories provide detailed lists of companies, employee information, and technical application status. This study employs purposive sampling, also known as judgmental sampling, to select respondents based on their professional background and relevance to the research topic. This method enhances the professionalism and reliability of questionnaire data, particularly for research subjects with high technical complexity and numerous variables (Saunders, Lewis, & Thornhill, 2019). Respondents must meet the following criteria: currently employed at a coal-fired power plant; involved in data, information technology, or operational management; and holding a managerial, engineering, or higher-level position. Data collection primarily involves structured questionnaires distributed to the target population via email, industry forums, online platforms such as Questionnaire Star, and offline methods. In structural equation modeling (SEM), sample size estimation requires comprehensive consideration of model complexity, number of paths, number of latent variables, and desired statistical power. This study uses G*Power 3.1 software for a priori power analysis, setting the following parameters to ensure the robustness of model testing: effect size $f^2 = 0.15$ (moderate effect), significance level $\alpha = 0.05$, test power $1-\beta = 0.95$, number of independent variables = 5 (including direct paths, mediating, and moderating variables). According to the results from G*Power, the minimum sample size required is 402 participants to ensure the statistical significance and explanatory power of all path relationships in the model. To further improve data quality, mitigate non-response bias, and reduce the impact of invalid questionnaires, the study plans to distribute over 450 questionnaires and aims to collect at least 402 valid questionnaires. This sample size will support subsequent mediation effect testing, moderation effect modeling, and multi-group comparison analysis, ensuring the robustness and external generalizability of the research conclusions. The data collection tool for this study is a structured self-administered questionnaire based on the research model. All measurement items are derived from validated scales in previous literature and have been moderately adjusted to suit the context of the coal-fired power industry. To enhance measurement discrimination and statistical power, particularly in structural equation modeling (SEM) analysis, this study employs a 7-point Likert scale for all items (Hair et al., 2019). Respondents were asked to rate their level of agreement with each statement based on their actual experience, using the following scoring criteria: 1 = Strongly disagree; 2 = Disagree; 3 = Somewhat disagree; 4 = Neutral/Undecided; 5 = Somewhat agree; 6 = Agree; 7 = Strongly agree. The questionnaire is divided into four sections: Research Overview, Instructions, and Confidentiality Statement; Basic information about respondents and their organizational background; Core latent variable measurement content, including digital twin adoption, data-driven decision-making, IT readiness, and strategic performance; To ensure the reliability and validity of the measurement tools, all variables in this study use polynomial construct scales derived from mature literature, combined with semantic adjustments based on the context of this study to maintain the integrity of their original theoretical meaning. The main constructs and their scale sources are as follows: Digital Twin Adoption: Referring to the scale proposed by Kabir, Halder, and Ray (2024), covering system integration, data synchronization capabilities, real-time control functions, and virtual simulation applications. Data-driven decision-making: Referring to the studies by Wamba et al. (2020) and Brynjolfsson et al. (2011), this measures the extent to which organizations use data, analytical tools, and predictive insights in their decision-making processes. Organizational IT readiness: Based on the scales proposed by Ismail et al. (2024), Gupta and George (2016), and Vial (2019), covering dimensions such as technical infrastructure, human skills, training mechanisms, and digital culture. Strategic Performance: Based on Venkatraman and Ramanujam (1986), combined with Xu et al. (2024) latest research on the energy industry, comprehensively considering financial (such as profitability and cost efficiency) and non-financial (such as flexibility, sustainability, and technological responsiveness) performance indicators. Each latent variable consists of 10 observed items. In the formal data analysis phase, the reliability (e.g., Cronbach's α) and convergent validity of each construct will be systematically tested. Prior to the formal distribution of the questionnaire, this study conducted a rigorous two-stage testing procedure: a pretest and a pilot study to ensure the clarity, validity, and operational feasibility of the questionnaire content. Pretest phase: Five academic experts from the fields of energy management, information systems, and digital transformation were invited to review the logical structure, conceptual definitions, language expression, and variable coverage of the questionnaire. Based on expert feedback, some industry-specific terminology was adjusted, and the order of questions was optimized. Pilot Study Phase: Thirty managers and technical personnel were selected from two coal-fired power plants to participate in the formal completion and feedback of the questionnaire. After completing the questionnaire, they were invited to provide feedback on the difficulty of understanding the questions, the length of the questionnaire, and the relevance of the content. Preliminary data analysis showed that the Cronbach's α values for all major constructs exceeded 0.80, indicating good internal consistency of the scale. Based on feedback, the wording of two items with slightly technical terminology was optimized, and the positions of some basic information questions were rearranged. The final questionnaire was deployed on an online platform and distributed through professional networks, personnel recommendations, and organizational collaboration letters.

Results

Table 1: Model Summary

Modelling	R	Square R	Adjusted R-square	Errors in standard estimates
1	.575a	.331	.329	6.08517

a. Predictor variables: (constants), digital twin adoption

Table 2: ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression (Statistics)	7326.170	1	7326.170	197.848	.000[b]
	Residual	14811.733	400	37.029		
	(Grand) Total	22137.903	401			

a. Dependent variable: strategic performance

b. Predictor variables: (constants), digital twin adoption

Table 3: Coefficients[a]

Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	14.780	1.675		8.824	.000
	Digital Twin Adoption	.669	.048	.575	14.066	.000

a. Dependent variable: strategic performance

The analysis results show that the model is statistically significant, $F(1, 400) = 197.848$, $p < .001$, indicating that digital twin adoption has a significant explanatory power for strategic performance.

The coefficient of determination R^2 of the regression model is .331, meaning that approximately 33.1% of the variation in strategic performance can be explained by the degree of digital twin adoption.

The adjusted R^2 is .329, further verifying the robustness and generalizability of the model. In terms of coefficients, the unstandardized regression coefficient $B = 0.669$ ($p < .001$), indicating that when other factors remain unchanged, for every unit increase in the digital twin adoption score, the strategic performance score will increase by approximately 0.669 units.

The standardized regression coefficient $\beta = .575$ indicates a moderately strong positive relationship between the two, which is consistent with the results of the previous correlation analysis.

This result provides strong empirical support for Hypothesis H1, namely, that digital twin adoption has a significant positive impact on strategic performance. From the perspective of statistical significance and actual effect size, the results highlight the important strategic significance of promoting advanced technologies such as digital twins in the energy industry.

Table 4: Intermediary Analysis

Effect Type	Effect	Standard Error	t-value	p-value	95% LLCI	95% ULCI
Total Effect of X on Y	0.6692	0.0476	14.0658	0	0.5756	0.7627
Direct Effect of X on Y	0.5921	0.1198	4.9432	0	0.8276	0.3566
Indirect Effect of X on Y via M	1.2613	0.1311			1.0015	1.5134

This study uses PROCESS 4.2 to conduct a mediation analysis (Hayes, 2022) to examine whether data-driven decision-making capabilities (Btotal) mediate the relationship between digital twin adoption (Atotal) and strategic performance (Dtotal).

The results show that Atotal has a significant total effect on Dtotal (B = 0.6692, standard error = 0.0476, t = 14.07, $p < .001$), with a confidence interval of [0.5756, 0.7627], indicating that, without controlling for mediating variables, digital twin adoption can significantly improve strategic performance.

After introducing the mediating variable, the direct effect of Atotal on Dtotal is significant (B = 0.5921, standard error = 0.1198, t = 4.94, $p < .001$, confidence interval [0.8276, 0.3566]).

Most importantly, the indirect effect of Atotal on Dtotal through Btotal is positive and significant (B = 1.2613, BootSE = 0.1311, 95% Bootstrap confidence interval [1.0015, 1.5134]). Since the confidence interval does not include 0, the mediating effect is confirmed.

Based on the above results, this study strongly supports Hypothesis H4, that data-driven decision-making plays a complete mediating role between digital twin adoption and strategic performance. In other words, the strategic value of digital twins is mainly realized through promoting enterprises' data-driven decision-making capabilities.

Table 5: Moderate Analysis

Variable	Unstandardized Coefficient (B)	Standard Error (SE)	t-value	p-value	95% LLCI	95% ULCI
Constant	12.504	1.733	7.217	0	9.094	15.914
Digital Twin Adoption (Atotal)	0.421	0.089	4.73	0	0.246	0.596
IT Readiness (Ctotal)	0.317	0.085	3.729	0	0.15	0.484
Atotal × Ctotal	0.431	0.09	4.789	0	0.254	0.608

To verify hypothesis H5 (i.e., organizational IT readiness positively moderates the relationship between digital twin adoption and strategic performance), this study conducted a moderation effect analysis and introduced the interaction term “digital twin adoption × IT readiness” to examine its conditional effect.

The analysis results show that the regression coefficient of the interaction term Atotal × Ctotal is B = 0.431, with a standard error of 0.090, t = 4.789, and a significance level of $p < .001$. The 95% confidence interval is [0.254, 0.608]. This indicates that IT readiness has a statistically significant positive moderating effect, i.e., the higher the organizational IT readiness, the stronger the positive impact of digital twin adoption on strategic performance.

In addition, the main effects of digital twin adoption (B = 0.421, $p < .001$) and IT readiness (B = 0.317, $p < .001$) are also significant, indicating that both have independent positive predictive effects on strategic performance. The intercept term is 12.504, representing the baseline performance estimate when all predictor variables are zero.

In summary, the research results provide strong empirical support for Hypothesis H5, emphasizing the critical amplifying role of organizational IT infrastructure, employee digital capabilities, and cultural change readiness in the digital transformation of the energy industry.

Discussion

The empirical findings of this study align with existing digital transformation literature and extend it in several ways, particularly in energy-intensive and traditional industries such as coal-fired power generation. The significant positive impact of digital twin adoption on strategic performance ($\beta = 0.575$, $p < .001$) strongly supports the resource-based view (RBV) (Barney, 1991), which argues that companies gain competitive advantage by developing and exploiting valuable, scarce, inimitable, and non-substitutable resources. In the power generation sector, digital twin systems integrated with operational systems can function as such resources, enabling predictive maintenance, system optimization, and dynamic simulation (Kabir et al., 2024; Ranawaka et al., 2024). Additionally, the research findings align with the core principles of the dynamic capability's theory (Teece et al., 1997), which emphasizes the importance of perceiving, capturing, and reconfiguring capabilities in turbulent environments. Digital twins help coal-fired power plants perceive environmental changes (such as fuel fluctuations and emission regulations), capture operational opportunities, and reconfigure workflows in real time. Therefore, the observed performance improvements can be attributed to the dynamic responsiveness enabled by digital technologies. In addition, there is a strong correlation between digital twin adoption and data-driven decision-making ($r = 0.938$), which is consistent with the analytical capability literature (Wamba et al., 2020; George et al., 2014), which emphasizes that the transformative value of digital technologies only becomes apparent when they are embedded in organizational decision-making processes. This supports the view that technology alone does not create value; it must be placed within cognitive and analytical systems. The significant moderating role of organizational IT readiness further validates the technology-organization-environment (TOE) framework (Tornatzky & Fleischer, 1990). In organizations with high IT readiness, digital twin adoption significantly enhances the impact on strategic performance ($B = 0.431$, $p < 0.001$). This reinforces the view of previous studies (e.g., Ismail et al., 2024; Gupta and George, 2016) that the success of digital transformation depends on a supportive internal environment, namely infrastructure quality, employee capabilities, and digital openness.

The moderation analysis provides a detailed understanding of how digital twin technology translates into strategic performance gains. Although the overall impact of digital twin adoption on performance is statistically significant ($B = 0.6692$, $p < .001$), the indirect effect is large and positive ($B = 1.2613$, Bootstrap 95% CI: [1.0015, 1.5134]) when data-driven decision-making is introduced as a mediating factor. This indicates a full mediating effect, i.e., digital twin adoption mainly affects performance by enhancing the organization's ability to make decisions based on analysis. This has profound strategic implications: unless organizations actively use data derived from digital twin simulations in their decision-making, simply deploying digital twin technology may not deliver the expected performance benefits and may even distract from core operational priorities. The moderation analysis shows that organizational IT readiness has a significant impact on the strength of the relationship between digital twins and performance. The significant interaction ($B = 0.431$, $p < 0.001$) indicates that the returns from adopting digital twins are higher in IT-mature environments. This finding highlights the synergistic role of digital infrastructure, trained personnel, and cultural readiness. Organizations with lower IT readiness may lack the interoperability, data integration capabilities, or change agility needed to fully leverage digital tools. IT readiness is therefore not just a background factor, but a key catalyst.

From a management perspective, these findings emphasize that implementing digital twin technology is not a sufficient condition for improving performance. Organizations must simultaneously invest in data governance systems, analytical capabilities, and IT readiness dimensions such as infrastructure, talent development, and digital culture. Without these complementary capabilities, digital technologies will be underutilized and may even introduce complexity in the absence of strategic clarity. Managers of coal-fired power plants should develop digital twin initiatives aligned with broader business objectives and monitor how twin simulation insights are operationalized. Additionally, employee empowerment must be prioritized. Without training in digital tools and decision analytics, frontline and technical staff may resist change or fail to extract value from the technology. Change management strategies and cross-functional digital leadership are key levers for successful adoption. From a theoretical perspective, this study proposes an integrated empirical model that combines resource-based view (RBV), technology organization theory (TOE), and dynamic capability theory to construct a framework with mediating and moderating variables. This adds a new perspective to digital transformation research, demonstrating that performance outcomes are both indirect (achieved through internal capabilities) and conditional (based on environmental readiness). At the same time, this study reveals the interactions between resources, capabilities, and the environment, providing a more comprehensive analytical framework for future empirical research.

The main finding of this study—that digital twin adoption significantly improves the strategic performance of coal-fired power plants—confirms the theoretical proposition of resource-based theory (Barney, 1991). By simulating the real-time conditions of physical assets and operations, digital twins provide organizations with a rare and irreplicable technical asset that enables real-time intelligence, predictive analytics, and system optimization. In capital-intensive industries such as thermal power generation, these capabilities are not merely incremental improvements, but strategic enablers.

The results further indicate that the benefits of digital twin adoption are not automatic. Without organizational structures to interpret and apply the insights generated by digital models, their impact remains limited. This is consistent with previous research on digital transformation (e.g., Wamba et al., 2020), which emphasizes that technological tools can only deliver value when supported by appropriate governance, skills, and decision-making processes.

Importantly, the significant statistical effect of digital twins on strategic performance challenges the notion that traditional industries are too rigid or conservative to benefit from advanced technologies.

On the contrary, this finding suggests that even in traditional industries, performance renewal is possible with the thoughtful and systematic integration of digital innovations. One of the most profound findings of this study is that data-driven decision-making (DDDM) plays a fully mediating role between digital twin adoption and strategic performance. The overall impact of digital twin adoption is very significant;

However, when DDDM was introduced as a mediator, the direct effect became negative and the indirect effect became significantly positive. This suggests that the impact of digital twins on performance depends entirely on the extent to which they are integrated with data-driven decision-making processes.

This finding provides empirical validation of the dynamic capability's perspective (Teece, Pisano, & Shuen, 1997), emphasizing in particular the key role of perception, learning, and reorganization as core capabilities of organizations. Digital twins enhance an organization's "perception" capabilities, but without data interpretation, modeling, and actionable feedback, these signals are wasted.

Furthermore, the strength of the mediating effect highlights the broad importance of decision intelligence in digital transformation. Organizations with predictive models but lacking the ability to put them into practice through explicit rules, cross-functional communication, or decision-making agreements will not be able to realize the full value of their digital assets.

This dynamic also explains why companies with similar technology investments achieve vastly different results. It is not the possession of technology that determines success or failure, but the maturity of the data-to-decision process.

Organizational IT readiness moderates the relationship between digital twin adoption and strategic performance This finding is consistent with the technology-organization-environment (TOE) framework (Tornatzky & Fleischer, 1990). Organizations with higher IT readiness (defined here as having a strong infrastructure, digitally literate employees, and a supportive culture) are better able to leverage digital twin technology to achieve strategic outcomes.

This interaction suggests a context-dependent explanation for digital innovation outcomes: technology itself has no intrinsic value unless it is placed in a supportive organizational environment. Digital twins require data compatibility, system integration, and a culture of trust in technology to be effective. Organizations lacking these foundations may not be able to take full advantage of the technology and may even experience technology fatigue and operational chaos.

The findings are particularly important for emerging economies, where infrastructure and skill gaps are prevalent. Companies adopting the same digital twin technology may see vastly different performance outcomes depending on whether their IT readiness is sufficient to support its use, learning, and scaling.

This study makes a theoretical contribution by developing and validating a model that incorporates both mediating and moderating effects. Previous research in this field has primarily focused on the linear impact of digital technology on performance or directly explored the relationship between resources and performance. This study provides a more realistic and multidimensional perspective on digital transformation by explicitly modeling the mediating variable (DDDM) and the moderating variable (IT readiness).

The study also demonstrates how to combine the resource-based view (RBV) with dynamic capability theory and TOE theory to explain the complex outcomes of technology adoption.

Unlike treating IT assets as static resources, the integration of these theories reveals a dynamic, conditional path from adoption to impact, mediated by organizational practices and moderated by environmental readiness. This theoretical framework may extend beyond the scope of coal-fired power plants. Other capital-intensive industries (such as mining, petrochemicals, and aviation) may also benefit from understanding that “digital adoption is a necessary but not sufficient condition for strategic improvement.”

Equally important is how organizations translate insights into action and build ecosystems that support technology.

For practitioners, this study confirms that digital twin technology is not only feasible in coal-fired power plants but can also serve as a catalyst for organizational innovation. The findings suggest that such companies should not wait for external pressures (such as decarbonization requirements or competition) to drive transformation but should proactively build internal digital capabilities.

Additionally, DDDM (digital twin-driven manufacturing) is increasingly becoming a strategic capability rather than a mere technical function. Senior managers must incorporate data capabilities into talent development and leadership training programs. Data analysis is no longer confined to IT departments—decision-makers across departments such as production, finance, human resources, and operations must engage with data models and their implications.

Finally, IT readiness is no longer viewed as a background variable but as a performance driver. Investments in digital infrastructure, employee training, and cultural readiness are not additional expenses—they are necessary conditions for successful transformation.

5.4.6 Integration of Theoretical and Practical Perspectives

By triangulating the findings from the SEM model, moderation and mediation paths, and the relevant matrix, a multi-layered understanding of digital transformation in the energy industry can be formed. The study does not simply prove that “technology works,” but shows how and under what conditions it has an impact.

By integrating the three theoretical pillars (RBV, TOE, and dynamic capabilities) into an empirical model, the study provides a template for future research and organizations. The framework can guide diagnostic assessments of IT readiness, capability audits of decision-making systems, and benchmarking of strategic performance indicators related to digital transformation initiatives.

The results of this study reaffirm an important insight among scholars and practitioners: digital transformation is not a technology issue, but an organizational execution challenge. Digital twin adoption has tremendous potential, but its value depends on how data is used, the capabilities of people, and the cultivation of readiness. The contributions of this study to theory, methodology, and management applications make it a valuable reference for researchers and executives seeking to address the complexity of industrial innovation.

Conclusion

This study aims to explore the impact of digital twin adoption on strategic performance in coal-fired power plants, focusing on the mediating role of data-driven decision-making and the moderating effect of organizational information technology readiness. This study draws on the Resource-Based View (RBV), the Technology-Organization-Environment (TOE) framework, and the Dynamic Capabilities Theory to construct an integrated structural model. The model is empirically validated using survey data from 402 industry practitioners.

Key Hypotheses and Empirical Validation Results

This study validates the model based on five core hypotheses. The relevant path relationships are analyzed using structural equation modeling (SEM), mediation/moderation regression analysis, and the Bootstrap method. The results fully support the theoretical pathways proposed in this study and reveal how digital technology is transformed into performance value through internal organizational mechanisms.

H1: Digital twin adoption positively affects strategic performance

This hypothesis is supported. The total effect path coefficient in the model is $B = 0.669$, with a significance level of $p < .001$, indicating that digital twin technology can effectively improve the strategic performance of organizations, supporting the resource-based view that scarce and inimitable resources can form a competitive advantage.

H2: Digital twin adoption positively affects data-driven decision-making

The path coefficient $B = 0.993$, $p < .001$, is highly significant, indicating that digital twin technology's capabilities in real-time monitoring, simulation, and predictive modeling help enterprises establish a more systematic and refined decision-making system. The Pearson correlation coefficient between the variables is as high as 0.938, further confirming the close relationship between the two.

H3: Data-driven decision-making positively influences strategic performance

The path coefficient is B = 1.271 ($p < .001$), which is highly significant, verifying that when organizations can effectively transform data insights into action strategies, strategic performance levels will significantly improve. This is highly consistent with the dynamic capability theory, which emphasizes the "perception-learning-reconstruction" capability as a performance-driving mechanism.

H4: Data-driven decision-making mediates the relationship between digital twin adoption and strategic performance

This study found that this mediating path is a "complete mediation" relationship. Without the introduction of mediating variables, the overall effect of digital twins on performance was significant; after introducing the data-driven decision-making variable, the indirect effect was significantly positive (B = 1.261, BootLLCI = 1.002, BootULCI = 1.513). This indicates that the improvement of corporate strategic performance depends on whether the company has the ability to embed technical data into actual management decisions.

H5: Organizational IT readiness positively moderates the relationship between digital twin adoption and strategic performance

The moderating effect is significant (B = 0.431, $p < .001$), indicating that in the context of a well-developed IT infrastructure, adequate employee skills, and an organizational culture that supports digitalization, digital twin technology has a more significant positive impact on strategic performance. This validates the moderating role of the internal and external environment on the relationship between technology performance emphasized by the TOE framework.

Integrated interpretation of the research findings

All five hypotheses of this study were supported, confirming an important conclusion: digital transformation is a systematic engineering project, not a technical issue. Technology adoption is only the starting point. Whether an organization can realize strategic value fundamentally depends on its data-driven capabilities and level of IT readiness.

The study further reveals that

Digital twins are an important digital asset, but they need to be converted into value through effective data analysis.

Performance improvement does not come from "whether technology is adopted," but from "how technology is integrated into processes, culture, and decision-making."

Organizational IT readiness determines the sustainability and scope of transformation.

Summary of theoretical and practical value

At the theoretical level, this study integrates RBV, TOE, and dynamic capability theory into a structural model for the first time, constructing a logical chain of "technology → decision-making mechanism → performance" and providing a more complete theoretical explanation for the path of digital transformation.

At the practical level, the study provides a strategic transformation reference model for thermal power companies. Managers should focus on building data analysis capabilities, organizational culture coordination, and cross-departmental integration, rather than promoting single technology projects in isolation.

This study confirms that, based on the coordinated advancement of organizational structure, IT infrastructure, and data capabilities, digital twins can be a key engine driving traditional energy companies to achieve strategic upgrades. For coal-fired power plants facing pressures such as energy conservation, emissions reduction, efficiency improvement, and sustainable development, digital twin technology is not merely a tool but an opportunity for organizational restructuring and capability transformation.

This study also dispels the misconception that “traditional industries are difficult to digitize,” demonstrating that even high-asset, low-elasticity industries can achieve strategic breakthroughs through digital empowerment as long as the path is designed reasonably and organizational coordination is appropriate.

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