ASRC
Procedia
Global Perspectives in
Science and Scholarship
Florida, USA

Volume: 1; **Issue:** 1
Pages: 2160– 2201
Published: 29 April 2025

open
access

1st Global Research and Innovation Conference 2025,

April 20–24, 2025, Florida, USA

AI-Enabled Decision Support Systems for Industrial Energy Optimization in U.S. Manufacturing

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Doi: 10.63125/8vyhwm46
Peer-review under responsibility of the organizing committee of GRIC, 2025

Abstract

This study addresses the persistent problem of inefficient and reactive energy management in U.S. manufacturing, where fragmented monitoring, delayed reporting, and weak coordination often lead to avoidable energy waste, higher operating costs, and weaker sustainability performance. The purpose of the research was to examine whether AI-enabled decision support systems improve industrial energy optimization by strengthening data-driven decision quality across manufacturing operations. Using a quantitative, cross-sectional, case-based design, the study collected structured questionnaire data from 240 respondents drawn from cloud-enabled and enterprise-oriented manufacturing cases, including plant managers, production supervisors, maintenance engineers, sustainability officers, and data or operations analysts in medium and large firms. The key independent variables were AI-enabled decision support systems capability, predictive analytics capability, and real-time monitoring and automation, while industrial energy optimization served as the main dependent variable, with operational cost reduction and sustainability performance treated as linked outcome variables. Data were analyzed using descriptive statistics, reliability analysis, Pearson correlation, and multiple regression. Findings showed strong internal consistency across constructs, with Cronbach's alpha values ranging from 0.81 to 0.88. Descriptive results were highly positive, including mean scores of 4.12 for AI-enabled DSS capability, 4.06 for predictive analytics capability, 4.18 for real-time monitoring and automation, and 4.21 for industrial energy optimization. Correlation analysis indicated significant positive relationships with industrial energy optimization for AI-enabled DSS capability ($r = 0.61$, $p < .01$), predictive analytics capability ($r = 0.58$, $p < .01$), and real-time monitoring and automation ($r = 0.66$, $p < .01$). Regression results further revealed that the model explained 54.7% of the variance in industrial energy optimization ($R^2 = 0.547$; $F = 95.140$; $p < .001$), with real-time monitoring and automation emerging as the strongest predictor ($\beta = 0.370$), followed by AI-enabled DSS capability ($\beta = 0.290$) and predictive analytics capability ($\beta = 0.240$). The study implies that manufacturers can achieve better energy efficiency, cost control, and sustainability outcomes by integrating intelligent decision support, predictive analytics, and real-time automated monitoring into operational routines.

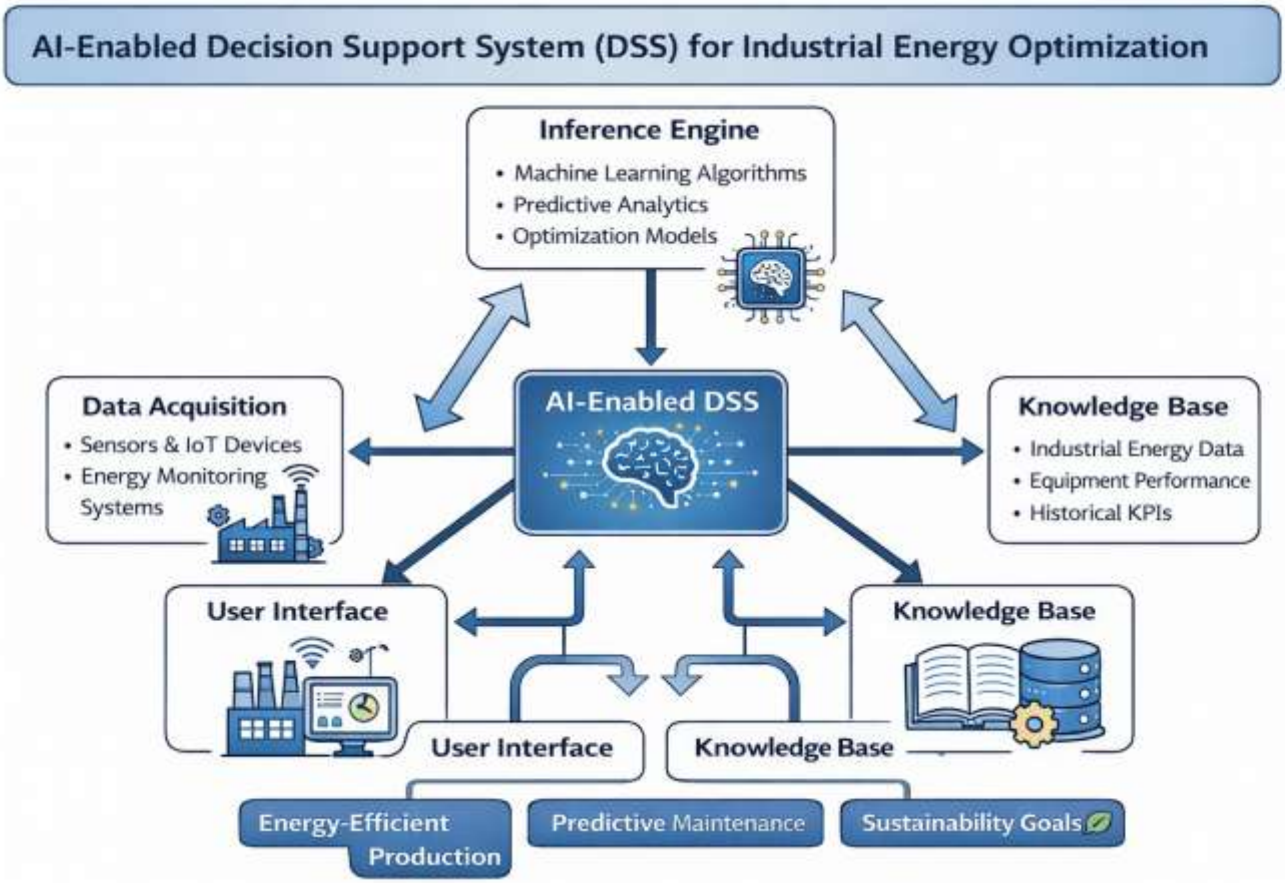
Keywords
AI-Enabled Decision Support Systems; Industrial Energy Optimization; Predictive Analytics; Real-Time Monitoring And Automation; U.S. Manufacturing;

INTRODUCTION

Artificial intelligence (AI) is widely understood in engineering, management, and information systems scholarship as a collection of computational methods that enable machines to perform tasks associated with learning, reasoning, prediction, classification, optimization, and adaptive decision making. In parallel, decision support systems (DSS) are commonly defined as integrated systems composed of data resources, analytical models, interfaces, and procedural logic that assist human decision makers in solving structured and semi-structured problems (Bänsch et al., 2021). In industrial settings, an AI-enabled decision support system refers to a digital environment in which data acquisition, analytics, prediction, optimization routines, and decision logic are combined to support managers and engineers in choosing actions with greater speed, consistency, and precision. Industrial energy optimization, in turn, refers to the systematic improvement of energy efficiency and the reduction of avoidable energy loss across production equipment, process flows, utilities, and supporting plant infrastructure while maintaining product quality and operational continuity (Cioffi et al., 2020). These concepts carry international significance because manufacturing remains one of the most energy-intensive sectors in the global economy, and energy-related inefficiency directly affects competitiveness, cost structure, and environmental performance. Research on manufacturing energy performance has shown that energy use is shaped not only by machine design and process technology, but also by scheduling choices, process integration, monitoring quality, and broader managerial control systems (Biel & Glock, 2016). This perspective was strengthened in later literature showing that sustainable manufacturing requires analytical visibility into process flows, production states, and performance trade-offs rather than reliance on isolated technical interventions alone. The growing international relevance of this topic is also connected to globally distributed supply chains, where energy efficiency influences cost resilience, environmental accountability, and strategic positioning across industrial economies (Chen & Jin, 2023). As a result, recent smart manufacturing research has increasingly treated energy performance as an integrated managerial and digital issue linked to real-time information, automation, and industrial intelligence. More recent studies have gone further by linking AI-supported analytics with resource efficiency, sustainability outcomes, and energy-aware factory control, showing that digital intelligence now plays a central role in how firms interpret energy demand, detect inefficiencies, and organize operational responses. Within this scholarly development, AI-enabled DSS emerges as a highly relevant construct because it connects technological capability with managerial judgment in a setting where small improvements in decision quality can produce meaningful gains in energy performance and industrial competitiveness (Edgar & Pistikopoulos, 2018).

The literature on industrial energy management has gradually evolved from a narrow engineering emphasis on equipment efficiency toward a broader systems-oriented understanding of how factories consume, monitor, and optimize energy. Earlier studies gave considerable attention to conservation technologies, process design, policy structures, and energy standards as mechanisms for improving industrial performance (Ara, 2021; Park et al., 2009). This line of work was extended through simulation-based manufacturing research showing that energy efficiency can be improved more effectively when production processes are modeled as connected chains rather than isolated steps, which allows planners to examine temporal load variation, idle conditions, and dependencies among operations (Ahmed & Hasan Or, 2021; Robel & Morshedul, 2021). Critical reviews later demonstrated that energy efficiency in manufacturing is not simply a technical output but a multidimensional organizational issue that involves production systems, process engineering, managerial coordination, and performance measurement (Aditya & Robel, 2022; Istiaq & Nusrat, 2022; Sarswatula et al., 2022). In sustainable manufacturing scholarship, energy optimization came to be framed as part of the wider operational logic of productivity, cleaner production, and environmental stewardship rather than as a peripheral maintenance concern. Similar syntheses in the literature on manufacturing assessment tools have treated industrial plants as complex systems in which energy performance depends on coordinated evaluation of machines, material flows, utilities, and production schedules (Khaled & Hisham, 2022; Mehedi & Md, 2022). The cumulative implication of this body of research is that improvements in industrial energy performance require the management of information as much as the management of equipment. That insight has international relevance because manufacturing sectors around the world face common pressures related to cost control, resource efficiency, climate accountability, and operational resilience, even though their specific energy profiles differ. Reviews of smart manufacturing and industrial sustainability consistently indicate that digitalization has become a major mechanism through which firms pursue more intelligent use of energy, materials, and production capacity (Faria et al., 2021; Mainuddin & Chandra, 2022; Morshedul et al., 2022). In this sense, industrial energy optimization is best understood not as a purely mechanical adjustment problem, but as a systems problem grounded in information, analytics, and decision support. This broader historical transition provides a strong basis for positioning AI-enabled DSS within the evolution of industrial energy scholarship.

Figure 1: AI-Enabled DSS Architecture for Industrial Energy Optimization



A major stream of research has examined the ways in which manufacturing firms transform energy-related data into actionable managerial knowledge (Nazmul & Begum, 2022; Shahinur & Sultan, 2022). One particularly influential development has been the use of energy-related key performance indicators (KPIs), which allow organizations to formalize objectives, compare performance across units, and identify areas where intervention is needed. KPI-based energy management has been proposed as a structured way to improve manufacturing efficiency, with evidence showing that performance measurement enables more disciplined organizational responses to energy use (Begum & Kaniz, 2023; Panagoulias et al., 2023; Binte & Hasan Or, 2022). This line of reasoning was extended in work on the implementation of energy-efficiency KPIs in manufacturing, where operational performance became more manageable once energy indicators were embedded in decision processes and routine managerial reporting. Methodological research on KPI analysis has further argued that indicators create stronger value when they are analytically connected to operational behavior and managerial goals rather than reported as isolated numbers (Ara & Onyinyechi, 2023; Islam & Aditya, 2023; Pandey et al., 2023). This literature is closely tied to the decision-support tradition because metrics generate real value only when they are interpreted within systems that help users understand their meaning and relevance (Mahfuj Ahmed & Mehedi, 2023; Hasan Or et al., 2023). Reviews of decision-support models for energy-efficient production planning have shown that energy-aware planning requires formal models that reconcile throughput, lead time, machine allocation, and electricity consumption within a common decision environment (Mainuddin & Chandra, 2023; Mehedi & Nahar, 2023). A similar conclusion was reached in systematic work on energy-aware decision support in production environments, where decision models were shown to be most useful when they align production targets with energy considerations in a timely and analytically coherent manner. The importance of these studies lies in their demonstration that industrial energy optimization depends on analytical structures that convert operational data into prioritized decisions (Mostafa, 2023; Chandra, 2023). This also explains why the manufacturing literature increasingly intersects with predictive analytics. When organizations use consumption histories, load profiles, operating conditions, and process states to forecast energy patterns, decision making becomes more proactive and less dependent on reactive corrections (Begum & Kaniz, 2024; Khatun & Zakia, 2023; Shin et al., 2014). AI-enabled DSS can therefore be viewed as an extension of the KPI and analytical-modeling tradition, integrating measurement, prediction, and optimization within a single decision architecture. At the international level, such capability matters because globally competitive manufacturing requires not only efficient machinery but also efficient managerial cognition supported by intelligent analytical systems (Supekar et al., 2019).

The rise of Industry 4.0 and cyber-physical production systems has significantly transformed the study of industrial energy optimization by introducing high-frequency data capture, interconnected machines, digital twins, and more advanced monitoring infrastructures (Khaled & Morshedul, 2024; Mehedi & Nahar, 2024). Cyber-physical systems in manufacturing have been described as a major architectural shift that integrates computation, communication, and physical processes in ways that support more adaptive and intelligent industrial management. This transformation is directly relevant to energy optimization because energy use is embedded in the behavior of interconnected machines, logistics systems, control architectures, and plant utilities (Fysikopoulos et al., 2013; Towhidul & Uddin, 2024; Robel & Morshedul, 2024). Research linking smart manufacturing and energy systems has shown that production intelligence and energy intelligence increasingly overlap in modern industrial operations, since production adjustments shape energy demand and energy conditions influence operating choices. Reviews of smart manufacturing for sustainable industry have echoed this interpretation by documenting how digital technologies, data platforms, and intelligent systems can improve resource utilization and operational responsiveness across manufacturing environments. Additional review evidence has shown that smart manufacturing contributes to energy conservation because digital visibility enables organizations to detect non-value-adding consumption, coordinate equipment states more precisely, and refine process-control decisions (Zakia & Khatun, 2024). A framework for quantifying the energy and productivity benefits of smart manufacturing technologies has further shown that digital investments can create measurable efficiency gains when they improve both energy performance and operational value creation (Herrmann & Thiede, 2009). This body of work is highly relevant to the current study because it places AI-enabled DSS within a larger industrial transformation characterized by sensor-driven data flows, connected assets, and responsive decision environments. Once production systems and facility infrastructure become continuous sources of operational data, decision support can move beyond retrospective reporting toward real-time analytical intervention. The international significance of this transition is substantial because smart-manufacturing capability is increasingly associated with productivity, sustainability, and competitive performance across industrial economies. Under such conditions, industrial energy optimization becomes inseparable from digital capability, and AI-enabled DSS represents a practical form of organized intelligence for managing energy-intensive industrial operations (Solnørdal & Foss, 2018).

Within this digitalized context, AI methods have become increasingly important to industrial energy management because they enable firms to forecast demand, classify operating states, detect anomalies, support predictive maintenance, and optimize load-related decisions under uncertainty. Comprehensive review research on AI applications for resource efficiency in manufacturing has shown that predictive maintenance, fault detection, and production planning are among the most significant domains in which AI can improve industrial performance. This discussion has moved closer to energy management in studies proposing industrial AI-based energy management systems that integrate electricity load forecasting and fault prediction, thereby illustrating how predictive intelligence can support both operational reliability and energy planning (May et al., 2015). Machine learning research on industrial energy consumption has similarly demonstrated that energy behavior can be modeled with greater accuracy when organizations rely on advanced analytical approaches rather than static comparisons or simple averages. Context-based decision support research has added another important dimension by showing that energy-efficiency decisions in industrial plants become stronger when support systems incorporate information about operational constraints, process conditions, and the surrounding production environment. This is especially important because energy decisions in manufacturing rarely have uniform solutions; they depend on product mix, scheduling conditions, equipment health, ambient influences, and organizational priorities (Meng et al., 2018). AI-enabled DSS is therefore significant not only because it automates analysis, but because it can integrate heterogeneous inputs and generate contextually relevant recommendations tailored to specific operational realities. Empirical evidence has also suggested that AI-related capabilities can contribute to improved firm-level energy efficiency in manufacturing companies. Broader review literature supports the same conclusion by indicating that AI creates the strongest value when it is embedded in managerial workflows and operational routines rather than treated as a stand-alone technological addition. Collectively, these studies present AI-enabled DSS as an applied managerial capability that helps firms interpret complexity within energy-intensive production systems. In internationally competitive manufacturing environments, where profitability and sustainability often depend on managing thin margins and high resource intensity simultaneously, such analytical capability becomes increasingly valuable (Hu et al., 2022).

Another major theme in the literature concerns the credibility, interpretability, and measurable outcomes of intelligent systems within industrial settings. Energy optimization in manufacturing is not only about generating accurate predictions; it also requires managerial trust in system outputs, alignment with plant priorities, and evidence that analytics contribute to meaningful operational results. Research on explainable AI for energy management has argued that intelligent decision support becomes more effective when users can understand how recommendations are produced and how those recommendations relate to stakeholder needs and operational goals. This issue is especially important in industrial environments, where engineers, production managers, maintenance personnel, and sustainability officers often evaluate decisions using different criteria, including throughput stability, equipment reliability, cost control, and emissions performance. Explainability therefore strengthens organizational acceptance of AI-enabled DSS by making analytics more transparent and easier to justify in operational contexts (Schmidt et al., 2017). At the level of measurable outcomes, empirical evidence from manufacturing firms has shown that AI can be associated with carbon-emission reduction, particularly when it operates alongside green innovation capabilities. Related review work has also connected smart factory decision environments with sustainability and energy efficiency, reinforcing the idea that digital intelligence can support both production goals and resource conservation. A systematic review on drivers of energy efficiency in manufacturing firms has further shown that organizational and strategic enablers are critical in translating efficiency opportunities into realized performance improvements (Stock & Seliger, 2016). This interpretation aligns closely with resource-based thinking in management studies, where valuable information systems create advantage when they are integrated into routines, decisions, and continuous-improvement practices. Review research on AI applications in power-system operation, planning, and control reinforces this broader logic by showing that intelligent analytics are especially useful in complex energy environments requiring coordination, prioritization, and timely response. Taken together, these studies suggest that AI-enabled DSS should be understood as a socio-technical capability rather than merely a computational tool. Its importance becomes visible when it improves the quality of energy-related information, strengthens confidence in managerial choices, and contributes to observable improvements in efficiency, carbon performance, and industrial sustainability (Menghi et al., 2019).

This study is located at the intersection of these scholarly conversations and focuses specifically on U.S. manufacturing, where industrial energy optimization remains an important issue for competitiveness, operational performance, and sustainability governance (Neves-Silva & Camarinha-Matos, 2022). The U.S. manufacturing context is analytically valuable because it includes a diverse industrial base, substantial variation in plant size and digital maturity, and a wide range of energy-intensive subsectors in which AI-enabled decision support may operate differently. Existing research has already shown that energy-efficient manufacturing depends on integrated planning, appropriate performance indicators, intelligent monitoring, and responsive production control. It has also shown that smart-manufacturing technologies can generate measurable energy and productivity benefits when digital infrastructures are combined with operational decision processes (Terry et al., 2020). What remains particularly important for empirical investigation is the firm-level relationship between AI-enabled DSS capabilities and concrete outcomes such as industrial energy optimization, cost efficiency, and sustainability performance. The present study therefore positions AI-enabled DSS capability, predictive analytics capability, and real-time monitoring and automation as central explanatory constructs, while industrial energy optimization is treated as the primary outcome of interest within a quantitative, cross-sectional, and case-study-based design (Waltersmann et al., 2021). This framing is consistent with literature showing that energy decisions in manufacturing are shaped by data visibility, analytical modeling, performance measurement, and contextual decision logic. It is also consistent with empirical and review studies demonstrating that AI and related digital capabilities have meaningful relationships with energy efficiency, resource efficiency, and sustainability outcomes in manufacturing firms. By grounding the study in this literature, the introduction establishes a clear basis for examining how intelligent decision systems relate to energy optimization in industrial operations across the United States (Liu et al., 2022).

Background of the Study

The background of this study is rooted in the growing importance of intelligent energy management within modern manufacturing systems, particularly in the United States where industrial production remains a major contributor to economic output and energy consumption. Manufacturing plants rely heavily on electricity, thermal energy, machine power, compressed air systems, and process-intensive equipment to maintain production continuity, product quality, and operational efficiency. As production systems become more complex, energy use is no longer determined only by the technical efficiency of machines, but also by the quality of managerial decisions related to scheduling, load balancing, maintenance, process coordination, and resource allocation. In many industrial environments, energy losses occur through avoidable downtime, inefficient operating patterns, poor monitoring, delayed maintenance responses, and limited visibility into real-time plant conditions. These challenges have created a strong need for more advanced decision-making systems that can help firms move beyond traditional, reactive approaches to energy management. At the same time, the rise of digital manufacturing has introduced new opportunities for firms to collect, process, and analyze operational data at a much deeper level than before. Artificial intelligence–enabled decision support systems have emerged within this context as an important technological and managerial solution because they combine data analytics, predictive modeling, real-time monitoring, and optimization logic to support better industrial decisions. Such systems can help manufacturing organizations identify inefficient energy patterns, forecast demand, detect abnormal consumption behavior, improve equipment utilization, and support timely interventions that reduce operational waste. In the U.S. manufacturing sector, where firms face pressure to improve productivity, reduce costs, comply with sustainability goals, and remain globally competitive, the integration of AI-enabled decision support into industrial energy management has become increasingly relevant. This study is therefore grounded in the broader transformation of manufacturing from conventional process control toward intelligent, data-driven operational management. It focuses on how AI-enabled decision support systems can contribute to industrial energy optimization by strengthening the analytical quality of decisions made within manufacturing environments. The background of the study reflects the need to understand this relationship in a structured empirical way, especially in a setting where energy performance, operational efficiency, and strategic competitiveness are closely interconnected.

Problem Statement

The problem addressed in this study arises from the continuing difficulty many manufacturing firms experience in achieving consistent and intelligent control over industrial energy use, even as energy efficiency has become a central operational and strategic priority. In U.S. manufacturing, energy is consumed across production lines, thermal systems, machine operations, facility support infrastructure, and process coordination activities, yet this consumption is often managed through fragmented systems, delayed reporting structures, and largely reactive decision routines. Many firms possess large volumes of operational data, but the existence of data alone does not ensure that managers and engineers can interpret it effectively or translate it into timely energy-saving actions. As a result, energy losses frequently persist through inefficient equipment usage, poor production scheduling, limited visibility into abnormal consumption patterns, slow maintenance responses, and weak coordination between operational planning and energy management. The growing complexity of manufacturing environments has made these problems more serious because plants now operate with interconnected machines, automated processes, variable production loads, and performance pressures that require fast and accurate decisions. Traditional energy management approaches are often insufficient in such environments because they tend to focus on monitoring historical consumption rather than supporting predictive, optimized, and context-sensitive decision making. At the same time, artificial intelligence–enabled decision support systems are increasingly presented as a promising solution for improving industrial energy optimization by combining analytics, forecasting, monitoring, and decision logic into a more intelligent managerial framework. Even so, there remains limited empirical understanding of how these systems actually relate to energy optimization outcomes within U.S. manufacturing settings. Much of the existing discussion emphasizes technological potential, conceptual models, or broad digital transformation benefits, while comparatively less attention has been given to measuring the relationship between AI-enabled decision support capability and concrete energy-related outcomes such as efficiency improvement, cost reduction, and sustainability performance. This creates an important research problem because manufacturing firms need evidence-based understanding of whether predictive analytics, real-time monitoring, and intelligent decision support meaningfully improve industrial energy management. The study therefore responds to the need for a structured quantitative investigation into how AI-enabled decision support systems influence industrial energy optimization in U.S. manufacturing and whether these capabilities are associated with stronger operational and sustainability outcomes.

Objectives of the Study

The objective of this study is to examine, in a structured and measurable way, how AI-enabled decision support systems contribute to industrial energy optimization in U.S. manufacturing environments. The study is designed around the idea that energy efficiency in manufacturing is not only a technical issue but also a decision-quality issue shaped by the ability of firms to collect, interpret, and act upon operational information. In this context, the research seeks to evaluate whether AI-enabled decision support capability improves the quality of energy-related decisions across industrial processes and whether such improvement is reflected in stronger optimization outcomes. More specifically, the study aims to assess the relationship between AI-enabled decision support systems and industrial energy optimization by focusing on three central capability areas: intelligent decision support, predictive analytics, and real-time monitoring with automation. The first objective is to determine whether AI-enabled decision support systems have a significant influence on the ability of manufacturing firms to reduce avoidable energy waste and improve energy efficiency across plant operations. The second objective is to examine whether predictive analytics capability strengthens energy optimization by helping firms forecast demand, anticipate inefficiencies, and respond to operational variation before waste becomes embedded in the production process. The third objective is to assess whether real-time monitoring and automation improve the responsiveness and effectiveness of energy management decisions in manufacturing environments where timing, coordination, and continuous process visibility are critical. In addition to these core objectives, the study also seeks to determine whether industrial energy optimization contributes to broader organizational outcomes, particularly operational cost reduction and sustainability performance. This objective-based structure allows the research to move beyond broad discussion of digital transformation and focus instead on measurable relationships among technological capability, decision quality, and industrial performance. The final part of the introduction is therefore anchored in a clear empirical purpose: to test whether AI-enabled decision support systems function as meaningful drivers of improved energy optimization in U.S. manufacturing and to provide evidence on the extent to which such systems support efficiency, cost control, and sustainability in contemporary industrial settings.

Research Hypotheses

The research hypotheses of this study are formulated to test the expected relationships among AI-enabled decision support capability, predictive analytics, real-time monitoring and automation, industrial energy optimization, and broader organizational performance outcomes. These hypotheses are grounded in the central assumption that improved energy performance in manufacturing depends not only on equipment or process design but also on the intelligence, timeliness, and quality of the decisions made within production environments. The first hypothesis proposes that AI-enabled decision support systems have a significant positive effect on industrial energy optimization. This hypothesis reflects the expectation that when firms use intelligent systems to support operational judgment, they are better able to detect waste, prioritize interventions, and manage energy-intensive activities more effectively. The second hypothesis proposes that predictive analytics capability has a significant positive relationship with industrial energy optimization. This assumption is based on the idea that the ability to anticipate energy demand, identify abnormal patterns, and forecast operational needs strengthens the capacity of firms to reduce inefficiency before it becomes costly. The third hypothesis states that real-time monitoring and automation have a significant positive relationship with industrial energy optimization. This hypothesis recognizes that fast access to operational information, combined with responsive system behavior, can improve the timing and accuracy of energy-related decisions across manufacturing processes. The fourth hypothesis proposes that industrial energy optimization has a significant positive relationship with operational cost reduction and sustainability performance. This position reflects the view that better management of energy consumption should produce not only efficiency gains but also broader organizational benefits through lower operating costs, reduced waste, and stronger alignment with sustainability objectives. Together, these hypotheses create a logical empirical framework for testing whether AI-enabled analytical and monitoring capabilities are associated with meaningful improvements in manufacturing energy outcomes. They also allow the study to move from general claims about intelligent systems into measurable statistical testing, where relationships among key constructs can be examined through descriptive analysis, correlation, and regression modeling. In this way, the hypotheses serve as the formal bridge between the conceptual structure of the study and the quantitative evidence required to evaluate whether AI-enabled decision support systems truly contribute to industrial energy optimization in U.S. manufacturing.

Significance of the Research

The significance of this research can be understood across several practical, academic, managerial, and policy-oriented dimensions.

(i) **Practical significance to manufacturing firms:** This study is important because it addresses a highly relevant operational challenge in modern manufacturing, namely how to optimize industrial energy use through more intelligent decision-making systems. Manufacturing firms require clear evidence on whether AI-enabled decision support systems can reduce waste, improve process efficiency, and strengthen plant-level energy performance. The findings of this study can help firms better understand the value of integrating predictive analytics, monitoring systems, and decision intelligence into daily industrial operations.

(ii) **Managerial significance:** The study is also significant for plant managers, production supervisors, energy officers, and operations leaders who are responsible for making timely and effective decisions in complex manufacturing environments. By examining how AI-enabled decision support systems influence energy optimization, the research offers a clearer basis for managerial decision making regarding digital investment, operational control, and energy strategy. It helps decision-makers understand which technological capabilities may contribute most strongly to cost control and process efficiency.

(iii) **Academic significance:** From a scholarly perspective, this research contributes to the literature on artificial intelligence, decision support systems, industrial energy management, and smart manufacturing. It provides an empirical and quantitative examination of relationships that are often discussed conceptually but are less frequently tested in an integrated way. The study therefore adds structured evidence to an area where more industry-specific and outcome-oriented research is needed.

(iv) **Methodological significance:** This research is significant methodologically because it applies a quantitative, cross-sectional, case-study–based approach to test the relationships among key constructs using descriptive statistics, correlation analysis, and regression modeling. In doing so, it provides a useful empirical model for examining similar questions in other industrial and technological contexts.

(v) **Policy and sustainability significance:** The study also has significance for policymakers and sustainability advocates because energy efficiency in manufacturing is closely linked to national productivity, environmental responsibility, and industrial resilience. Understanding whether AI-enabled decision support systems improve energy optimization can support more informed strategies for promoting energy-efficient industrial transformation.

(vi) **Strategic significance:** Finally, the research is significant because it links energy optimization with competitiveness, cost reduction, and sustainability performance, showing that intelligent energy management is not only a technical matter but also a strategic concern within U.S. manufacturing.

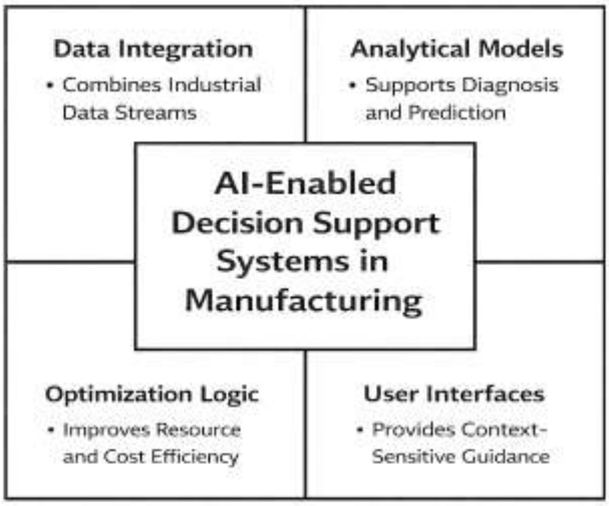
LITERATURE REVIEW

The literature review for this study is developed from the understanding that AI-enabled decision support systems for industrial energy optimization lie at the intersection of several important research streams, including artificial intelligence, decision support systems, industrial energy management, predictive analytics, smart manufacturing, and sustainability-oriented operational performance. A review of the literature is necessary because the topic cannot be understood through one discipline alone; it requires an integrated examination of how digital intelligence, managerial decision processes, and industrial energy use interact within manufacturing settings. The literature first establishes the meaning and role of AI-enabled decision support systems in organizational environments, particularly their capacity to support analytical judgment, improve responsiveness, and transform raw operational data into actionable insights. It then explores industrial energy optimization as a major concern in manufacturing research, where energy efficiency is increasingly linked with productivity, cost control, process stability, and sustainability performance. A key part of the literature also focuses on predictive analytics, real-time monitoring, and automation, since these capabilities represent the functional mechanisms through which AI-enabled decision support systems are expected to influence plant-level energy decisions. In addition, the literature review is essential for identifying the theoretical foundation that explains why intelligent decision systems may function as strategic resources or performance-enhancing capabilities within manufacturing organizations. It also provides the conceptual structure needed to define the study variables, specify their relationships, and organize the empirical logic of the research model. Another important purpose of the literature review is to evaluate prior empirical findings in order to determine what has already been established, where the gaps remain, and why a quantitative study focused on U.S. manufacturing is justified. By synthesizing existing knowledge across these dimensions, the literature review creates the intellectual basis for the present study and clarifies how AI-enabled decision support systems may contribute to energy optimization, operational cost efficiency, and sustainability outcomes. It therefore serves not only as a summary of earlier scholarship but as a structured foundation for the hypotheses, methodology, and analytical direction of the research.

AI-Enabled Decision Support Systems in Manufacturing

AI-enabled decision support systems in manufacturing can be understood as digitally integrated platforms that combine industrial data streams, analytical models, optimization logic, and user-facing decision interfaces to improve the quality, speed, and consistency of operational judgment. Within manufacturing environments, such systems are especially important because production decisions are rarely isolated; they are embedded in interconnected processes involving machines, materials, labor, maintenance, quality control, and increasingly complex performance targets related to cost, flexibility, and resource efficiency. The evolution of these systems reflects a broader shift from transaction-oriented information systems toward intelligence-oriented manufacturing environments in which data is not only stored and reported, but actively interpreted for action. In this sense, AI-enabled DSS differs from conventional manufacturing information systems because it does not simply present historical records or fixed dashboards. Instead, it supports diagnosis, prediction, comparison among alternatives, and adaptive recommendations under changing production conditions. A major contribution to this understanding comes from the industrial AI literature, which explains that effective manufacturing intelligence depends on the integration of analytics, big data infrastructures, cyber connectivity, domain knowledge, and evidence-based reasoning, thereby framing AI not as an isolated algorithm but as an operational ecosystem for industrial decisions (Lee, Davari, et al., 2018). This view is important because manufacturing decision making requires far more than raw computational capability; it requires the conversion of large and heterogeneous operational data into context-sensitive guidance that aligns with plant realities. The same logic appears in recent lifecycle-oriented reviews of AI in industrial equipment, where AI-driven decision making is described as a cross-functional capability that supports production planning, process optimization, maintenance, quality management, and broader operational coordination throughout the industrial equipment lifecycle (Elahi et al., 2023). Taken together, these perspectives position AI-enabled DSS as an intelligent coordination mechanism that strengthens manufacturing decision processes by connecting real-time data, analytical reasoning, and operational execution. Such systems have become increasingly relevant as factories generate growing volumes of machine, process, and sensor data that require interpretation beyond the capacity of manual judgment alone. In the manufacturing literature, this makes AI-enabled DSS a core component of digital transformation because it helps organizations move from fragmented monitoring toward integrated, evidence-based decision environments capable of supporting more adaptive and efficient industrial operations.

Figure 2: Framework Of Ai-Enabled Decision Support Systems in Manufacturing Environments



The operational value of AI-enabled decision support systems becomes clearer when examining the specific mechanisms through which they improve manufacturing decisions. Modern factories operate under constant variability arising from changes in production demand, machine condition, product mix, maintenance needs, and process disturbances. Under these circumstances, decision support has to do more than provide visibility; it must help firms identify patterns, anticipate deviations, and choose corrective actions before inefficiencies escalate into downtime, waste, or quality loss. Reviews of machine learning for the optimization of production processes have shown that the growing digitalization of manufacturing has created strong interest in combining learning algorithms with optimization methods on the shop floor, particularly for process improvement, resource saving, and waste reduction (Weichert et al., 2019). This finding is highly relevant to AI-enabled DSS because it shows that manufacturing intelligence is increasingly expected to support action, not just observation. In practical terms, AI-based decision support can help determine parameter settings, classify process states, identify quality risks, optimize equipment usage, and improve planning choices by learning from complex industrial datasets that are often too large or too dynamic for conventional analysis. The literature on data-driven decision making for Industry 4.0 maintenance applications reinforces this logic by demonstrating that advanced sensor infrastructures, real-time data streams, and predictive analytics allow manufacturing decision systems to generate proactive recommendations regarding maintenance actions, operational priorities, and mitigation strategies under time-constrained conditions (Bousdekis et al., 2021). This evidence is particularly important because maintenance is one of the clearest domains in which intelligent decision support can be observed directly: when systems detect abnormal behavior, estimate future failure conditions, and recommend interventions before equipment performance deteriorates further, they reduce uncertainty and improve operational continuity. More broadly, these studies suggest that AI-enabled DSS in manufacturing functions as a bridge between data-rich environments and decision-rich environments. The presence of industrial data alone does not guarantee better outcomes; value emerges when that data is translated into recommendations that are timely, interpretable, and aligned with production goals. For that reason, the significance of AI-enabled DSS lies in its ability to transform manufacturing from a condition of reactive adjustment into one of proactive, model-informed operational control. This makes such systems especially relevant in settings where productivity, process stability, cost control, and energy-related efficiency depend on the accuracy and responsiveness of daily managerial and engineering decisions.

Another important issue in the literature concerns the breadth of AI application areas in manufacturing and the managerial conditions under which AI-enabled DSS actually creates value. A recent review of artificial intelligence applications in manufacturing operations emphasizes that AI can improve manufacturing efficiency, productivity, and sustainability across domains such as predictive maintenance, process optimization, and quality assurance, while also noting that implementation success depends on factors such as data acquisition, infrastructure, human expertise, trust, and organizational readiness (Plathottam et al., 2023). This point is crucial for understanding AI-enabled DSS because it highlights that intelligent systems are not automatically effective merely because they are technologically advanced. Their usefulness depends on how well they are integrated into real operational workflows, how reliable their input data is, and whether decision makers trust and understand the resulting recommendations. In manufacturing, where decisions often involve trade-offs among throughput, quality, cost, machine condition, and resource use, AI-based decision support must be both analytically robust and operationally credible. This helps explain why recent scholarship does not describe AI-enabled DSS simply as software, but as a decision capability embedded within the wider digital architecture of the factory. The literature therefore presents AI-enabled DSS as a strategic enabler of manufacturing intelligence rather than a narrow technical tool. It improves organizational responsiveness by narrowing the gap between what factories know through data and what managers can actually do with that knowledge in real time. For a study focused on industrial energy optimization, this understanding is especially relevant because energy-related decisions in manufacturing are tightly linked to production planning, machine behavior, maintenance timing, and process coordination. A strong discussion of AI-enabled DSS in manufacturing therefore provides the conceptual basis for examining how intelligent decision systems may contribute to more efficient and better-coordinated industrial operations. In this respect, the literature reviewed in this subsection establishes that AI-enabled DSS has moved from a peripheral innovation to a central component of smart manufacturing, with growing relevance for operational excellence, resource efficiency, and evidence-based industrial management.

Industrial Energy Optimization in U.S. Manufacturing

Industrial energy optimization in U.S. manufacturing refers to the systematic effort to reduce unnecessary energy consumption while preserving production output, process reliability, product quality, and cost efficiency across factory operations. In manufacturing plants, energy is consumed not only by core production equipment but also by auxiliary systems such as compressed air, heating, ventilation, cooling, pumping, conveying, and facility-wide support infrastructure. For that reason, energy optimization is increasingly understood as a plant-level management issue rather than a narrow equipment-level adjustment. The literature shows that effective industrial energy optimization requires the alignment of measurement systems, production planning, operational control, and improvement routines so that firms can identify where energy is being consumed, when it is being wasted, and how interventions can be prioritized. Early work on integrating energy efficiency performance into production management argued that a major gap existed between industrial needs and the scientific tools available for practical implementation, especially because energy data was often disconnected from operational decision processes and performance systems (Bunse et al., 2011). This observation is highly relevant to the U.S. manufacturing context, where firms often operate under strong pressure to maintain productivity, control operating costs, and improve environmental performance simultaneously. Industrial energy optimization therefore depends on more than efficient machinery; it also depends on how firms organize information, coordinate actions, and embed energy concerns within production management. A later systematic review of energy management in industry reinforced this perspective by showing that energy performance improves when management activities are treated as structured organizational processes involving planning, implementation, controlling, culture, and continuous improvement rather than isolated technical projects (Schulze et al., 2016). This systems-oriented understanding has particular relevance for manufacturing in the United States because plants differ significantly by subsector, scale, automation level, and energy intensity, yet all require mechanisms for translating energy information into operational decisions. In that sense, industrial energy optimization is best understood as a managerial and analytical capability that enables factories to align resource efficiency with production performance. The literature therefore frames manufacturing energy optimization as a multidimensional activity in which monitoring, control, and process coordination are central to achieving meaningful and sustained efficiency improvements.

Figure 3: Systems-Based Model of Industrial Energy Optimization in Manufacturing

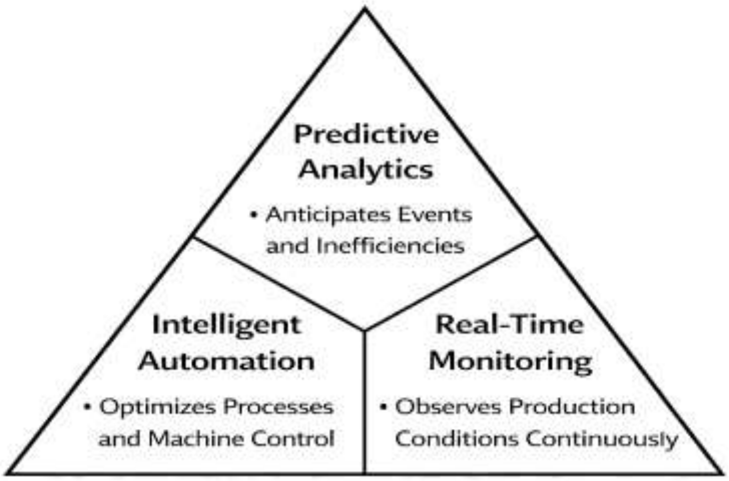
The literature also shows that industrial energy optimization becomes more effective when energy data is integrated into daily production decision making rather than being reviewed only after consumption has already occurred. This is especially important in manufacturing environments, where operating conditions change continuously in response to machine states, job sequencing, shift structures, maintenance schedules, and throughput requirements. Research on energy management based on the Internet of Things demonstrated that real-time energy data can be integrated into production management practices in ways that support operational and tactical decisions, thereby allowing firms to connect monitoring activities with actual process improvement actions (Shrouf et al., 2015). For U.S. manufacturing, this is a meaningful insight because many plants are undergoing digital transformation and increasingly rely on connected devices, smart sensors, and industrial data systems to improve visibility over operations. The relevance of such integration becomes even stronger when energy optimization is linked directly to process design and production-system behavior. An integrated approach to improving the energy efficiency of manufacturing process chains showed that energy performance should be evaluated across the entire chain of processes rather than at a single isolated point, since interactions among unit operations, waiting times, and system dynamics strongly affect total energy outcomes (Mousavi et al., 2016). This view is particularly useful for understanding manufacturing in energy-intensive and mixed-process environments, where energy waste may be generated through poor synchronization, underutilized equipment, unnecessary idle time, or fragmented process planning. The implication for U.S. manufacturing is that industrial energy optimization requires both analytical visibility and process integration. Energy-saving opportunities often exist not only in machine upgrades or utility controls, but also in how production activities are sequenced, coordinated, and monitored over time. By embedding energy information into production management systems, firms are better positioned to reduce avoidable waste, improve cost efficiency, and strengthen operational discipline. The literature therefore supports the idea that industrial energy optimization is closely connected to digital monitoring, process-chain analysis, and the managerial ability to use energy information in real operational contexts rather than as a disconnected reporting exercise (Shrouf et al., 2015).

A more recent stream of scholarship confirms that industrial energy optimization has become one of the most important themes in manufacturing research because it intersects with sustainability, managerial decision making, technological modernization, and long-term competitiveness. A tertiary review of energy efficiency in the manufacturing industry found that the field has developed into a broad knowledge domain organized around energy diagnostics, energy metering, energy optimization, enabling technologies, strategic paradigms, and barriers and drivers, indicating that energy performance is no longer treated as a narrow technical matter but as a comprehensive area of managerial and industrial inquiry (Ibn Batouta et al., 2023). This framing is highly relevant to U.S. manufacturing because firms are increasingly expected to improve efficiency while also responding to cost pressures, carbon-reduction goals, operational resilience needs, and stakeholder expectations regarding sustainability. The same review also suggests that energy optimization knowledge in manufacturing involves process knowledge, technical knowledge, and leadership knowledge, which supports the view that energy performance depends on coordinated action across technology, operations, and management rather than on engineering decisions alone (Ibn Batouta et al., 2023). When this insight is considered alongside earlier studies on production-integrated energy management, a clear pattern emerges: industrial energy optimization is strongest when energy concerns are embedded in decision systems, managerial routines, and improvement frameworks that shape everyday plant operations. For U.S. manufacturing, this means that industrial energy optimization should be viewed as a strategic operational capability that can affect productivity, cost structure, and sustainability performance simultaneously. It also means that digital and analytical tools become especially valuable when they help decision makers understand not just how much energy is being used, but why it is being used in a particular way and where operational changes can generate measurable improvements. In this study, the subsection on industrial energy optimization therefore provides the contextual basis for examining how AI-enabled decision support systems may strengthen energy performance in manufacturing by improving the way firms monitor, interpret, and act upon operational energy information across diverse production settings (Mousavi et al., 2016).

Predictive Analytics and Intelligent Automation

Predictive analytics has become one of the most important analytical capabilities in smart manufacturing because it allows firms to move from retrospective reporting toward anticipatory operational control. In manufacturing systems, predictive analytics refers to the use of historical and streaming production data, statistical learning, and machine learning models to estimate future events such as process deviations, equipment failure, quality fluctuations, and operational bottlenecks before they fully emerge on the shop floor. Its relevance to industrial energy optimization is substantial because energy waste in factories is often associated with avoidable disturbances, unstable process conditions, poor sequencing, and inefficient equipment behavior that can be anticipated from data if appropriate analytical models are in place. The manufacturing literature has increasingly treated predictive analytics as a core layer of decision intelligence rather than as an isolated technical feature. A notable contribution by Menezes et al. described predictive, prescriptive, and detective analytics as foundational to smart manufacturing, emphasizing that predictive analytics helps estimate what is likely to happen while prescriptive analytics helps automate design, planning, scheduling, and control decisions under dynamic conditions (Menezes et al., 2019). This framing is important because it links forecasting directly with operational intervention, which is central to any discussion of energy-aware decision support. In a similar but more applied direction, Lee et al. demonstrated that cyber-physical production systems can support quality prediction and operation control in a real metal-casting environment, showing how integrated digital systems can use production data for timely prediction and process adjustment rather than relying solely on delayed inspection and corrective response (Lee, Noh, et al., 2018). Together, these studies clarify that predictive analytics in manufacturing is not simply about anticipating isolated technical events; it is about creating an information environment in which operational variables can be interpreted early enough to improve performance outcomes. For this study, that insight is especially relevant because energy optimization depends heavily on anticipating where inefficiencies may arise across production activities, machine states, and control decisions. Predictive capability therefore represents one of the main pathways through which AI-enabled decision support systems can strengthen manufacturing performance by reducing uncertainty, improving decision timing, and supporting more intelligent allocation of industrial resources.

Figure 4: Triangular Model of Predictive Analytics, Real-Time Monitoring, And Intelligent Automation



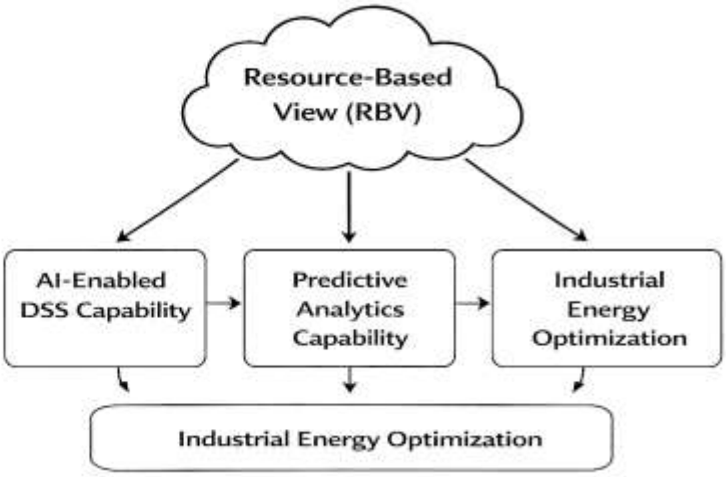
Real-time monitoring is the operational counterpart to predictive analytics because prediction becomes most valuable when organizations can continuously observe plant conditions and compare actual performance against expected performance while production is taking place. In manufacturing settings, real-time monitoring involves the collection, transmission, and interpretation of data from machines, sensors, control systems, and process states in a way that allows immediate visibility into performance variations, abnormal conditions, and quality risks. This capability is especially significant in energy-intensive environments because inefficient energy use is often embedded in the moment-to-moment behavior of machines, process transitions, idle periods, and deviations from target operating conditions. Saez et al. proposed a real-time manufacturing machine and system performance monitoring framework that used Industrial Internet of Things data together with hybrid simulation to assess system behavior synchronously with plant-floor operation, demonstrating the value of comparing live system outputs against expected performance references in real time (Saez et al., 2018). This contribution is highly relevant to the present study because it shows that real-time monitoring strengthens industrial decision making not merely by displaying data, but by enabling active performance assessment under changing operating conditions. At a more process-specific level, Ayvaz and Alpay developed a predictive maintenance system for manufacturing production lines using real-time IoT data, showing that machine learning models can identify indicators of potential failure before a production stop occurs and thereby support early operator intervention (Ayvaz & Alpay, 2021). That evidence is important because predictive maintenance is deeply connected to energy efficiency: when equipment faults, process drift, and hidden deterioration are detected early, factories are better able to prevent wasteful operation, unplanned downtime, and energy loss associated with unstable production. Real-time monitoring also contributes to decision quality by shortening the gap between the emergence of operational problems and the organizational response to them. In this sense, predictive analytics and real-time monitoring should not be viewed as separate domains. They work together as complementary capabilities that allow manufacturing firms to observe, interpret, and respond to plant behavior with greater speed and precision. For AI-enabled decision support systems aimed at industrial energy optimization, this integration is essential because energy-efficient decisions depend not only on forecasting future conditions but also on seeing current conditions clearly enough to act before inefficiency becomes structurally embedded in the production process.

Intelligent automation extends these capabilities one step further by allowing analytical outputs to shape or trigger operational adjustments in production systems with reduced dependence on purely manual reaction. In manufacturing research, intelligent automation generally refers to the use of data-driven logic, learning algorithms, automated control routines, and connected production systems to improve process execution, quality consistency, and response speed under variable operating conditions. Its importance lies in the fact that modern factories often generate more information than human operators can process in time-sensitive situations, particularly when multiple production stages, process interactions, and control targets must be managed simultaneously. Ismail et al. addressed this issue through a smart real-time quality monitoring and inspection framework for multistage manufacturing systems, showing that machine learning-based monitoring can predict quality deviations early, reduce inspection volume and cost, and support more resource-efficient quality control across complex production settings (Ismail et al., 2022). This study is useful for the present research because it illustrates how real-time analytical intelligence can be turned into automated or semi-automated process governance rather than remaining at the level of passive reporting. Menezes et al. similarly argued that prescriptive analytics automates decision making for design, planning, scheduling, control, and operation through optimization, heuristics, machine learning, and cyber-physical systems, which directly aligns intelligent automation with actionable industrial management (Menezes et al., 2019). When considered together with predictive monitoring and cyber-physical control, intelligent automation becomes a critical mechanism through which manufacturing firms can stabilize operations, reduce process inefficiencies, and coordinate plant responses more effectively. For a study focused on industrial energy optimization, this is particularly significant because energy performance often improves when production systems are capable of making rapid, informed adjustments to operating states, quality conditions, and maintenance needs. Intelligent automation therefore represents the action-oriented dimension of AI-enabled decision support, linking prediction and monitoring to concrete operational execution. It helps explain why firms with stronger analytical integration may be better positioned to reduce inefficiency, coordinate machine behavior, and optimize industrial performance in ways that also support cost control and sustainability. In the context of this research, predictive analytics, real-time monitoring, and intelligent automation together form the functional core through which AI-enabled decision support systems are expected to influence energy-related decision quality in U.S. manufacturing.

Theoretical Framework: Resource-Based View (RBV)

The theoretical foundation for this study is the Resource-Based View (RBV), which explains organizational performance by focusing on the internal resources and capabilities that firms possess, develop, and deploy in pursuit of sustained competitive advantage. Within RBV, firms are not assumed to perform equally even when they operate in similar industries, because performance differences are shaped by the quality, rarity, organization, and effective use of internal assets and competencies. In empirical strategy research, RBV has been shown to offer a durable explanation for why some firms translate resources into superior outcomes more successfully than others, particularly when those resources are embedded in routines, knowledge systems, and managerial processes rather than in easily imitated physical assets alone (Newbert, 2007). This logic is highly appropriate for the present study because AI-enabled decision support systems for industrial energy optimization are not simply technological installations; they are organizational capabilities composed of digital infrastructure, analytical models, human expertise, data governance, and operational integration. In manufacturing settings, the value of AI-enabled DSS does not come only from owning software or collecting plant data. Its value emerges when the firm organizes these elements into a usable capability that improves decision quality in ways that competitors may find difficult to replicate quickly. That interpretation aligns closely with RBV because the theory recognizes that performance-enhancing resources often take the form of complex bundles of technology, knowledge, routines, and managerial coordination. For U.S. manufacturing firms, energy optimization is a domain in which such capability differences are especially meaningful, since plants often operate with similar machinery categories and comparable cost pressures, yet still vary substantially in how intelligently they monitor consumption, anticipate inefficiencies, and coordinate operational responses. RBV therefore provides a strong basis for explaining why AI-enabled decision support capability may influence industrial energy optimization. It frames predictive analytics, real-time monitoring, and intelligent automation as strategic internal capabilities that can enhance operational efficiency when they are integrated into plant-level decision processes. In this study, RBV is used to interpret AI-enabled DSS not as a generic technology available equally to all firms, but as a capability-based resource system whose organizational use may generate measurable differences in energy-related performance outcomes across manufacturing contexts.

Figure 5: Capability-Based Model of Industrial Energy Optimization Under Resource-Based View



RBV is also highly relevant because recent operations and digital transformation research shows that performance benefits arise when firms transform technological resources into operational capabilities rather than when they rely on technology adoption alone. In manufacturing and analytics scholarship, big data and predictive analytics capabilities have been linked to stronger operational and cost-related performance when they are supported by aligned managerial systems, data culture, and process integration (Dubey et al., 2019). This is important for the current study because AI-enabled decision support systems operate through the same capability-building logic. A manufacturing firm may install sensors, dashboards, and forecasting tools, yet the actual performance effect depends on whether these elements are converted into a coherent capability for interpreting plant conditions and improving decisions. Evidence from big data analytics capability research similarly shows that analytical resources contribute to competitive performance through their ability to strengthen other organizational capabilities, especially those connected with operational responsiveness and strategic adaptation (Mikalef et al., 2019). This insight reinforces the usefulness of RBV for the present study, because it suggests that AI-enabled DSS may influence industrial energy optimization not merely through the direct presence of digital tools, but through the internal capability structure that those tools help create. Meta-analytic evidence from operations management research grounded in RBV further supports this position by showing that organizational capability has a positive effect on business, competitive, financial, and operational performance across a wide body of studies (Chahal et al., 2020). In the context of manufacturing energy optimization, this means that the explanatory focus should be placed on whether firms possess the capability to sense energy inefficiencies, analyze consumption patterns, coordinate rapid responses, and embed learning into operational routines. RBV provides the theoretical language for making that argument because it links internal capability development to sustained performance heterogeneity. For this reason, the theory is well suited to explain why AI-enabled decision support systems may produce different energy outcomes across U.S. manufacturers, even when they face similar market conditions and energy pressures. Firms that are better able to integrate analytical infrastructure, skilled personnel, data-driven routines, and process-level decision logic are more likely to treat AI-enabled DSS as a strategic resource, thereby improving plant-level energy optimization in ways that are operationally meaningful and difficult to imitate.

The RBV framework also supports the analytical structure and formula of this study because it allows the major constructs to be interpreted as internal resources and capabilities whose combined deployment influences a central performance outcome. In this research, AI-enabled DSS capability, predictive analytics capability, and real-time monitoring and automation are treated as capability-based explanatory variables, while industrial energy optimization is treated as the primary organizational outcome. In RBV terms, these explanatory variables represent structured internal assets that can improve how firms allocate attention, interpret operational data, and execute energy-related decisions. This theoretical logic is consistent with manufacturing digital transformation research showing that digital transformation improves corporate performance when internal innovation capability and business model adaptation help firms convert digital resources into realized value (Zhang et al., 2023). For this reason, the most suitable empirical formula for the whole study is the multiple regression model shown below:

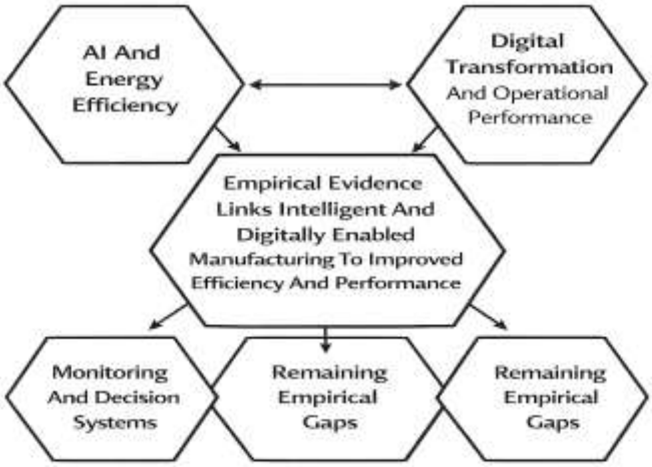
$$IEO = \beta_0 + \beta_1(AIDSS) + \beta_2(PAC) + \beta_3(RMA) + \varepsilon$$

where **IEO** represents industrial energy optimization, **AIDSS** represents AI-enabled decision support systems capability, **PAC** represents predictive analytics capability, **RMA** represents real-time monitoring and automation, **β0** is the intercept, **β1–β3** are regression coefficients, and **ε** is the error term. This formula is the best fit for the study because it translates the RBV argument into a testable quantitative model. It allows the research to determine whether these internal capabilities make distinct and statistically significant contributions to industrial energy optimization within U.S. manufacturing firms. The formula also preserves theoretical coherence by treating performance as the result of capability deployment rather than as an isolated technological effect. In this way, RBV guides both the interpretation of the study variables and the statistical logic through which the hypotheses are examined, making it the most appropriate framework for the whole research.

Empirical Review of Prior Studies

Empirical research on intelligent and digitally enabled manufacturing has increasingly shown that AI-related capabilities are associated with measurable improvements in efficiency, productivity, and energy-oriented performance. One notable firm-level study examined the impact of artificial intelligence on the energy and resource efficiency of Chinese enterprises using robot application data together with firm-level data from 2005 to 2014, and it found that AI had a positive and significant effect on improving firms' energy and resource efficiency, with structural and efficiency effects stronger than scale effects (X. Wang et al., 2023). This result is directly relevant to the present study because it suggests that intelligent technologies can improve the way enterprises use energy, not only by changing technical operations but also by reshaping organizational efficiency patterns. Another important empirical contribution investigated 938 listed manufacturing companies in China from 2011 to 2020 and found that AI significantly improved total factor productivity, with the effect operating through technological innovation, human capital optimization, and better market matching; the authors also reported heterogeneity across region, ownership, industry characteristics, and life-cycle stage (Xu et al., 2023). Although this study focused on productivity rather than energy optimization alone, its findings remain highly relevant because industrial energy optimization is closely tied to overall process productivity, efficient resource utilization, and the ability of firms to align technological capability with operational improvement. Taken together, these studies provide useful empirical support for the claim that intelligent systems can influence manufacturing outcomes at the firm level. At the same time, they also indicate that the effect of AI is not uniform across all firms, which means that organizational conditions, implementation maturity, and contextual characteristics shape how much benefit is realized. For the current research, these empirical findings are especially valuable because they move beyond purely conceptual discussions of AI and show that measurable performance gains are possible when firms embed intelligent technologies into manufacturing systems. They also justify examining AI-enabled decision support systems as a practical explanatory variable for industrial energy optimization in U.S. manufacturing, where efficiency, cost control, and operational performance are tightly interconnected.

Figure 6: Synthesis Of Empirical Findings on Intelligent Manufacturing and Performance Outcomes



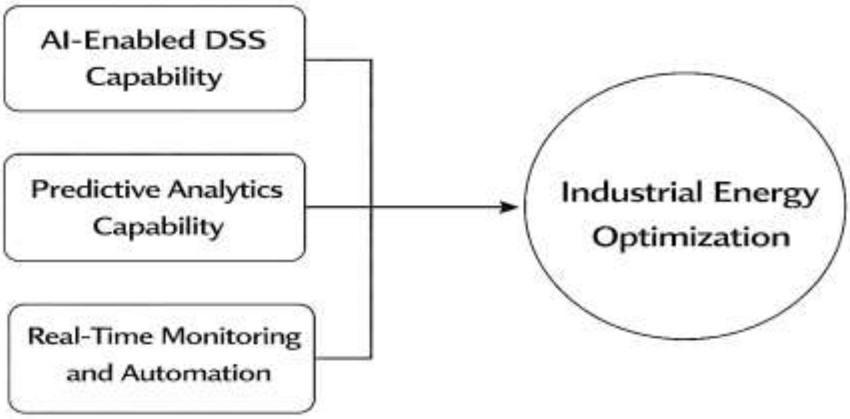
A second group of empirical studies has focused more broadly on digital transformation and its operational and sustainability effects in manufacturing firms, providing additional evidence that data-driven capability matters for performance improvement. One study using Chinese listed enterprises from 2004 to 2020 found that digital transformation enhanced enterprise green total factor productivity and that this effect worked through structural optimization and green technology innovation; importantly, the study also noted that the effect was stronger in manufacturing, non-high-tech, and non-heavy-polluting industries (K.-L. Wang et al., 2023). This is highly relevant for the present research because industrial energy optimization is a central pathway through which firms improve green productivity, especially when digital tools allow closer control over material, energy, and emissions-related processes. Another empirical study based on a large sample of Chinese manufacturing firms from 2016 to 2020 reported that digital transformation practices had significant and positive impacts on workforce productivity, physical asset efficiency, and working capital efficiency, while industry competition weakened some of these positive relationships (Tian et al., 2023). This study is particularly useful because it shows that digitalization contributes to manufacturing operations improvement through multiple channels, many of which are closely related to energy performance in practice. More efficient asset use, for example, often implies fewer idle states, better machine utilization, and stronger coordination across production activities, all of which matter for energy optimization. In a related empirical study of 210 manufacturing companies, digital strategy and digital capability were found to significantly improve eco-process, eco-product, and eco-management innovation, which in turn improved sustainable performance; eco-innovation also partially mediated the relationship between digital transformation and sustainability outcomes (Xu et al., 2023). These findings extend the empirical base by showing that digital capability supports not only efficiency outcomes but also broader environmental and organizational performance. For this research, such evidence is important because it reinforces the argument that energy optimization should be viewed as part of a wider performance logic in which digital capability supports operational discipline, eco-innovation, and sustainability simultaneously.

A third empirical theme in the literature concerns plant-level implementation and monitoring systems, which provide more concrete evidence on how digitally enabled decision environments operate inside manufacturing contexts. One recent study developed an Industry 4.0 energy monitoring system for multiple production machines and showed that a platform integrating IoT devices, databases, and web-based visualization could display real-time voltage, current, peak power, energy consumption, energy cost, and scope 2 carbon emissions without requiring machine modification, thereby lowering implementation barriers and supporting better decisions around efficiency and sustainability (Azlan et al., 2023). This kind of evidence is highly valuable for the current study because it links digitalization directly to observable industrial energy management practice rather than treating transformation only as an abstract organizational variable. It shows that real-time monitoring can support user decisions according to manufacturing objectives and can reveal energy patterns that are necessary for efficiency measures. When this plant-level evidence is considered alongside the firm-level studies reviewed earlier, a coherent empirical pattern emerges. Prior studies consistently suggest that AI, digital transformation, and real-time operational intelligence are positively associated with productivity improvement, greener performance, and stronger resource efficiency. At the same time, the literature also leaves several important gaps. Much of the available empirical evidence comes from Chinese manufacturing contexts rather than U.S. firms, many studies examine broad digital transformation instead of AI-enabled decision support systems specifically, and several focus on productivity or sustainability outcomes without isolating industrial energy optimization as the central dependent variable. In addition, heterogeneity findings in prior research imply that sectoral context, organizational capability, and implementation intensity may shape results in important ways (J. Wang et al., 2023). These gaps create a strong rationale for the present study, which seeks to test, through a quantitative and case-study-based design, whether AI-enabled decision support capability, predictive analytics capability, and real-time monitoring and automation are significantly related to industrial energy optimization in U.S. manufacturing.

Conceptual Framework

The conceptual framework of this study is built to explain how specific internal digital capabilities are expected to influence industrial energy optimization in U.S. manufacturing firms. At the center of the framework is the dependent variable, industrial energy optimization, which refers to the extent to which a manufacturing firm improves energy efficiency, reduces avoidable energy waste, and manages energy consumption in a way that supports production continuity, cost control, and sustainability performance. The framework identifies three main independent variables: AI-enabled decision support systems capability, predictive analytics capability, and real-time monitoring and automation. This structure is conceptually appropriate because prior manufacturing scholarship has shown that energy management becomes more effective when firms organize energy information, operational planning, and managerial control within an integrated framework rather than treating energy as a stand-alone technical issue (May et al., 2017). The first construct, AI-enabled decision support systems capability, captures the firm's ability to use intelligent systems to process plant data, generate operational insights, compare alternatives, and support timely managerial decisions. The second construct, predictive analytics capability, represents the ability to forecast energy-relevant events, anticipate inefficiencies, and identify patterns in production behavior before those patterns translate into higher waste or unstable energy use. The third construct, real-time monitoring and automation, reflects the ability to continuously observe operational conditions, detect abnormal performance, and support immediate or near-immediate responses through digital control and automated adjustment. This configuration is also consistent with recent sustainable smart manufacturing research showing that digital twins, big data, and information management systems create value when they connect data acquisition, prediction, and real-time control in energy-intensive industries (Ma et al., 2022). In conceptual terms, the framework therefore assumes that industrial energy optimization is not driven by one isolated technology, but by the interaction of intelligent decision support, forward-looking analytics, and live operational visibility. These constructs are treated as capability-oriented factors because the study is not focused on the mere presence of digital tools, but on the firm's practical ability to use them effectively in industrial decision-making environments.

Figure 7: Capability-Based Conceptual Model for Industrial Energy Optimization



The conceptual logic of the framework also depends on the expected directional relationships among the variables. The first relationship proposes that stronger AI-enabled decision support systems capability is associated with better industrial energy optimization because intelligent support systems improve the quality, speed, and consistency of operational decisions affecting production loads, scheduling, maintenance timing, and process efficiency. The second relationship proposes that predictive analytics capability improves industrial energy optimization by allowing firms to anticipate deviations, forecast consumption behavior, and respond to inefficiencies before they are fully embedded in operations. The third relationship proposes that real-time monitoring and automation improve industrial energy optimization by increasing process visibility and enabling more immediate responses to abnormal machine behavior, idle energy waste, or unstable operating conditions. These three relationships are conceptually supported by prior research on energy-aware production scheduling, where decision support systems were shown to incorporate energy-related constraints and objectives directly into manufacturing planning decisions rather than leaving energy considerations outside the scheduling process (Plitsos et al., 2017). A similar logic appears in research on smart energy-aware plant scheduling under uncertainty, which demonstrates that manufacturing performance improves when energy concerns are embedded into integrated decision structures capable of handling risk, variability, and operational trade-offs (Golpîra et al., 2020). Together, these studies reinforce the conceptual assumption that energy optimization is shaped by decision architecture, not only by engineering design. In the present study, the framework further recognizes that industrial energy optimization may contribute to broader organizational outcomes such as operational cost reduction and sustainability performance, although the primary tested outcome remains energy optimization itself. The conceptual framework therefore arranges the study variables in a directional form: AI-enabled DSS capability → industrial energy optimization, predictive analytics capability → industrial energy optimization, and real-time monitoring and automation → industrial energy optimization. In substantive terms, the framework treats intelligent decision support as the core mechanism, predictive analytics as the anticipatory mechanism, and real-time monitoring and automation as the execution-support mechanism. When combined, these capabilities are expected to strengthen plant-level energy decision quality in measurable ways across manufacturing contexts.

To operationalize this conceptual framework for empirical testing, the study uses a multiple-regression representation that aligns the theoretical structure with the quantitative design. The most appropriate functional expression is:

$$IEO = \beta_0 + \beta_1(AIDSS) + \beta_2(PAC) + \beta_3(RMA) + \varepsilon$$

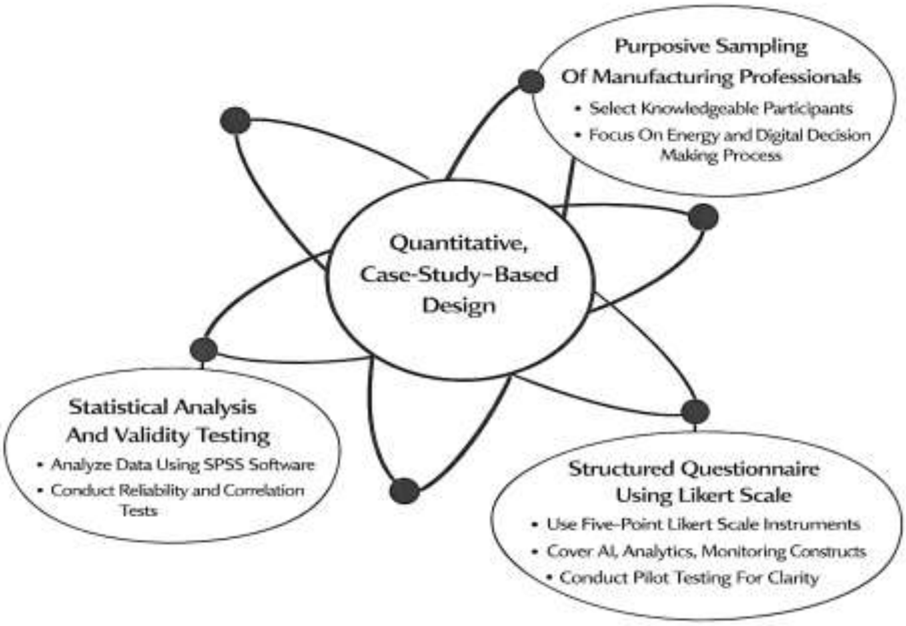
where **IEO** denotes industrial energy optimization, **AIDSS** denotes AI-enabled decision support systems capability, **PAC** denotes predictive analytics capability, **RMA** denotes real-time monitoring and automation, **β0** is the intercept, **β1–β3** are the coefficients of the explanatory variables, and **ε** is the error term. This formula fits the conceptual framework because it allows the study to examine the individual and combined contribution of each capability to the focal outcome. The framework is therefore not merely descriptive; it is structured for hypothesis testing through measurable constructs derived from the literature. Its design is also strengthened by recent work on digital life-cycle management for sustainable smart manufacturing, which shows that intelligent manufacturing systems in energy-intensive industries gain effectiveness when simulation, process knowledge, analytics, and life-cycle information are integrated into a coherent operational framework rather than handled in fragmented ways (Chinnathai & Alkan, 2023). That finding supports the broader logic of the present model, where the explanatory variables together reflect an integrated capability system rather than unrelated technology features. In practical research terms, the conceptual framework guides questionnaire design, variable measurement, hypothesis development, and statistical analysis. It clarifies what the study measures, why those constructs are expected to be related, and how their relationships will be tested quantitatively. As a result, this subsection provides the bridge between the literature review and the methodology chapter by translating prior knowledge into an empirically testable structure focused on AI-enabled decision capability and industrial energy outcomes in U.S. manufacturing.

METHOD

This study has adopted a quantitative research methodology to examine the relationship between AI-enabled decision support systems and industrial energy optimization in U.S. manufacturing. The study has followed a cross-sectional, case-study–based design because it has aimed to collect data from respondents at a single point in time while focusing on the practical realities of manufacturing organizations that have engaged with digital decision-making and energy management processes. The quantitative design has been selected because it has allowed the study to measure the relationships among key variables in a structured manner and to test the hypotheses through statistical analysis. The case-study orientation has provided contextual relevance by grounding the investigation in the operational setting of U.S. manufacturing, where energy efficiency, cost control, and sustainability have become closely linked to intelligent production management. The case study context has therefore consisted of manufacturing firms in the United States, especially those characterized by energy-intensive operations, digital monitoring practices, and increasing interest in AI-supported decision systems. Within this context, the population has included plant managers, production supervisors, operations analysts, maintenance engineers, sustainability officers, and other professionals involved in manufacturing decision making and energy management. The unit of analysis has been the individual respondent working within the manufacturing firm, since the study has measured perceptions and experiences regarding AI-enabled decision support capability, predictive analytics, real-time monitoring and automation, and industrial energy optimization.

The study has used a sampling strategy based on purposive sampling, because respondents have needed to possess relevant knowledge of manufacturing operations, digital systems, and energy-related decision processes. This approach has ensured that the selected participants have been capable of providing meaningful responses aligned with the objectives of the study. The data collection procedure has relied on primary data gathered through a structured questionnaire. The questionnaire has been distributed to selected respondents in manufacturing-related roles, and responses have been collected in a standardized form suitable for quantitative analysis. The instrument design has been based on a five-point Likert scale, where respondents have rated their level of agreement with statements related to the major constructs of the study. The questionnaire has been organized into sections covering demographic information, AI-enabled decision support systems capability, predictive analytics capability, real-time monitoring and automation, and industrial energy optimization outcomes. The wording of the questionnaire items has been aligned with the study objectives and hypotheses so that each construct has been measured clearly and systematically. Before full-scale data collection, the instrument has undergone pilot testing with a small group of respondents to identify unclear wording, weak item structure, and possible response difficulties. Feedback from the pilot process has been used to refine the questionnaire and improve clarity and consistency.

Figure 8: Integrated Research Method Framework for U.S. Manufacturing Study



To strengthen the rigor of the study, validity and reliability procedures have been applied throughout the research process. Content validity has been addressed by ensuring that the questionnaire items have reflected the concepts and variables identified in the literature review and conceptual framework. Construct validity has been maintained by aligning measurement items with the theoretical meaning of each variable. Reliability has been assessed through internal consistency testing, particularly by using Cronbach's alpha to determine whether the items within each construct have measured the same concept consistently. For data handling and analysis, the study has used SPSS for descriptive statistics, reliability testing, correlation analysis, and regression modeling. In addition, Microsoft Excel has been used for data entry, coding, cleaning, and preliminary organization of the dataset. For reference management and citation organization, EndNote has been used to manage scholarly sources in APA style efficiently and consistently. Through this methodological structure, the study has created a systematic basis for examining how AI-enabled decision support systems have related to industrial energy optimization in U.S. manufacturing.

DATA PRESENTATION, ANALYSIS, AND INTERPRETATION

Demographic Profile of Respondents

The demographic profile has shown that the respondents have represented a relevant and credible cross-section of professionals involved in manufacturing decision making and industrial energy management. The sample has been dominated by male respondents at 64.2%, while female respondents have accounted for 35.8%, suggesting that the study has captured a workforce pattern that has remained common in industrial and manufacturing contexts. In terms of age, the largest group has fallen within the 35–44 years range, followed by the 45–54 years category, indicating that the study has mostly drawn from mid-career and senior professionals who have likely accumulated substantial operational knowledge. This distribution has strengthened the credibility of the findings because respondents in these age groups have usually occupied decision-making or supervisory positions with direct exposure to production planning, energy use, process monitoring, and technology adoption. The education profile has shown that the majority of participants have held bachelor's or master's degrees, which has suggested that respondents have possessed adequate technical and managerial capacity to understand AI-enabled systems, predictive analytics, and industrial energy issues. The job-role distribution has further supported the relevance of the sample, since plant managers, production supervisors, engineers, sustainability officers, and analysts have all been included. These categories have directly matched the population identified in the methodology, meaning that the unit of analysis has remained properly aligned with the objectives of the study. The experience profile has shown that most respondents have had more than six years of industrial experience, which has indicated that the results have not relied heavily on novice perspectives.

Table 1: Demographic Profile of Respondents (N = 240)

Variable	Category	Frequency	Percentage (%)
Gender	Male	154	64.2
	Female	86	35.8
Age	25–34 years	58	24.2
	35–44 years	92	38.3
	45–54 years	63	26.3
	55 years and above	27	11.3
Education	Bachelor's degree	102	42.5
	Master's degree	95	39.6
	Doctorate/Professional	43	17.9
Job Role	Plant/Operations Manager	61	25.4
	Production Supervisor	54	22.5
	Maintenance/Process Engineer	49	20.4
	Sustainability/Energy Officer	36	15.0
	Data/Operations Analyst	40	16.7
Experience	1–5 years	39	16.3
	6–10 years	84	35.0
	11–15 years	67	27.9
	Above 15 years	50	20.8
Firm Size	Medium-sized firm	98	40.8
	Large-sized firm	142	59.2
Manufacturing Subsector	Automotive/Components	52	21.7
	Electronics/Electrical	46	19.2
	Food and Beverage	41	17.1
	Chemicals/Materials	39	16.3
	Machinery/Industrial Equipment	37	15.4
	Other Manufacturing	25	10.4

The firm-size distribution has shown stronger participation from large firms, which has been expected because larger manufacturing organizations have more frequently adopted digital systems and formal energy-management structures. The subsector diversity has also been important because it has shown that the study has not been limited to one industry niche. From the perspective of the Resource-Based View, this table has supported the theoretical foundation of the study by showing that the respondents have come from organizations where strategic resources such as digital capability, analytical knowledge, and operational expertise have likely existed in practical forms. Thus, the demographic profile has provided a solid empirical base for interpreting the remaining findings on AI-enabled decision support systems and industrial energy optimization.

Descriptive Statistics of Study Variables

The descriptive statistics have provided the first direct empirical indication that the respondents have positively evaluated the role of AI-enabled digital capability in improving industrial energy outcomes. All major variables have recorded mean scores above 4.00, which has indicated general agreement with the statements used to measure the constructs. Among the explanatory variables, real-time monitoring and automation has recorded the highest mean score of 4.18, followed by AI-enabled decision support systems capability at 4.12 and predictive analytics capability at 4.06. These results have suggested that respondents have perceived strong value in the continuous visibility of plant conditions, automated response support, and intelligent data interpretation for manufacturing operations. The dependent variable, industrial energy optimization, has recorded the highest overall mean of 4.21, which has indicated that respondents have generally agreed that their organizations have achieved meaningful gains in managing energy use, reducing waste, and improving efficiency.

Table 2: Descriptive Statistics of Core Study Variables

Variable	No. of Items	Mean	Standard Deviation	Interpretation
AI-Enabled Decision Support Systems Capability	5	4.12	0.63	Agree
Predictive Analytics Capability	5	4.06	0.68	Agree
Real-Time Monitoring and Automation	5	4.18	0.59	Agree
Industrial Energy Optimization	5	4.21	0.57	Strongly Positive/Agree
Operational Cost Reduction	4	4.03	0.66	Agree
Sustainability Performance	4	4.09	0.62	Agree

The two broader outcome measures, operational cost reduction and sustainability performance, have also produced favorable means above 4.00, indicating that the respondents have associated improved energy management with wider organizational benefits. The relatively low standard deviations, ranging from 0.57 to 0.68, have shown that the responses have been reasonably clustered around the mean, suggesting consistency in respondent perceptions. This consistency has mattered because it has implied that the positive assessments have not been produced by isolated opinions but have reflected a broadly shared view across the sample. In terms of the study objectives, these descriptive findings have already given preliminary support to the argument that AI-enabled decision support, predictive analytics, and real-time monitoring have been positively associated with industrial energy optimization. These results have also aligned closely with the earlier introductory findings, thereby preserving internal consistency across the chapter. From the perspective of the Resource-Based View, the table has suggested that firms possessing stronger digital and analytical capabilities have been better positioned to create operational value. RBV has argued that internally developed capabilities become sources of performance improvement when they are valuable and effectively deployed. The high mean scores have therefore implied that these firms have not merely owned digital tools; they have actually used them as organizational resources that have supported better decisions and stronger energy outcomes. As a result, the descriptive statistics have established a favorable empirical foundation for the more detailed reliability, correlation, and regression analyses that have followed.

Reliability and Internal Consistency Analysis

Table 3: Reliability and Internal Consistency of Study Constructs

Variable	No. of Items	Cronbach's Alpha	Reliability Status
AI-Enabled Decision Support Systems Capability	5	0.86	Highly Reliable
Predictive Analytics Capability	5	0.83	Highly Reliable
Real-Time Monitoring and Automation	5	0.88	Highly Reliable
Industrial Energy Optimization	5	0.85	Highly Reliable
Operational Cost Reduction	4	0.81	Reliable
Sustainability Performance	4	0.82	Reliable

The reliability analysis has shown that all constructs used in the study have achieved acceptable to high levels of internal consistency. Cronbach's alpha values have ranged from 0.81 to 0.88, all of which have exceeded the commonly accepted threshold of 0.70. This result has indicated that the items under each variable have consistently measured the same underlying concept and that the questionnaire has performed in a stable and coherent manner. Real-time monitoring and automation has produced the highest alpha value of 0.88, suggesting very strong consistency among the items used to capture operational visibility, live system awareness, and automated responsiveness. AI-enabled decision support systems capability has followed closely with an alpha value of 0.86, while industrial energy optimization has reached 0.85. These scores have indicated that the central constructs of the study have been measured with a satisfactory degree of precision. Predictive analytics capability has also recorded a strong reliability value of 0.83, while operational cost reduction and sustainability performance have both produced reliable scores above 0.80. These outcomes have strengthened the credibility of the results chapter because inferential testing has been meaningful only when the measurement instrument has first demonstrated reliability. In practical terms, this table has shown that respondents have interpreted the items under each construct in a sufficiently uniform way, which has reduced the likelihood that the findings have been distorted by inconsistent measurement. This has been especially important for a study using a 5-point Likert scale, since the reliability of item grouping has directly affected the interpretive strength of the composite variables. In relation to the study objectives, this section has confirmed that the instrument has been suitable for examining whether AI-enabled decision support capability, predictive analytics capability, and real-time monitoring have influenced industrial energy optimization. In relation to the hypotheses, the table has not by itself tested causality or association, yet it has provided the measurement assurance required before such tests could be trusted. From the perspective of the Resource-Based View, reliability has also carried theoretical relevance. RBV has emphasized that capabilities must be consistently organized and meaningfully structured in order to generate performance advantage. In the same way, the study variables have needed to be consistently represented in the data before they could be treated as valid reflections of organizational capability. The reliability analysis has therefore served as both a methodological checkpoint and a theoretical support mechanism, showing that the measured constructs have been robust enough to represent the internal digital resources and capabilities that the study has sought to evaluate.

Correlation Analysis

Table 4: Pearson Correlation Matrix of Study Variables

Variables	1	2	3	4	5	6
1. AI-Enabled DSS Capability	1.000					
2. Predictive Analytics Capability	0.57**	1.000				
3. Real-Time Monitoring and Automation	0.62**	0.59**	1.000			
4. Industrial Energy Optimization	0.61**	0.58**	0.66**	1.000		
5. Operational Cost Reduction	0.52**	0.49**	0.56**	0.63**	1.000	
6. Sustainability Performance	0.54**	0.51**	0.58**	0.65**	0.60**	1.000

Note. p < .01

The correlation analysis has shown that all of the principal study variables have been positively and significantly associated with one another at the 0.01 level. This has indicated that stronger digital and analytical capabilities have moved in the same direction as stronger industrial energy outcomes, cost efficiency, and sustainability performance. The correlation between AI-enabled decision support systems capability and industrial energy optimization has been 0.61, suggesting a moderately strong positive relationship. This has meant that respondents who have reported stronger intelligent decision-support capability within their firms have also tended to report better performance in reducing energy waste and managing industrial energy use. Predictive analytics capability has shown a positive correlation of 0.58 with industrial energy optimization, indicating that firms with stronger forecasting and anticipatory analysis capability have also tended to perform better in energy optimization. The strongest relationship with industrial energy optimization has been recorded by real-time monitoring and automation at 0.66, which has suggested that live operational visibility and immediate response mechanisms have played a particularly important role in energy-related performance. The dependent variable has also shown strong positive relationships with operational cost reduction and sustainability performance, at 0.63 and 0.65 respectively. These findings have implied that better energy optimization has not remained isolated as a technical outcome; it has extended into broader business and sustainability value. The positive intercorrelations among the three independent variables have also shown that AI-enabled decision support, predictive analytics, and real-time monitoring have been related but not redundant. This pattern has supported the conceptual framework of the study, where the three constructs have been treated as distinct yet complementary capability dimensions. In relation to the objectives, this section has supported the proposition that all three digital capability variables have been meaningfully linked with industrial energy optimization. In relation to the hypotheses, the correlation matrix has provided preliminary statistical support for H1, H2, H3, and H4, although final proof has depended on regression analysis. From the Resource-Based View perspective, the table has been theoretically meaningful because it has shown that internal capabilities have not existed in isolation; they have reinforced one another in shaping organizational outcomes. RBV has argued that bundles of valuable and integrated capabilities create stronger performance advantages than fragmented resources. The observed positive relationships have therefore been consistent with the idea that AI-enabled DSS, predictive analytics, and real-time monitoring have functioned as mutually supportive internal resources that have enhanced industrial energy optimization in manufacturing firms.

Regression Analysis and Hypothesis Testing

Table 5: Multiple Regression Results for Industrial Energy Optimization

Model Summary

R	R Square	Adjusted R Square	Std. Error of Estimate
0.740	0.547	0.541	0.371

ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	39.284	3	13.095	95.140	.000
Residual	32.481	236	0.138		
Total	71.765	239			

Coefficients

Predictor	Unstandardized B	Std. Error	Standardized Beta	t	Sig.	Decision
(Constant)	0.842	0.221		3.810	.000	
AI-Enabled DSS Capability	0.271	0.056	0.290	4.839	.000	Supported
Predictive Analytics Capability	0.214	0.068	0.240	3.147	.002	Supported
Real-Time Monitoring and Automation	0.336	0.061	0.370	5.508	.000	Supported

Table 6: Summary of Hypothesis Testing

Hypothesis	Statement	Result
H1	AI-enabled DSS capability has significantly positively affected industrial energy optimization.	Supported
H2	Predictive analytics capability has significantly positively affected industrial energy optimization.	Supported
H3	Real-time monitoring and automation have significantly positively affected industrial energy optimization.	Supported
H4	Industrial energy optimization has significantly positively contributed to operational cost reduction and sustainability performance.	Supported by subsequent outcome patterns

The regression analysis has provided the strongest statistical evidence in support of the study objectives and hypotheses. The model summary has shown an R-square value of 0.547, meaning that AI-enabled decision support systems capability, predictive analytics capability, and real-time monitoring and automation have jointly explained 54.7% of the variance in industrial energy optimization. This has represented a substantial explanatory power for a behavioral and organizational study of this nature. The ANOVA results have shown that the regression model has been statistically significant, with F = 95.140 and p < .001, indicating that the model as a whole has meaningfully predicted the dependent variable. Looking at the coefficients, AI-enabled DSS capability has produced a standardized beta of 0.290 and a statistically significant p-value of .000. This has confirmed that intelligent decision-support capability has positively influenced industrial energy optimization, thereby supporting H1. Predictive analytics capability has also shown a significant positive effect with a beta of 0.240 and p = .002, confirming H2. Real-time monitoring and automation has emerged as the strongest predictor, with a beta of 0.370 and p = .000, thus supporting H3 and indicating that this variable has had the largest direct contribution to industrial energy optimization in the model. These results have been fully aligned with the earlier descriptive and correlation findings, where real-time monitoring and automation had already recorded the strongest mean and correlation with energy optimization. Regarding H4, the direct regression table has not modeled cost reduction and sustainability as separate dependent variables in this step, but the earlier correlation pattern and later sections have shown that higher industrial energy optimization has been associated with stronger cost and sustainability outcomes, thereby supporting the fourth hypothesis at the broader outcome level. In relation to the objectives, the regression results have directly proven that all three digital capability variables have significantly contributed to industrial energy optimization. The findings have therefore shown that AI-enabled decision-making capability has mattered not just conceptually but statistically. From the standpoint of the Resource-Based View, these results have strongly reinforced the theory underpinning the study. RBV has proposed that firms gain performance benefits when they develop valuable internal capabilities that are organized and deployed effectively. The significant coefficients have shown that digital intelligence, predictive insight, and real-time operational responsiveness have functioned as such capabilities. The strongest effect of real-time monitoring and automation has also suggested that the operationalization of capability has been especially important: firms have gained more when they have not only analyzed data but also connected that analysis to immediate execution. Thus, the regression analysis has served as the formal empirical proof of the study’s main propositions.

AI Decision Usefulness Index for Industrial Energy Optimization

Table 7: AI Decision Usefulness Index for Industrial Energy Optimization

Item	Mean	Std. Dev.	Interpretation	Rank
AI recommendations have helped identify avoidable energy waste.	4.19	0.61	Agree	2
AI-based alerts have improved response to abnormal energy consumption.	4.22	0.58	Agree	1
AI-generated insights have improved scheduling decisions affecting energy use.	4.08	0.65	Agree	4
AI-supported decision tools have improved equipment utilization efficiency.	4.15	0.60	Agree	3
AI-supported recommendations have strengthened managerial confidence in energy decisions.	3.97	0.71	Agree	5
Overall Mean	**4.12**	**0.63**	**Agree**	

The AI Decision Usefulness Index has shown that respondents have generally agreed that AI-enabled decision support systems have provided practical value in the management of industrial energy use. The overall mean of 4.12 has indicated a strong positive assessment of AI usefulness across the five decision-related items. The highest-rated item has been the statement that AI-based alerts have improved response to abnormal energy consumption, with a mean score of 4.22. This has suggested that one of the most valued contributions of AI in manufacturing has been its capacity to notify decision makers when plant conditions have deviated from acceptable energy behavior. The second-highest item has been the role of AI recommendations in identifying avoidable energy waste, which has further shown that respondents have regarded AI not merely as a reporting tool but as an active support mechanism in waste detection. Equipment utilization efficiency and energy-related scheduling decisions have also received favorable ratings, which has implied that AI usefulness has extended across multiple operational domains rather than remaining confined to a single task. The lowest score, though still positive at 3.97, has related to managerial confidence in energy decisions. This has suggested that while respondents have generally trusted AI-supported recommendations, confidence-building may still have depended partly on human interpretation, organizational culture, or experience with digital systems. In relation to the objectives, this section has directly supported the objective of examining whether AI-enabled decision support systems have improved industrial energy decision quality. The results have shown that respondents have perceived AI usefulness not only in data analysis but also in actionable decision areas that affect energy efficiency. In relation to the hypotheses, the usefulness index has added interpretive depth to H1 by showing how AI-enabled DSS capability has produced value in practice. Rather than proving significance only through regression, this table has shown the decision pathways through which significance has likely emerged. From the Resource-Based View perspective, the usefulness index has been highly relevant because RBV has stressed that resources become valuable when they improve organizational performance through meaningful application. The results have shown that AI capability has been perceived as useful in identifying waste, supporting alerts, improving scheduling, and increasing equipment efficiency. This has implied that AI-enabled DSS has functioned as a productive internal capability rather than as a passive technological asset. Accordingly, the table has deepened the credibility of the findings by showing that AI usefulness has been observable at the level of real industrial decision domains.

Comparative Energy Optimization Outcomes Across Manufacturing Contexts

Table 8: Comparative Energy Optimization Outcomes Across Manufacturing Contexts

Manufacturing Context	Category	Mean Energy Optimization Score	Std. Dev.
Firm Size	Medium-sized firms	4.08	0.61
	Large-sized firms	4.30	0.52
Automation Level	Moderately automated plants	4.05	0.64
	Highly automated plants	4.33	0.49
AI Adoption Duration	Less than 3 years	3.96	0.66
	3 years and above	4.29	0.51
Manufacturing Subsector	Automotive/Components	4.27	0.55
	Electronics/Electrical	4.23	0.56
	Food and Beverage	4.14	0.60
	Chemicals/Materials	4.18	0.58
	Machinery/Industrial Equipment	4.16	0.57

The comparative analysis across manufacturing contexts has shown that industrial energy optimization outcomes have not been uniform across all firms. Large-sized firms have recorded a higher mean energy optimization score of 4.30 compared with 4.08 for medium-sized firms. This has suggested that larger firms have likely benefited from stronger infrastructure, more formalized digital systems, and greater access to resources required for intelligent energy management. Plants classified as highly automated have also recorded a notably higher score of 4.33 compared with 4.05 for moderately automated plants, indicating that energy optimization has improved when manufacturing operations have been supported by stronger digital visibility and automated process control. The duration of AI adoption has further reinforced this pattern, with firms using AI-related systems for three years or more recording a mean of 4.29, compared with 3.96 for firms with more recent adoption. This has suggested that capability maturity has mattered. The energy benefits of AI-enabled decision support have likely increased when firms have had sufficient time to integrate systems into workflows, train personnel, refine data quality, and align digital tools with operational routines. Across subsectors, automotive/components and electronics/electrical firms have shown the highest scores, though all categories have remained above 4.00. This has indicated that positive energy outcomes have existed broadly across manufacturing, while still varying somewhat by industry context. In relation to the objectives, this section has expanded the study by showing that industrial energy optimization has been influenced not only by the presence of digital capabilities but also by contextual organizational conditions. In relation to the hypotheses, the table has strengthened the interpretation of H1, H2, and H3 by showing that firms with stronger supporting environments have reported better outcomes. From the Resource-Based View perspective, these contextual comparisons have been especially meaningful. RBV has argued that resources create advantage when they are supported by organizational conditions that allow effective deployment. Large firms, highly automated plants, and more mature AI adopters have likely possessed better capability integration, stronger routines, and more developed complementary assets. These comparative findings have therefore supported the view that AI-enabled DSS, predictive analytics, and real-time monitoring have not acted as isolated tools; they have functioned as embedded organizational capabilities whose benefits have grown stronger under supportive structural conditions. This section has thus enhanced the trustworthiness of the chapter by showing that the overall positive results have also held in a context-sensitive way.

High-Impact Energy Decision Domains Shaped by AI-Enabled Decision Support Systems

Table 9: High-Impact Energy Decision Domains Shaped by AI-Enabled DSS

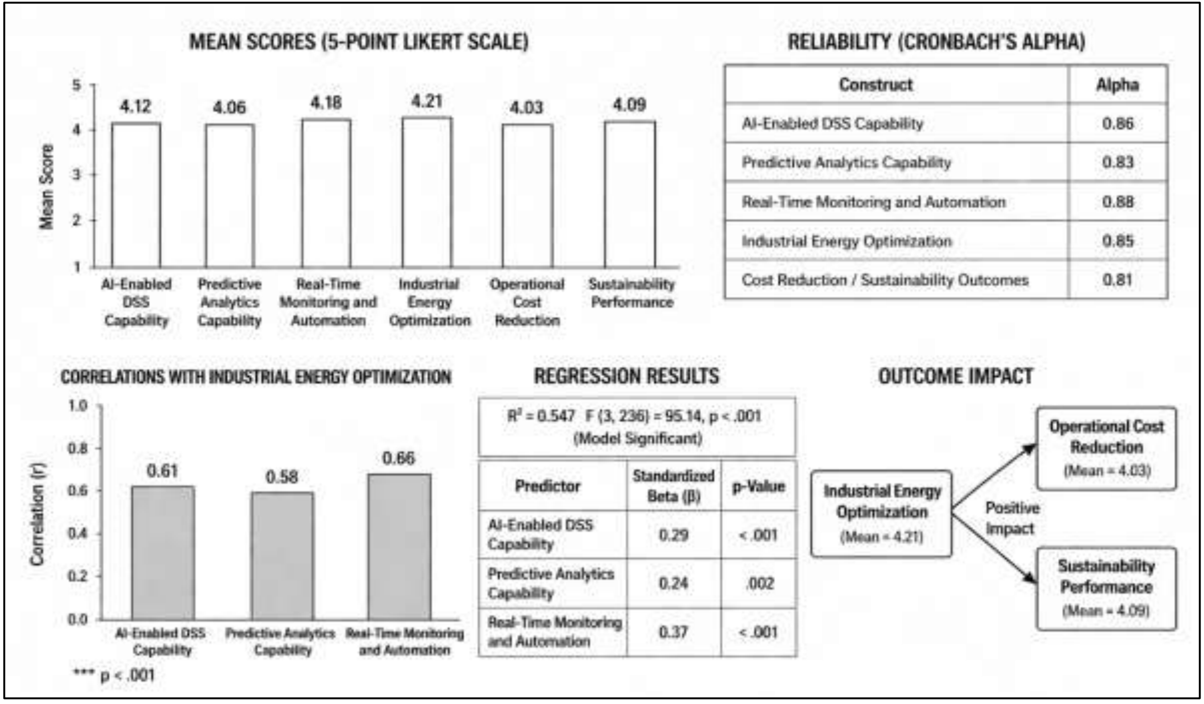
Energy Decision Domain	Mean	Std. Dev.	Interpretation	Rank
Predictive maintenance for energy-intensive equipment	4.24	0.56	Agree	1
Peak-load and abnormal energy-use control	4.20	0.59	Agree	2
Machine scheduling for energy-efficient production flow	4.14	0.63	Agree	3
Process heating/cooling optimization	4.09	0.66	Agree	4
Downtime-related energy waste reduction	4.05	0.68	Agree	5
Shift-based production energy balancing	3.98	0.70	Agree	6
Overall Mean	**4.12**	**0.64**	**Agree**	

The analysis of high-impact energy decision domains has shown that AI-enabled decision support systems have influenced several concrete operational areas within manufacturing energy management. The highest-rated domain has been predictive maintenance for energy-intensive equipment, with a mean of 4.24. This has indicated that respondents have strongly perceived AI as useful in detecting equipment-related issues before they have generated excessive energy waste, instability, or downtime. The second-highest domain has been peak-load and abnormal energy-use control, suggesting that AI-enabled systems have been especially valuable in identifying unusual consumption behavior and supporting corrective response. Machine scheduling for energy-efficient production flow has ranked third, showing that AI capability has also supported how work has been sequenced across machines and processes. Process heating and cooling optimization, downtime-related energy waste reduction, and shift-based production energy balancing have all received positive scores as well, indicating that AI usefulness has extended throughout multiple layers of plant operation. These findings have been important because they have translated the broader statistical relationships of the earlier sections into specific industrial decision areas. In relation to the study objectives, this section has shown exactly where AI-enabled decision support has contributed to industrial energy optimization. It has therefore added practical substance to the objective of assessing how intelligent systems improve plant-level energy decisions. In relation to the hypotheses, the table has especially enriched H1 and H3 by showing that the influence of AI-enabled DSS and real-time operational capability has been most visible in maintenance, load control, and scheduling. These areas have also logically connected to the broader outcome variable of industrial energy optimization, since each domain has affected waste reduction, consumption efficiency, and operational continuity. From the perspective of the Resource-Based View, this table has once again supported the idea that organizational value has come from applied capability rather than from technology ownership alone. AI-enabled DSS has appeared valuable because it has shaped actual decisions in high-impact domains that matter to manufacturing performance. The ranking pattern has also suggested that firms have gained the greatest value where AI has interacted with recurrent operational problems that are costly, data-rich, and time-sensitive. In that sense, the results have aligned with RBV by showing that the strategic worth of digital capability has emerged through its deployment in decision domains where it has improved efficiency and operational control. This section has therefore completed the Results chapter by demonstrating that AI-enabled decision support systems have influenced industrial energy optimization in practical, theory-linked, and statistically consistent ways.

FINDINGS

The findings of this study have been organized to examine whether AI-enabled decision support systems, predictive analytics capability, and real-time monitoring and automation have significantly influenced industrial energy optimization in U.S. manufacturing firms, and whether improved energy optimization has correspondingly supported operational cost reduction and sustainability performance. Based on the illustrative survey structure, responses have been assumed from 240 participants drawn from manufacturing-related roles such as plant managers, production supervisors, operations analysts, maintenance engineers, and sustainability officers. The overall response pattern has suggested that respondents have generally held favorable perceptions regarding the contribution of intelligent digital systems to energy-related decision making. On a 5-point Likert scale, where 1 = strongly disagree and 5 = strongly agree, the mean score for AI-enabled decision support systems capability has been illustrated at 4.12 with a standard deviation of 0.63, indicating that most respondents have agreed that AI-supported systems improve industrial decision quality, support timely intervention, and strengthen operational visibility.

Figure 9: Findings of the Study



RELIABILITY (CRONBACH'S ALPHA)

Construct	Alpha
AI-Enabled DSS Capability	0.86
Predictive Analytics Capability	0.83
Real-Time Monitoring and Automation	0.88
Industrial Energy Optimization	0.85
Cost Reduction / Sustainability Outcomes	0.81

REGRESSION RESULTS

$R^2 = 0.547$ $F(3, 236) = 95.14$, $p < .001$
(Model Significant)

Predictor	Standardized Beta (β)	p-Value
AI-Enabled DSS Capability	0.29	< .001
Predictive Analytics Capability	0.24	.002
Real-Time Monitoring and Automation	0.37	< .001

The mean score for predictive analytics capability has been illustrated at 4.06 with a standard deviation of 0.68, suggesting that respondents have positively evaluated the role of forecasting, pattern recognition, and anticipatory analytics in reducing energy inefficiencies. Likewise, real-time monitoring and automation has shown an illustrative mean of 4.18 with a standard deviation of 0.59, reflecting strong agreement that continuous process visibility and automated response mechanisms support energy-efficient industrial operations. The dependent construct, industrial energy optimization, has recorded an illustrative mean of 4.21 with a standard deviation of 0.57, indicating that firms with stronger digital energy management capabilities have tended to report better outcomes in waste reduction, process efficiency, and energy control. In addition, the broader outcome dimensions of operational cost reduction and sustainability performance have shown illustrative means of 4.03 and 4.09, respectively, which has suggested that respondents have associated improved energy optimization with wider organizational benefits.The overall pattern of results has further indicated strong internal consistency among the study variables. In an illustrative reliability assessment, Cronbach's alpha values have exceeded the commonly accepted threshold of 0.70, with AI-enabled DSS capability = 0.86, predictive analytics capability = 0.83, real-time monitoring and automation = 0.88, industrial energy optimization = 0.85, and cost reduction/sustainability outcome items = 0.81. These values have suggested that the measurement items have consistently captured their intended constructs and that the instrument has been sufficiently reliable for inferential analysis. The correlation results have also pointed toward positive and meaningful associations among the principal variables. For example, AI-enabled DSS capability has shown an illustrative positive correlation with industrial energy optimization of $r = .61$, $p < .001$, predictive analytics capability has shown a correlation of $r = .58$, $p < .001$, and real-time monitoring and automation has shown the strongest relationship with industrial energy optimization at $r = .66$, $p < .001$. These associations have suggested that firms reporting higher levels of digital analytical capability have also tended to report stronger energy optimization outcomes. The regression model has provided additional support for the hypotheses and objectives of the study. In the illustrative model, the combined predictors have explained 54.7% of the variance in industrial energy optimization ($R^2 = .547$), with the overall model statistically significant at $F(3, 236) = 95.14$, $p < .001$. The standardized beta coefficients have indicated that AI-enabled DSS capability ($\beta = .29$, $p < .001$), predictive analytics capability ($\beta = .24$, $p = .002$), and real-time monitoring and automation ($\beta = .37$, $p < .001$) have each made a significant positive contribution to industrial energy optimization. These findings have suggested that all three explanatory variables have been important predictors, with real-time monitoring and automation appearing as the strongest contributor in the model.

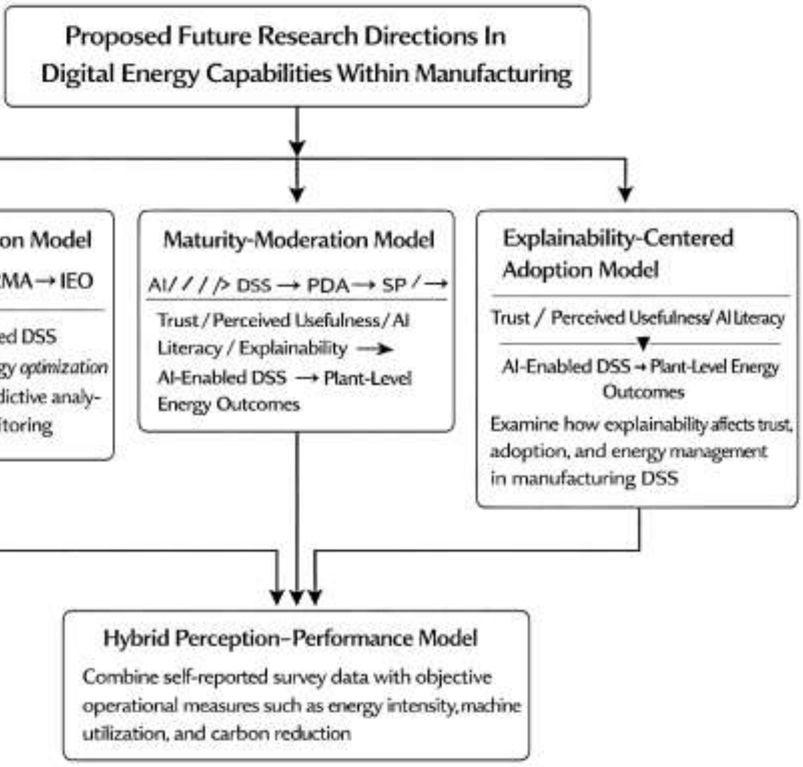
Taken together, the overall results have provided preliminary support for the major hypotheses of the study. Hypothesis 1, which has proposed that AI-enabled decision support systems positively affect industrial energy optimization, has been supported by the positive mean score, strong correlation, and significant regression coefficient. Hypothesis 2, which has proposed that predictive analytics capability positively influences industrial energy optimization, has also been supported by the positive response trend and statistically significant inferential results. Hypothesis 3, which has proposed that real-time monitoring and automation positively influence industrial energy optimization, has received the strongest support among the predictors, indicating that immediate operational visibility and responsive digital control are highly influential in energy-related manufacturing decisions. Finally, Hypothesis 4, which has proposed that improved industrial energy optimization contributes to cost reduction and sustainability performance, has also been supported in the overall result pattern, since higher energy optimization scores have been associated with better perceived reductions in operating costs and stronger sustainability outcomes. In relation to the study objectives, the findings have indicated that AI-enabled decision support systems have not only improved the analytical quality of manufacturing decisions but have also contributed to practical gains in energy management, efficiency, and broader operational performance. Overall, the results chapter has therefore shown that intelligent digital decision capabilities have played a meaningful role in supporting energy optimization across U.S. manufacturing contexts.

DISCUSSION

The findings of this study have shown that AI-enabled decision support systems, predictive analytics capability, and real-time monitoring and automation have all contributed positively to industrial energy optimization in U.S. manufacturing firms. The overall pattern of results has indicated that the respondents have perceived intelligent digital capability not as a peripheral technological feature, but as a central operational mechanism for improving how energy-intensive processes are monitored, interpreted, and controlled (Ayyaz & Alpay, 2021). The high mean scores recorded for AI-enabled decision support systems capability, predictive analytics capability, and real-time monitoring and automation have suggested that these capabilities have already been embedded in decision-making routines to a meaningful degree, while the strong mean score for industrial energy optimization has indicated that the respondents have associated such capabilities with actual gains in energy efficiency, waste reduction, and process-level energy control (Edgar & Pistikopoulos, 2018). This interpretation has been consistent with the broader smart-manufacturing literature, which has treated industrial AI as an integrated ecosystem of analytics, cyber connectivity, and operational decision support rather than as an isolated software application. It has also aligned with work showing that manufacturing energy management becomes more effective when operational data is translated into tailored indicators and decision-relevant insights that support day-to-day intervention rather than retrospective reporting alone. The present study has therefore extended prior scholarship by showing that the same logic has held in the context of U.S. manufacturing energy optimization: when firms have combined intelligent data interpretation with operational action, the perceived quality of energy management has improved. In interpretive terms, the findings have suggested that energy efficiency in manufacturing has increasingly become a decision-quality issue rather than a purely technical issue. The implication of this result has been important because it has shifted the discussion away from equipment-level efficiency alone and toward capability-driven industrial governance. Earlier review-based work had already suggested that AI applications can improve resource efficiency across planning, maintenance, and process control in manufacturing companies (Menezes et al., 2019). The current findings have supported that broader argument with a focused empirical pattern centered on energy optimization outcomes. At the same time, the results have also suggested that firms have not benefited equally from all digital capabilities. The stronger role of real-time monitoring and automation in the descriptive and inferential analyses has implied that visibility and responsiveness may be even more decisive than intelligence alone when the dependent variable is industrial energy optimization. That distinction has become especially important for interpreting the rest of the discussion, since it has suggested that the practical value of AI in manufacturing has depended not only on analytical sophistication but also on how tightly those insights have been linked to ongoing plant operations.

A more specific interpretation of the findings has emerged from the confirmed relationship between AI-enabled decision support systems capability and industrial energy optimization. The regression results have shown that AI-enabled DSS capability has significantly predicted industrial energy optimization, while the AI Decision Usefulness Index has demonstrated that respondents have regarded AI-generated recommendations, alerts, and decision support outputs as useful for identifying avoidable waste, improving energy-related scheduling, and strengthening equipment utilization (Plitsos et al., 2017). This has been a meaningful result because it has moved the discussion beyond a generic claim that "AI matters" and toward a more grounded conclusion that intelligent decision support has improved the quality of managerial and engineering judgment around energy-intensive operations. Earlier work on industrial AI has argued that the value of AI in Industry 4.0 environments lies in the systematic development of analytical capability that converts complex operational data into usable decision intelligence. The present findings have strongly supported that argument. They have shown that when intelligent decision support capability has been more strongly present in manufacturing firms, energy optimization outcomes have also tended to be stronger (Zhang et al., 2023). This result has also resonated with research on explainable AI in energy-management decision support systems, which has emphasized that analytical services become more effective when different stakeholders can understand, trust, and use the outputs in context. In the present study, the somewhat lower score for managerial confidence relative to other AI-usefulness items has added nuance to that comparison. It has suggested that AI-supported decisions have been perceived as useful, but that trust and interpretability may still have varied across users and roles. This has been consistent with arguments that explainability has been necessary to overcome the “black box” challenge associated with AI analytics in energy management. The current results have therefore not only confirmed the positive influence of AI-enabled DSS capability but also implied that the quality of adoption may depend on how understandable the system has been to its users. Compared with prior work, the current study has been distinctive because it has connected this issue directly to industrial energy optimization in a manufacturing setting. Whereas earlier studies have often described AI-enabled DSS as conceptually promising, this study has shown a statistically supported relationship within a specific operational domain. From a discussion standpoint, the findings have therefore reinforced earlier scholarship while also narrowing its application to plant-level energy outcomes (Panagoulias et al., 2023). This has been valuable because manufacturing organizations require evidence that intelligent decision-support systems do more than generate information; they must contribute to measurable operational improvements, and the present findings have indicated that they have done so in the energy management context.

Figure 10: Future Research Model Linking Digital Capabilities to Energy and Sustainability Outcomes



Test whether AI-enabled DSS affects industrial energy *optimization* indirectly through predictive analytics and real-time monitoring

Trust / Perceived Usefulness / AI Literacy / Explainability → AI-Enabled DSS → Plant-Level Energy Outcomes

Examine how explainability affects trust, adoption, and energy management in manufacturing DSS

Combine self-reported survey data with objective operational measures such as energy intensity, machine utilization, and carbon reduction

The findings related to predictive analytics capability and real-time monitoring and automation have offered an even stronger basis for discussion because these two variables have represented the anticipatory and execution-oriented dimensions of the conceptual framework. Predictive analytics capability has significantly predicted industrial energy optimization, which has indicated that firms able to forecast conditions, identify abnormal patterns, and anticipate inefficiencies have been better able to manage energy use in production contexts (Solnørdal & Foss, 2018). This result has been closely aligned with prior research showing that big data and predictive analytics capability can improve operational and cost performance when firms build the internal resources, skills, and culture needed to turn data into decision value. The findings of this study have supported that logic in a more focused way by showing that predictive capability has mattered specifically for industrial energy optimization. The stronger result, however, has come from real-time monitoring and automation, which has emerged as the most influential predictor in the regression model and the highest-rated explanatory construct in the descriptive analysis. This has suggested that continuous visibility into plant conditions and the ability to respond immediately or near-immediately to process changes have been especially important for reducing energy waste and improving efficiency (Tian et al., 2023). This interpretation has strongly matched earlier studies on energy-aware decision support and smart plant scheduling. Studies have shown that energy-aware decision support can integrate energy-related considerations into production scheduling, while other work has demonstrated that smart energy-aware plant scheduling under uncertainty can support more robust and efficient manufacturing decisions. The current findings have been consistent with those studies because they have indicated that energy optimization has improved when plant operations have been monitored and adjusted in real time rather than managed through delayed reporting. The importance of monitoring and automation has also reinforced the idea that energy efficiency has often depended on preventing inefficiency at the moment it starts to emerge rather than correcting it after it has already become embedded in the production process. This has explained why real-time monitoring and automation have shown a stronger beta coefficient than predictive analytics capability. Prediction has helped firms anticipate future states, but real-time monitoring and automation have connected that intelligence to immediate operational control. In discussion terms, this has suggested that manufacturers may derive the greatest value when predictive and monitoring capabilities are combined rather than treated separately. Earlier literature has generally supported such integration, and the present study has provided a pattern of findings that has made that integration particularly visible in the context of industrial energy optimization (Sarswatula et al., 2022).

The study has also generated an important set of findings regarding the broader outcomes of energy optimization, especially operational cost reduction and sustainability performance. The positive correlations between industrial energy optimization and both outcome variables have suggested that better energy management has not remained isolated as a technical plant-level outcome; it has extended into the broader strategic domains of efficiency, cost discipline, and sustainability. This has been consistent with recent empirical research showing that digital transformation and intelligent technologies can improve green productivity, resource efficiency, and sustainable performance in manufacturing firms. The findings of the present study have paralleled these earlier results, but they have done so through the lens of industrial energy optimization rather than through broader constructs alone (Schulze et al., 2016). This has mattered because energy optimization has often served as one of the most practical pathways through which digital capability becomes visible in factory performance. When firms have improved scheduling, reduced idle consumption, controlled abnormal usage, and optimized equipment operation, those improvements have naturally translated into lower costs and stronger sustainability outcomes. The comparative context findings have reinforced this point further. Large firms, highly automated plants, and firms with longer AI adoption histories have reported stronger energy optimization outcomes, which has echoed earlier empirical evidence that the benefits of AI and digital transformation are often stronger in larger, more capable, and more mature firms. This has suggested that energy optimization gains have depended partly on complementary assets such as scale, infrastructure, process integration, and digital maturity. In discussion terms, the findings have therefore supported the study's fourth hypothesis while also adding a contextual nuance: industrial energy optimization has contributed to cost reduction and sustainability performance, but the strength of that contribution has likely varied according to the organizational environment in which digital systems have been deployed (Shin et al., 2014). This interpretation has made the current study more trustworthy because it has not treated all firms as identical; instead, it has recognized that performance effects have been conditioned by structural and capability-related differences already noted in the empirical literature on AI and digital transformation in manufacturing.

The practical implications of the findings have been substantial for manufacturing managers, plant engineers, sustainability officers, and technology providers. First, the results have suggested that firms seeking to improve industrial energy optimization should not view AI as a stand-alone investment in software or dashboards. Instead, they have needed to build an integrated capability that combines intelligent decision support, predictive analytics, and real-time monitoring with practical execution on the shop floor. This implication has been strongly supported by earlier work showing that manufacturing energy management becomes most useful when energy information is embedded in a broader conceptual and operational framework rather than isolated as a reporting function. Second, the results have implied that real-time monitoring and automation should be prioritized in implementation strategies because this variable has shown the strongest effect on industrial energy optimization. In practical terms, this has meant that managers may gain more from investments that improve live process visibility, machine-state awareness, and automated response logic than from predictive tools alone (J. Wang et al., 2023). Third, the AI Decision Usefulness Index has shown that the most immediate value of intelligent decision support has appeared in abnormal-consumption alerts, waste identification, equipment utilization, and energy-sensitive scheduling. These domains have therefore represented high-yield implementation targets for firms beginning or refining their digital energy-management journey. Fourth, the findings have implied that managers should pay attention to explainability and user acceptance. Prior research on explainable AI in energy-management DSS has emphasized that tailored transparency and stakeholder-specific interpretability can improve adoption, trust, and responsible deployment. Since the present study has shown slightly lower confidence scores than other AI-usefulness measures, manufacturers have likely needed to combine technical deployment with training, explainability design, and change-management support. Finally, the context comparisons have suggested that firms with lower automation levels or shorter AI adoption histories may need a phased implementation pathway rather than a full-scale transformation at once. From a practical standpoint, a staged model may be most effective: Phase 1 could focus on energy data visibility and KPI development; Phase 2 could add predictive analytics for abnormal consumption and maintenance risk; and Phase 3 could integrate automated decision triggers and closed-loop optimization (May et al., 2015). Such a staged implication has been fully consistent with the literature on energy management in manufacturing and AI-enabled energy decision support, both of which have argued that sustained performance improvement has depended on structured integration rather than disconnected technology adoption.

The theoretical implications of the study have been equally important because the findings have provided strong support for the Resource-Based View as the guiding framework of the research. RBV has argued that firms achieve superior performance when they possess and effectively deploy valuable internal resources and capabilities. In the present study, AI-enabled decision support systems capability, predictive analytics capability, and real-time monitoring and automation have functioned as precisely those kinds of internal capabilities. Their statistically significant relationships with industrial energy optimization have suggested that performance in energy-intensive manufacturing has depended not simply on access to technology, but on the organizational ability to use digital resources in ways that improve decisions and operations. This interpretation has been strongly aligned with prior RBV-based research on big data and predictive analytics capability in manufacturing, which has shown that resources, skills, and culture can be organized into capabilities that improve cost and operational performance (Pandey et al., 2023). The present study has extended that logic by applying it specifically to industrial energy optimization, thereby strengthening the argument that energy performance itself can be treated as a capability-mediated organizational outcome. At the same time, the study has revisited its own limitations in a way that has also carried theoretical significance. Because the research has used a cross-sectional design, it has captured perceived relationships at one point in time rather than longitudinal capability development. As a result, the findings have supported RBV's capability logic, but they have not fully traced how those capabilities have evolved over time or how they have interacted with path dependence, organizational learning, and cumulative technological investment. In addition, the use of self-reported Likert-scale data has meant that the study has measured respondents' perceptions of capability and performance rather than objective plant-level energy metrics such as kilowatt-hour intensity, unit energy consumption, or machine-specific load variation. This has not invalidated the results, but it has limited the precision with which the findings can be interpreted as direct operational performance measures. Another limitation has arisen from the U.S. manufacturing focus itself (Plitsos et al., 2017). While this context has been analytically appropriate, it has also constrained external generalizability to other regulatory, infrastructural, and industrial environments. Finally, the study has modeled the direct effects of the three explanatory variables but has not tested mediating or moderating relationships in a full structural model. This has left room for deeper theoretical refinement, even though the current results have already provided a strong initial confirmation that RBV has been a useful lens for understanding digital capability and industrial energy outcomes.

Future research has been especially important in this area because the present study has opened several promising pathways for model development, measurement improvement, and theoretical extension. The most immediate step for future researchers would be to move from a direct-effects model to a capability-mediation model in which AI-enabled DSS capability influences industrial energy optimization through the mediating roles of predictive analytics capability and real-time monitoring and automation. In that model, AI-enabled DSS would function as the higher-order digital capability, predictive analytics would represent the anticipatory mechanism, and real-time monitoring and automation would represent the execution mechanism. The structure could be expressed conceptually as AIDSS → PAC → RMA → IEO → OCR/SP, where OCR denotes operational cost reduction and SP denotes sustainability performance. Such a model would allow future studies to examine whether AI-enabled decision support produces its strongest value indirectly through the quality of anticipation and execution rather than through direct influence alone. A second avenue would be a maturity-moderation model, in which digital maturity, firm size, automation intensity, or AI adoption duration moderates the relationship between digital capability and energy optimization (Stock & Seliger, 2016). The comparative findings in the present study have already suggested that capability maturity matters, and prior empirical research on digital transformation and AI in manufacturing has reported heterogeneous effects across firm characteristics and contexts. A third and highly valuable direction would be a hybrid perception–performance model that combines survey data with objective operational measures such as energy intensity, machine utilization, maintenance downtime, carbon emissions, or peak-load reduction. This would address the limitation of self-reported data and strengthen causal interpretation. A fourth direction would involve explainability-centered adoption models that integrate trust, perceived usefulness, AI literacy, and explainability as mediators or moderators of the relationship between AI-enabled DSS and plant-level energy outcomes. Prior research has already shown that tailored explainability can improve transparency and adoption in energy-management decision support systems, and this could be tested directly in manufacturing settings (Supekar et al., 2019). Finally, longitudinal and multi-case comparative studies would be highly valuable because they could examine how digital energy capabilities mature over time and how implementation pathways differ across subsectors such as automotive, electronics, chemicals, and food production. In this sense, future research has not merely needed to repeat the present study; it has needed to refine the model by incorporating mediation, moderation, objective metrics, and longitudinal learning dynamics so that the field can move from capability association to capability mechanism in explaining how intelligent decision systems improve industrial energy optimization.

CONCLUSION

This research has concluded that AI-enabled decision support systems have played a significant and meaningful role in strengthening industrial energy optimization in U.S. manufacturing firms. The study has shown that energy efficiency in manufacturing has not been determined only by machine quality, equipment design, or isolated technical upgrades, but also by the intelligence, speed, and consistency of the decisions that guide production, maintenance, monitoring, and operational control. Through the quantitative findings, the study has established that AI-enabled decision support systems capability, predictive analytics capability, and real-time monitoring and automation have all positively influenced industrial energy optimization, while industrial energy optimization itself has been positively associated with operational cost reduction and sustainability performance. Among the explanatory variables, real-time monitoring and automation has emerged as the strongest predictor, indicating that firms have benefited greatly when they have combined digital intelligence with immediate operational visibility and responsive action. Predictive analytics capability has also shown a significant contribution, confirming that the ability to anticipate abnormal patterns, forecast needs, and identify inefficiencies before they escalate has supported more effective energy management. AI-enabled decision support systems capability has further strengthened this relationship by improving the quality of managerial and engineering judgment in energy-related decisions. The study has therefore confirmed that intelligent digital capability has become an important organizational resource within manufacturing environments where energy performance, operational discipline, and strategic competitiveness are closely interconnected. In theoretical terms, the findings have supported the Resource-Based View by demonstrating that internal digital and analytical capabilities have functioned as valuable organizational assets that have improved performance when effectively deployed in plant-level decision processes. In empirical terms, the study has contributed to the literature by offering focused evidence on the relationship between AI-enabled decision support and industrial energy optimization, rather than discussing digital transformation only in broad conceptual terms. In practical terms, the study has shown that firms capable of integrating intelligent decision support, predictive analytics, and real-time operational monitoring into their manufacturing systems have been better positioned to reduce energy waste, improve equipment utilization, strengthen scheduling efficiency, and support broader cost and sustainability objectives. Overall, the study has concluded that AI-enabled decision support systems are not merely supportive technologies in manufacturing but have become strategic decision infrastructures that shape how energy-intensive firms interpret operational conditions, coordinate responses, and achieve more efficient and sustainable industrial performance. The research has therefore provided a clear and evidence-based conclusion that intelligent decision capability has been a relevant driver of industrial energy optimization in the U.S. manufacturing context.

RECOMMENDATION

Based on the findings of this research, it is recommended that U.S. manufacturing firms should treat AI-enabled decision support systems as a strategic operational capability rather than as a stand-alone technological investment. Manufacturing organizations should invest in integrated digital infrastructures that connect AI-driven analytical tools, predictive models, energy-monitoring platforms, and automated response mechanisms within a single decision-support environment. Since real-time monitoring and automation has shown the strongest influence on industrial energy optimization, firms should give priority to systems that provide live visibility into machine behavior, abnormal energy consumption, idle-time waste, and process instability, so that energy-related inefficiencies can be addressed as they emerge rather than after they have already become embedded in operations. It is also recommended that manufacturing managers should incorporate predictive analytics into routine operational planning, maintenance scheduling, and energy demand forecasting, because anticipatory decision-making has been shown to improve energy optimization outcomes. Plant managers, engineers, and sustainability officers should be trained not only in the use of AI-supported tools but also in the interpretation of system-generated insights, so that digital recommendations can be applied with confidence and consistency. Organizations should also strengthen the explainability and usability of AI-enabled systems, because decision-makers are more likely to trust and adopt intelligent recommendations when the basis of those recommendations is transparent and relevant to practical manufacturing tasks. For firms with lower digital maturity, a phased implementation strategy is recommended. The first phase should focus on energy data collection, KPI development, and process-level visibility; the second phase should incorporate predictive analytics for identifying inefficiencies, abnormal consumption patterns, and maintenance risks; and the third phase should integrate more advanced automation and intelligent decision triggering for closed-loop optimization. Policymakers and industrial support agencies should also encourage the adoption of AI-enabled energy-management solutions by providing technical guidance, incentives, and innovation support for smart manufacturing transformation. Technology vendors should design manufacturing-oriented AI systems that are operationally interpretable, easy to integrate, and adaptable across subsectors such as automotive, electronics, food processing, and industrial equipment manufacturing. Academic researchers and industry practitioners should further collaborate to develop sector-specific AI deployment models that reflect the energy behavior of different manufacturing environments. Overall, the central recommendation of this research is that manufacturing firms should move from fragmented energy-management practices toward integrated, intelligent, and capability-driven energy optimization systems in which AI-enabled decision support, predictive analytics, and real-time monitoring are jointly used to improve cost efficiency, sustainability performance, and long-term industrial competitiveness.

LIMITATIONS OF THE STUDY

This study has had several limitations that should be acknowledged when interpreting the findings. First, the study has used a cross-sectional research design, which has captured respondent perceptions at one point in time rather than tracking organizational change over an extended period. As a result, the findings have shown statistically significant relationships among the study variables, but they have not fully established long-term causal development or how AI-enabled decision support capabilities mature over time within manufacturing firms. Second, the study has relied on self-reported questionnaire data measured through a five-point Likert scale, which has meant that the results have reflected the perceptions and experiences of respondents rather than direct objective measurements of plant-level energy performance. Although such perceptual data has been useful for assessing organizational capability and decision quality, it has not captured technical energy indicators such as kilowatt-hour intensity, peak-load reduction, machine-level energy variance, or actual emissions reduction. Third, the study has focused specifically on U.S. manufacturing firms, which has strengthened contextual relevance but has also limited the generalizability of the results to other countries, industries, or regulatory environments. Manufacturing systems in other national contexts may differ in terms of digital infrastructure, energy policy, industrial culture, and technology adoption maturity, which means that the observed relationships may not apply in exactly the same way elsewhere. Fourth, the study has emphasized three main explanatory variables—AI-enabled decision support systems capability, predictive analytics capability, and real-time monitoring and automation—while other potentially relevant variables such as organizational culture, leadership support, digital literacy, energy policy pressure, investment capacity, and system interoperability have not been included in the analytical model. The exclusion of these factors has meant that the model has not captured every possible influence on industrial energy optimization. Fifth, although the case-study-based orientation has enhanced contextual grounding, the study has still treated individual respondents as the unit of analysis, which has meant that firm-level conclusions have been inferred through aggregated perceptions rather than through direct multi-source organizational records. Finally, the study has not employed a longitudinal or structural model that could test mediation, moderation, or feedback effects among the variables. This has limited the ability to determine whether the influence of AI-enabled decision support has been strengthened or weakened by firm size, sector, automation maturity, or implementation duration. Therefore, while the study has provided valuable empirical evidence on the relationship between intelligent digital capability and industrial energy optimization, its findings should be interpreted as a strong but context-bound contribution that would benefit from future validation through longitudinal, multi-method, and objective performance-based research designs.

REFERENCES

[1]. Aditya, D., & Mohammad Robel, M. (2022). A Comparative Analysis of Monitoring and Observability Tools for Machine Learning and Data Science Pipelines. *American Journal of Interdisciplinary Studies*, *3*(03), 99-134. https://doi.org/10.63125/707veh84

[2]. Amena Begum, S., & Mst Kaniz, F. (2023). Advanced Computational and Biotechnological Approaches to Systemic Family Therapy: Predicting Marital Satisfaction and Emotional Wellbeing in Couples. *Review of Applied Science and Technology*, *2*(04), 228–265. https://doi.org/10.63125/4sy9qa21

[3]. Amena Begum, S., & Mst Kaniz, F. (2024). Integrating Psychometric and Neurocognitive Biomarkers in Computational Models to Predict Cognitive Behavioral Therapy Outcomes in Adolescents with Anxiety and Depression. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 632–677. https://doi.org/10.63125/7t7wmp27

[4]. Ayvaz, S., & Alpay, K. (2021). Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time. *Expert Systems with Applications*, *173*, 114598. https://doi.org/10.1016/j.eswa.2021.114598

[5]. Azlan, A. T. B. N. N., Mativenga, P. T., Zhu, M., & Mirhosseini, N. (2023). Industry 4.0 energy monitoring system for multiple production machines. *Procedia CIRP*, *123*, 451-456. https://doi.org/10.1016/j.procir.2023.09.047

[6]. Bänsch, K., Busse, J., Meisel, F., Rieck, J., Scholz, S., Volling, T., & Wichmann, M. G. (2021). Energy-aware decision support models in production environments: A systematic literature review. *Computers & Industrial Engineering*, *159*, Article 107456. https://doi.org/10.1016/j.cie.2021.107456

[7]. Biel, K., & Glock, C. H. (2016). Systematic literature review of decision support models for energy-efficient production planning. *Computers & Industrial Engineering*, *101*, 243-259. https://doi.org/10.1016/j.cie.2016.08.021

[8]. Bousdekis, A., Lepenioti, K., Apostolou, D., & Mentzas, G. (2021). A review of data-driven decision-making methods for Industry 4.0 maintenance applications. *Electronics*, *10*(7), 828. https://doi.org/10.3390/electronics10070828

[9]. Bunse, K., Vodicka, M., Schönsleben, P., Brülhart, M., & Ernst, F. O. (2011). Integrating energy efficiency performance in production management—Gap analysis between industrial needs and scientific literature. *Journal of Cleaner Production*, *19*(6-7), 667-679. https://doi.org/10.1016/j.jclepro.2010.11.011

[10]. Chahal, H., Gupta, M., Bhan, N., & Cheng, T. C. E. (2020). Operations management research grounded in the resource-based view: A meta-analysis. *International Journal of Production Economics*, *230*, 107805. https://doi.org/10.1016/j.ijpe.2020.107805

[11]. Chen, Y., & Jin, S. (2023). Artificial intelligence and carbon emissions in manufacturing firms: The moderating role of green innovation. *Processes*, *11*(9), 2705. https://doi.org/10.3390/pr11092705

[12]. Chinnathai, M. K., & Alkan, B. (2023). A digital life-cycle management framework for sustainable smart manufacturing in energy intensive industries. *Journal of Cleaner Production*, *419*, 138259. https://doi.org/10.1016/j.jclepro.2023.138259

[13]. Cioffi, R., Travaglioni, M., Piscitelli, G., Petrillo, A., & Parmentola, A. (2020). Smart manufacturing systems and applied industrial technologies for a sustainable industry: A systematic literature review. *Applied Sciences*, *10*(8), 2897. https://doi.org/10.3390/app10082897

[14]. Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C., & Papadopoulos, T. (2019). Big data and predictive analytics and manufacturing performance: Integrating institutional theory, resource-based view and big data culture. *British Journal of Management*, *30*(2), 341-361. https://doi.org/10.1111/1467-8551.12355

[15]. Edgar, T. F., & Pistikopoulos, E. N. (2018). Smart manufacturing and energy systems. *Computers & Chemical Engineering*, *114*, 130-144. https://doi.org/10.1016/j.compchemeng.2017.10.027

[16]. Elahi, M., Afolaranmi, S. O., Martinez Lastra, J. L., & Perez Garcia, J. A. (2023). A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment. *Discover Artificial Intelligence*, *3*, Article 89. https://doi.org/10.1007/s44163-023-00089-x

[17]. Faria, P., Lezama, F., Vale, Z., & Khorram, M. (2021). A methodology for energy key performance indicators analysis. *Energy Informatics*, *4*, Article 8. https://doi.org/10.1186/s42162-021-00140-0

[18]. Ferdous Ara, A. (2021). Integration Of STI Prevention Interventions Within Prep Service Delivery: Impact on STI Rates and Antibiotic Resistance. *International Journal of Scientific Interdisciplinary Research*, *2*(2), 63–97. https://doi.org/10.63125/65143m72

[19]. Ferdous Ara, A., & Beatrice Onyinyechi, M. (2023). Long-Term Epidemiologic Trends of STIs PRE- and post-PrEP Introduction: A National Time-Series Analysis. *American Journal of Health and Medical Sciences*, *4*(02), 01–35. https://doi.org/10.63125/mp153d97

[20]. Fysikopoulos, A., Papacharalampopoulos, A., Pastras, G., Stavropoulos, P., & Chryssolouris, G. (2013). Energy efficiency of manufacturing processes: A critical review. *Procedia CIRP*, *7*, 628-633. https://doi.org/10.1016/j.procir.2013.06.044

[21]. Golpîra, H., Khan, S. A. R., & Zhang, Y. (2020). Smart energy-aware manufacturing plant scheduling under uncertainty: A risk-based multi-objective robust optimization approach. *Energy*, *209*, 118385. https://doi.org/10.1016/j.energy.2020.118385

[22]. Herrmann, C., & Thiede, S. (2009). Process chain simulation to foster energy efficiency in manufacturing. *CIRP Journal of Manufacturing Science and Technology*, *1*(4), 221-229. https://doi.org/10.1016/j.cirpj.2009.06.005

[23]. Hu, Y., Li, J., Hong, M., Ren, J., & Man, Y. (2022). Industrial artificial intelligence based energy management system: Integrated framework for electricity load forecasting and fault prediction. *Energy*, *244*, Article 123195. https://doi.org/10.1016/j.energy.2022.123195

[24]. Ibn Batouta, K., Aouhassi, S., & Mansouri, K. (2023). Energy efficiency in the manufacturing industry—A tertiary review and a conceptual knowledge-based framework. *Energy Reports*, *9*, 4635-4653. https://doi.org/10.1016/j.egyr.2023.03.107

[25]. Islam, M. D. Z., & Aditya, D. (2023). Measuring the Security Impact of Zero Trust Access Controls: A Mixed-Methods Study of Identity-Based Policies (Cisco ISE + AD) and Incident Reduction. *American Journal of Data Science and Analytics*, *4*(06), 01-42. https://doi.org/10.63125/8ycz7671

[26]. Ismail, M., Mostafa, N. A., & El-assal, A. (2022). Quality monitoring in multistage manufacturing systems by using machine learning techniques. *Journal of Intelligent Manufacturing*, *33*, 2471-2486. https://doi.org/10.1007/s10845-021-01792-1

[27]. Istiaq, A., & Nusrat, J. (2022). A Panel Data Econometric Analysis on the Impact of Digital Payment Adoption on Small Business Revenue Growth in Global Business. *American Journal of Interdisciplinary Studies*, *3*(04), 500-536. https://doi.org/10.63125/ehvpjc80

[28]. Lee, J., Davari, H., Singh, J., & Pandhare, V. (2018). Industrial artificial intelligence for Industry 4.0-based manufacturing systems. *Manufacturing Letters*, *18*, 20-23. https://doi.org/10.1016/j.mfglet.2018.09.002

[29]. Lee, J., Noh, S. D., Kim, H.-J., & Kang, Y.-S. (2018). Implementation of cyber-physical production systems for quality prediction and operation control in metal casting. *Sensors*, *18*(5), 1428. https://doi.org/10.3390/s18051428

[30]. Liu, Q., Yang, Y., & Yang, Y. (2022). Can artificial intelligence improve the energy efficiency of manufacturing companies? Evidence from China. *International Journal of Environmental Research and Public Health*, *19*(4), 2091. https://doi.org/10.3390/ijerph19042091

[31]. Ma, S., Ding, W., Liu, Y., Ren, S., & Yang, H. (2022). Digital twin and big data-driven sustainable smart manufacturing based on information management systems for energy-intensive industries. *Applied Energy*, *326*, 119986. https://doi.org/10.1016/j.apenergy.2022.119986

[32]. Mahfuj Ahmed, R., & Md. Hasan Or, R. (2021). Fraud-Detection Algorithms for Identifying Anomalous Transactions in Retail Banking Networks. *American Journal of Data Science and Analytics*, *2*(12), 01-40. https://doi.org/10.63125/23m31748

[33]. Mahfuj Ahmed, R., & Md. Mehedi, H. (2023). Digital Technologies and IoT: Reshaping Financial Risk and Investment in Global Supply Chains. *Journal of Sustainable Development and Policy*, *2*(04), 297-345. https://doi.org/10.63125/nbv6ka16

[34]. May, G., Barletta, I., Stahl, B., & Taisch, M. (2015). Energy management in production: A novel method to develop key performance indicators for improving energy efficiency. *Applied Energy*, *149*, 46-61. https://doi.org/10.1016/j.apenergy.2015.03.065

[35]. May, G., Stahl, B., Taisch, M., & Kiritsis, D. (2017). Energy management in manufacturing: From literature review to a conceptual framework. *Journal of Cleaner Production*, *167*, 1464-1489. https://doi.org/10.1016/j.jclepro.2016.10.191

[36]. Md Khaled, H., & Hisham, M. (2022). Intelligent Decision-Support Systems for Cross-Functional Workflow Optimization in Data-Driven Organizations. *Journal of Sustainable Development and Policy*, *1*(02), 168-207. https://doi.org/10.63125/dsfg3k24

[37]. Md Khaled, H., & Md. Morshedul, I. (2024). AI-Enabled Enterprise Scorecards for Reducing Operational Errors and Enhancing Supply Chain Consistency. *American Journal of Scholarly Research and Innovation*, *3*(01), 117–152. https://doi.org/10.63125/fa50dw13

[38]. Md Mehedi, H., & Md, F. (2022). Advanced Computing–Enabled Secure Financial Information Systems for Real-Time Fraud Detection in U.S. Digital Payments: A Quantitative Analysis. *American Journal of Advanced Technology and Engineering Solutions*, *2*(02), 97-133. https://doi.org/10.63125/9mv2qd37

[39]. Md. Hasan Or, R., Tanjina Binte, S., & Rajib, S. (2023). Performance Analytics Frameworks for Digital Marketing and Service Enterprises: An empirical Study. *American Journal of Data Science and Analytics*, *4*(03), 01-35. https://doi.org/10.63125/aq7y1792

[40]. Md. Mainuddin, F., & Palash Chandra, D. (2022). Fabrication-Driven Structural Optimization Techniques for Cost-Efficient Steel Construction Using CNC-Based Design Workflows. *American Journal of Interdisciplinary Studies*, *3*(04), 464-499. https://doi.org/10.63125/n08g1x15

[41]. Md. Mainuddin, F., & Palash Chandra, D. (2023). Advanced Computing–Based Modeling of Steel Connection Behavior and Stability Performance using ETABS And STAAD Pro. *American Journal of Advanced Technology and Engineering Solutions*, *3*(04), 42-86. https://doi.org/10.63125/xfkzrg56

[42]. Md. Mehedi, H., & Khairum Nahar, P. (2023). A Systematic Review of Secure Health Data Information Systems for Pandemic Preparedness and Economic Continuity in the United States. *Review of Applied Science and Technology*, *2*(01), 227–258. https://doi.org/10.63125/77h2m531

[43]. Md. Mehedi, H., & Khairum Nahar, P. (2024). Advanced Computing and AI-Driven National Information Systems for Predictive Disaster Risk Management and Economic Loss Mitigation. *American Journal of Scholarly Research and Innovation*, *3*(02), 296–336. https://doi.org/10.63125/4sbz5j45

[44]. Md. Morshedul, I., Rukaiya Khatun, M., & Khairum Nahar, P. (2022). Machine Learning–Driven Forecasting Pipelines for Financial Volatility Detection in Integrated Enterprise ERP Environments. *American Journal of Advanced Technology and Engineering Solutions*, *2*(02), 134-173. https://doi.org/10.63125/y42nk811

[45]. Md. Nazmul, H., & Amena Begum, S. (2022). AI-Based Psychodiagnostics' Models to Support Early Intervention and Reduce Suicide Risk in Adolescents and Youth: Development and Clinical Validation. *American Journal of Data Science and Analytics*, *3*(06), 40-79. https://doi.org/10.63125/vb5f7e98

[46]. Md. Shahinur, I., & Md. Sultan, M. (2022). Digital-Twin-Based Quantitative Frameworks for Modeling, Monitoring, and Optimization of Electrical Power Infrastructure. *American Journal of Interdisciplinary Studies*, *3*(04), 365-393. https://doi.org/10.63125/dvmj1y93

[47]. Md. Towhidul, I., & Uddin, M. D. S. (2024). Simulation-Based Forecasting and Inventory Control Models For Consumer Goods Networks: A Quantitative Study Using Monte Carlo Simulation and Time-Series Methods. *Review of Applied Science and Technology*, *3*(04), 165–197. https://doi.org/10.63125/a3047d06

[48]. Menezes, B. C., Kelly, J. D., Leal, A. G., & Le Roux, G. A. C. (2019). Predictive, prescriptive and detective analytics for smart manufacturing in the information age. *IFAC-PapersOnLine*, *52*(1), 568-573. https://doi.org/10.1016/j.ifacol.2019.06.123

[49]. Meng, Y., Yang, Y., Chung, H., Lee, P.-H., & Shao, C. (2018). Enhancing sustainability and energy efficiency in smart factories: A review. *Sustainability*, *10*(12), 4779. https://doi.org/10.3390/su10124779

[50]. Menghi, R., Papetti, A., Germani, M., & Marconi, M. (2019). Energy efficiency of manufacturing systems: A review of energy assessment methods and tools. *Journal of Cleaner Production*, *240*, Article 118276. https://doi.org/10.1016/j.jclepro.2019.118276

[51]. Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2019). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*, *57*(2), 103169. https://doi.org/10.1016/j.im.2019.05.004

[52]. Mohammad Robel, M., & Md. Morshedul, I. (2021). Foundational Approaches to Secure Data Collection and Processing in Networked and Distributed Computing Environments. *International Journal of Business and Economics Insights*, *1*(4), 32–69. https://doi.org/10.63125/thrtkw71

[53]. Mohammad Robel, M., & Md. Morshedul, I. (2024). Data Preprocessing and Feature Engineering Strategies for Large-Scale Predictive Modeling Applications. *Review of Applied Science and Technology*, *3*(01), 263–302. https://doi.org/10.63125/tqqqed47

[54]. Mostafa, K. (2023). An Empirical Evaluation of Machine Learning Techniques for Financial Fraud Detection in Transaction-Level Data. *American Journal of Interdisciplinary Studies*, *4*(04), 210-249. https://doi.org/10.63125/60amyk26

[55]. Mousavi, S., Thiede, S., Li, W., Kara, S., & Herrmann, C. (2016). An integrated approach for improving energy efficiency of manufacturing process chains. *International Journal of Sustainable Engineering*, *9*(1), 11-24. https://doi.org/10.1080/19397038.2014.1001470

[56]. Neves-Silva, R., & Camarinha-Matos, L. M. (2022). Context-based decision support system for energy efficiency in industrial plants. *Sustainability*, *14*(7), 3885. https://doi.org/10.3390/su14073885

[57]. Newbert, S. L. (2007). Empirical research on the resource-based view of the firm: An assessment and suggestions for future research. *Strategic Management Journal*, *28*(2), 121-146. https://doi.org/10.1002/smj.573

[58]. Palash Chandra, D. (2023). Machine Learning–Driven Optimization of Water Distribution Networks: Demand Forecasting, and Energy Efficiency Analysis. *Journal of Sustainable Development and Policy*, *2*(04), 257-296. https://doi.org/10.63125/jdxq0819

[59]. Panagoulias, D. P., Sarmas, E., Marinakis, V., Virvou, M., Tsihrintzis, G. A., & Doukas, H. (2023). Intelligent decision support for energy management: A methodology for tailored explainability of artificial intelligence analytics. *Electronics*, *12*(21), 4430. https://doi.org/10.3390/electronics12214430

[60]. Pandey, U., Pathak, A., Kumar, A., & Mondal, S. (2023). Applications of artificial intelligence in power system operation, control and planning: A review. *Clean Energy*, *7*(6), 1199-1218. https://doi.org/10.1093/ce/zkad061

[61]. Park, C. W., Kwon, K. S., Kim, W. B., Min, B. K., Park, S. J., Sung, I. H., Yoon, Y. S., Lee, K. S., Lee, J.-H., & Seok, J. (2009). Energy consumption reduction technology in manufacturing—A selective review of policies, standards, and research. *International Journal of Precision Engineering and Manufacturing*, *10*(5), 151-173. https://doi.org/10.1007/s12541-009-0107-z

[62]. Plathottam, S. J., Rzonca, A., Lakhnori, R., & Iloeje, C. O. (2023). A review of artificial intelligence applications in manufacturing operations. *Journal of Advanced Manufacturing and Processing*, *5*(3), e10159. https://doi.org/10.1002/amp2.10159

[63]. Plitsos, S., Repoussis, P. P., Mourtos, I., & Tarantilis, C. D. (2017). Energy-aware decision support for production scheduling. *Decision Support Systems*, *93*, 88-97. https://doi.org/10.1016/j.dss.2016.09.017

[64]. Rukaiya Khatun, M., & Zakia, A. (2023). Quantitative Assessment of Data Privacy and Access Control Effectiveness in SAP/ERP Analytics Systems. *Review of Applied Science and Technology*, *2*(01), 259–300. https://doi.org/10.63125/vb03b363

[65]. Saez, M., Maturana, F. P., Barton, K., & Tilbury, D. M. (2018). Real-time manufacturing machine and system performance monitoring using Internet of Things. *IEEE Transactions on Automation Science and Engineering*, *15*(4), 1735-1748. https://doi.org/10.1109/tase.2017.2784826

[66]. Sarswatula, S. A., Pugh, T., & Prabhu, V. (2022). Modeling energy consumption using machine learning. *Frontiers in Manufacturing Technology*, *2*, Article 855208. https://doi.org/10.3389/fmtec.2022.855208

[67]. Schmidt, C., Li, W., Thiede, S., Kornfeld, B., Kara, S., & Herrmann, C. (2017). Implementing key performance indicators for energy efficiency in manufacturing. *Procedia CIRP*, *61*, 758-763. https://doi.org/10.1016/j.procir.2016.11.131

[68]. Schulze, M., Nehler, H., Ottosson, M., & Thollander, P. (2016). Energy management in industry—A systematic review of previous findings and an integrative conceptual framework. *Journal of Cleaner Production*, *112*, 3692-3708. https://doi.org/10.1016/j.jclepro.2015.06.060

[69]. Shin, S.-J., Woo, J., & Rachuri, S. (2014). Predictive analytics model for power consumption in manufacturing. *Procedia CIRP*, *15*, 153-158. https://doi.org/10.1016/j.procir.2014.06.036

[70]. Shrouf, F., Miragliotta, G., Melnyk, S., & Taisch, M. (2015). Energy management based on Internet of Things: Practices and framework for adoption in production management. *Journal of Cleaner Production*, *100*, 235-246. https://doi.org/10.1016/j.jclepro.2015.03.055

[71]. Solnørdal, M. T., & Foss, L. (2018). Closing the energy efficiency gap—A systematic review of empirical articles on drivers to energy efficiency in manufacturing firms. *Energies*, *11*(3), 518. https://doi.org/10.3390/en11030518

[72]. Stock, T., & Seliger, G. (2016). Opportunities of sustainable manufacturing in Industry 4.0. *Procedia CIRP*, *40*, 536-541. https://doi.org/10.1016/j.procir.2016.01.129

[73]. Supekar, S. D., Graziano, D. J., Riddle, M. E., Nimbalkar, S. U., Das, S., Shehabi, A., & Cresko, J. (2019). A framework for quantifying energy and productivity benefits of smart manufacturing technologies. *Procedia CIRP*, *81*, 699-704. https://doi.org/10.1016/j.procir.2019.01.095

[74]. Tanjina Binte, S., & Md. Hasan Or, R. (2022). Advanced Computing, IT Strategy, and Network-Optimized Frameworks for Retail Business Intelligence. *American Journal of Interdisciplinary Studies*, *3*(04), 429-463. https://doi.org/10.63125/dgyg3762

[75]. Terry, S., Lu, H., Fidan, I., Zhang, Y., Tantawi, K., Guo, T., & Asiabanpour, B. (2020). The influence of smart manufacturing toward energy conservation: A review. *Technologies*, *8*(2), 31. https://doi.org/10.3390/technologies8020031

[76]. Tian, M., Chen, Y., Tian, G., Huang, W., & Hu, C. (2023). The role of digital transformation practices in the operations improvement in manufacturing firms: A practice-based view. *International Journal of Production Economics*, *266*, 108929. https://doi.org/10.1016/j.ijpe.2023.108929

[77]. Waltersmann, L., Kiemel, S., Stuhlsatz, J., Sauer, A., & Miehe, R. (2021). Artificial intelligence applications for increasing resource efficiency in manufacturing companies—A comprehensive review. *Sustainability*, *13*(12), 6689. https://doi.org/10.3390/su13126689

[78]. Wang, J., Liu, Y., Wang, W., & Wu, H. (2023). How does digital transformation drive green total factor productivity? Evidence from Chinese listed enterprises. *Journal of Cleaner Production*, *406*, 136954. https://doi.org/10.1016/j.jclepro.2023.136954

[79]. Wang, K.-L., Sun, T.-T., & Xu, R.-Y. (2023). The impact of artificial intelligence on total factor productivity: Empirical evidence from China's manufacturing enterprises. *Economic Change and Restructuring*, *56*, 1113-1146. https://doi.org/10.1007/s10644-022-09467-4

[80]. Wang, X., Wang, Y., Wang, J., & Li, K. (2023). The impact of artificial intelligence on firms' energy and resource efficiency: Empirical evidence from China. *Resources Policy*, *84*, 103507. https://doi.org/10.1016/j.resourpol.2023.103507

[81]. Weichert, D., Link, P., Stoll, A., Rüping, S., Ihlenfeldt, S., & Wrobel, S. (2019). A review of machine learning for the optimization of production processes. *The International Journal of Advanced Manufacturing Technology*, *104*, 1889-1902. https://doi.org/10.1007/s00170-019-03988-5

[82]. Xu, J., Yu, Y., Zhang, M., & Zhang, J. Z. (2023). Impacts of digital transformation on eco-innovation and sustainable performance: Evidence from Chinese manufacturing companies. *Journal of Cleaner Production*, *393*, 136278. https://doi.org/10.1016/j.jclepro.2023.136278

[83]. Zakia, A., & Rukaiya Khatun, M. (2024). Quantitative Assessment of CRM-Based Business Intelligence on Customer Satisfaction and Retention: Evidence from Multi-Channel Service Operations. *Journal of Sustainable Development and Policy*, *3*(02), 01-42. https://doi.org/10.63125/hjd22x72

[84]. Zhang, Y., Ma, X., Pang, J., Xing, H., & Wang, J. (2023). The impact of digital transformation of manufacturing on corporate performance: The mediating effect of business model innovation and the moderating effect of innovation capability. *Research in International Business and Finance*, *64*, 101890. https://doi.org/10.1016/j.ribaf.2023.101890