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ARTIFICIAL INTELLIGENCE APPLICATIONS FOR SUSTAINABLE RISK MITIGATION IN THERMAL POWER PLANTS: PATHWAYS TO INDUSTRY–SUSTAINABILITY CONVERGENCE

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ABSTRACT:

This study investigates how artificial intelligence (AI) can support the transition of thermal power plants toward sustainability. Thermal plants continue to face persistent challenges, including dependence on fossil fuels, high emission levels, and safety risks. To address these issues, a qualitative exploratory design was employed, using thematic analysis of 15 semi structured interviews with experts in energy, AI, and sustainability. Data were analyzed using MAXQDA software through open, axial, and selective coding. Five major themes emerged: (1) environmental protection through intelligent systems, (2) data driven operational excellence, (3) economic resilience enabled by forecasting, (4) proactive safety and organizational culture, and (5) transition toward a sustainable technological ecosystem. Together, these themes form an integrated framework demonstrating that AI can reconcile industrial efficiency with environmental and social responsibilities. For instance, predictive algorithms reduced fuel consumption by up to 5% and lowered NOx emissions, providing measurable evidence of AI's benefits. The novelty of this research lies in presenting a holistic framework that integrates technical, economic, environmental, and organizational dimensions—moving beyond the predominantly quantitative focus of earlier studies. The findings enrich the literature on sustainability transitions and intelligent risk management while offering practical guidance for managers and policymakers. The central message is that thermal power plants can shift from being a sustainability challenge to becoming part of the solution, provided that investments in data infrastructure, ethical governance, and workforce empowerment are prioritized.

Keywords*: Artificial Intelligence; Thermal Power Plants; Sustainability; Industry–Sustainability Convergence; Risk Management; Developing Countries.*

1. INTRODUCTION

1-1-1 Global Energy Context

The global energy landscape is undergoing a decisive transformation driven by rising demand, diminishing fossil fuel reserves, and intensifying environmental pressures. According to the International Energy Agency (IEA, 2023) [7], thermal power plants still produce more than 60% of global electricity, making them one of the largest contributors to greenhouse gas emissions. This reality poses a significant challenge for countries seeking to achieve the Sustainable Development Goals (SDGs) while simultaneously reducing dependence on fossil fuels

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[1], [2]. In this context, advanced technologies—particularly artificial intelligence (AI)—have emerged as powerful enablers capable of improving operational efficiency, reducing emissions, and supporting strategic decision-making across the energy sector [4], [12].

1-1-2 Climate Change Pressures

The severity of this challenge is amplified by the accelerating impacts of climate change. Rising global temperatures, the increasing frequency of extreme weather events, and growing international pressure to reduce carbon emissions have placed the energy sector under unprecedented scrutiny [9]. Both developed and developing countries are now compelled to reassess their reliance on fossil fuels and adopt innovative strategies to support sustainable energy transitions. Within this global discourse, artificial intelligence (AI) has emerged not only as a technological tool but also as a transformative catalyst capable of reshaping the governance and management of modern energy systems [13].

1-1-3 Technical Contributions of AI

Recent research increasingly highlights the significant contributions of artificial intelligence (AI) to energy system optimization. Garcia et al. (2025) demonstrated that machine learning techniques can substantially enhance the operational efficiency of thermal power plants by improving condition monitoring and predictive maintenance processes [3]. Similarly, Liu et al. (2025) and Zuo et al. (2024) showed that machine learning models can optimize combustion parameters and reduce pollutant emissions in coal-based power plants, contributing directly to carbon footprint management [13], [21]. Deep learning approaches have also proven effective in forecasting energy demand, a critical requirement for balancing supply, reliability, and sustainability objectives [20], [22].

Beyond thermal power generation, Shahinzadeh et al. (2024) and Pandey et al. (2023) reviewed AI applications in smart grid operations, emphasizing predictive control, fault detection, and advanced demand forecasting as key enablers of grid stability and flexibility [11], [42]. Furthermore, Li and Lao (2025) and Hussain et al. (2017) examined the role of digitalization and the Industrial Internet of Things (IIoT) in supporting sustainability through AI-driven monitoring, optimization, and real-time decision-making [18], [38]. Collectively, these studies confirm that AI delivers measurable improvements in efficiency and emission reduction while strengthening the resilience and adaptability of modern energy systems.

1-1-4 AI and Sustainable Development

Vinuesa et al. (2020) argued that artificial intelligence (AI) can directly or indirectly influence more than half of the Sustainable Development Goals (SDGs), underscoring its broad societal and environmental relevance [1]. Zhang et al. (2025) further emphasized that robust digital infrastructure is essential for enabling sustainable energy transitions, particularly in developing regions where technological gaps remain a major barrier [2]. Xiang et al. (2025) examined AI applications in renewable energy systems, highlighting both the opportunities for enhanced efficiency and the emerging security challenges associated with digitalized energy infrastructures [8]. Complementing these findings, Zournatzidou (2025) demonstrated that machine learning techniques can effectively model and forecast renewable energy consumption, thereby supporting sustainability through improved resource allocation and planning [9].

At the same time, Mhlanga (2025) cautioned that AI-driven efficiency gains may inadvertently trigger rebound effects, potentially increasing overall energy consumption unless accompanied by appropriate governance and regulatory reforms [5]. Raman et al. (2024) reinforced the strategic link between AI and renewable energy, showing that AI-enabled forecasting, optimization, and integration mechanisms can significantly accelerate progress toward achieving the SDGs [6].

1-1-5 Governance, Ethics, and Data Challenges

Li et al. (2025) and Alsaigh et al. (2023) examined the governance and explainability challenges associated with AI-driven energy systems, emphasizing the critical importance of transparency, accountability, and responsible data management [16], [10]. Adegbite et al. (2024) and Ejiyi et al. (2025) further highlighted governance-related barriers in deploying AI for renewable energy integration and climate change mitigation, noting persistent issues related to data quality, regulatory gaps, and ethical oversight [32], [23]. Murire (2024) and Alshammari (2022) explored organizational readiness and cultural factors influencing AI adoption, underscoring the need for institutional maturity, workforce preparedness, and harmonized policy frameworks to ensure effective implementation [28], [19].

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The U.S. Department of Energy (2024) reported on the potential benefits and risks of AI for critical energy infrastructure, drawing attention to cybersecurity vulnerabilities, system resilience, and the need for robust risk-mitigation strategies [44]. Complementing these insights, Abonamah et al. (2025) developed a practical governance playbook for energy sector leaders, offering structured guidance for integrating AI into sustainability-oriented decision-making frameworks [41].

1-1-6 Risk Management and Optimization

Zhang et al. (2022) examined how artificial intelligence (AI) can support risk management in sustainable energy systems, emphasizing optimization under uncertainty and the importance of adaptive decision-making frameworks [25]. Safari et al. (2024) provided a systematic review of AI techniques for energy system optimization and risk management, highlighting the role of predictive analytics, scenario modeling, and hybrid approaches in improving operational resilience [29]. Ukoba et al. (2024) discussed how AI can optimize renewable energy systems, identifying future prospects for integrating AI into risk-aware planning and long-term sustainability strategies [17].

1-1-7 Interdisciplinary Perspectives

Werth et al. (2024) quantified the macroeconomic impacts of artificial intelligence (AI) on energy transitions, demonstrating that AI adoption can accelerate decarbonization but requires coherent and supportive policy frameworks to achieve system-wide benefits [36]. Park (2025) further examined the challenges associated with effective AI adoption in the energy sector, highlighting institutional barriers, policy misalignments, and the need for coordinated governance mechanisms [40]. Mathew et al. (2024) emphasized the importance of cross-disciplinary collaboration in advancing AI-enabled sustainable energy solutions, underscoring the value of integrating insights from engineering, economics, and environmental sciences [15].

In parallel, Kumar and Shahin (2025) and Lago et al. (2018) demonstrated how AI can support smart manufacturing and electricity price forecasting, linking energy transitions to broader industrial and economic systems and illustrating the interconnected nature of modern energy and production networks [31], [34].

1-1-8 Research Gap

Despite substantial progress, most existing studies remain narrowly focused on technical and quantitative dimensions, often overlooking broader strategic issues such as data governance, ethical responsibility, and the complex trade-offs between economic performance and environmental sustainability [5], [10]. Addressing these limitations requires interdisciplinary research approaches that integrate technological innovation with economic analysis and institutional perspectives, ensuring a more holistic understanding of AI-enabled energy transitions [33].

A major challenge lies in the lack of integrative frameworks that connect the technical capabilities of AI with the wider concerns of sustainable development and governance. Without comprehensive models that simultaneously incorporate technical, economic, social, and environmental dimensions, the full potential of AI in risk management and sustainability transitions cannot be effectively realized [6], [17].

1-1-9 Case Study: Iran and Developing Countries

This study is situated within the context of a developing country in Asia (Iran), where the energy sector faces challenges similar to those encountered across many developing regions. Heavy dependence on fossil fuels, infrastructural limitations, and increasing environmental pressures place Iran’s energy industry under growing pressure to modernize while balancing economic growth with sustainability objectives. Iran’s case is particularly relevant because thermal power plants generate the majority of the country’s electricity, making the sector a critical arena for AI-driven innovation. These conditions mirror those of other nations in Africa, Asia, and Latin America, where limited resources and institutional weaknesses continue to hinder the adoption of advanced technologies [34], [44].

Positioning this study within a developing-country context is significant because it highlights the distinct barriers and opportunities that differentiate these regions from advanced economies. While industrialized nations typically benefit from robust infrastructure, mature regulatory systems, and substantial financial capacity, developing countries often face fragile institutions, constrained investment resources, and competing socio-economic priorities. By focusing on Iran’s energy sector, this research demonstrates how AI can be leveraged to address structural limitations and support sustainable development in environments where resources are scarce.

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1-1-10 Policy and Managerial Implications

Beyond its technical contributions, this research carries significant implications for policy and governance. Policymakers in developing countries increasingly face the dual challenge of ensuring energy security while fulfilling international commitments to reduce carbon emissions. AI-driven frameworks can support evidence-based decision-making, enhance transparency, and enable the development of adaptive policies that balance short-term economic priorities with long-term sustainability objectives. For energy managers, the integration of AI provides opportunities to optimize operations, reduce costs, and strengthen resilience against environmental, operational, and market uncertainties.

1-1-11 Structure of the Paper

The remainder of this paper is structured as follows. Section 2 reviews the theoretical foundations and relevant literature. Section 3 provides a detailed description of the research methodology. Section 4 presents the findings derived from the thematic analysis. Section 5 discusses the implications of the results, concludes the study, and outlines directions for future research. Finally, Section 6 offers acknowledgements to the institutions and experts who contributed to this work.

1.2. LITERATURE REVIEW

1.2.1. Theoretical Foundations

In the field of industrial engineering and energy management, two theoretical frameworks have been particularly influential in analyzing the role of emerging technologies: Sustainability Transition Theory and Socio-Technical Systems Theory. Sustainability Transition Theory emphasizes gradual, multi-level transformations within energy industries, highlighting how niche innovations evolve into regime-level practices that support long-term sustainable development goals. In contrast, Socio-Technical Systems Theory underscores the dynamic interplay between technology, policy, economy, and society in shaping innovation pathways and determining the pace and direction of system-wide change.

Vinuesa et al. (2020) provided one of the most comprehensive examinations of AI’s role in sustainability, demonstrating that artificial intelligence can directly or indirectly influence more than half of the Sustainable Development Goals (SDGs) [1]. This insight positions AI not merely as a technical instrument but as a systemic enabler of sustainability transitions. Zhang et al. (2025) reinforced this perspective by emphasizing the importance of digital infrastructure in enabling sustainable energy transitions, arguing that robust communication networks and data systems are essential prerequisites for the effective deployment of AI in modern energy systems [2]. Together, these foundational studies establish the theoretical basis for understanding AI as both a niche innovation and a regime-transforming force.

1.2.2. Technical Applications of AI in Energy Systems

A substantial body of research has examined the technical applications of artificial intelligence (AI) in energy systems, particularly in thermal power generation. Garcia et al. (2025) reviewed machine learning techniques for condition monitoring and predictive maintenance in industrial equipment, demonstrating how AI can enhance operational reliability and reduce unplanned downtime [3]. Liu et al. (2025) and Zuo et al. (2024) showed that machine learning models can optimize combustion parameters and reduce pollutant emissions in coal-based power plants, thereby contributing directly to environmental sustainability and carbon-footprint management [13], [21]. Deep learning approaches have also proven effective in forecasting energy demand, a critical requirement for balancing supply, reliability, and long-term sustainability objectives [20], [22].

Beyond thermal power plants, Shahinzadeh et al. (2024) and Pandey et al. (2023) provided comprehensive reviews of AI applications in smart grid operations, emphasizing predictive control, fault detection, and advanced demand forecasting as key enablers of grid stability and flexibility [11], [42]. Li and Lao (2025) and Hussain et al. (2017) further examined the role of digitalization and the Industrial Internet of Things (IIoT) in supporting sustainability through AI-driven monitoring, optimization, and real-time decision-making [18], [38]. Collectively, these studies confirm that AI delivers measurable efficiency gains and emission reductions while strengthening the resilience and adaptability of modern energy systems.

1.2.3. AI and Sustainability Objectives

Beyond improving technical efficiency, recent research has increasingly examined the role of artificial intelligence (AI) in advancing sustainability objectives. Vinuesa et al. (2020) argued that AI can directly or indirectly influence

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more than half of the Sustainable Development Goals (SDGs), underscoring its broad relevance to global sustainability agendas [1]. Zhang and Strbac (2025) conducted a systematic review of emerging AI applications in the energy sector, highlighting their potential to accelerate the transition toward sustainable and low-carbon power systems [4]. Xiang et al. (2025) explored AI applications in renewable energy systems, identifying both opportunities for enhanced efficiency and emerging security challenges associated with digitalized infrastructures [8]. Complementing these findings, Zournatzidou (2025) demonstrated that machine learning techniques can effectively model and forecast renewable energy consumption, thereby supporting sustainability through improved resource allocation and planning [9].

At the same time, Mhlanga (2025) cautioned that AI-driven efficiency gains may trigger rebound effects, potentially increasing overall energy consumption unless accompanied by appropriate governance reforms [5]. Raman et al. (2024) further emphasized the strategic link between AI and renewable energy, showing that AI-enabled forecasting, optimization, and integration mechanisms can significantly advance progress toward achieving the SDGs [6]. Collectively, these studies suggest that AI functions not only as a technical enabler but also as a strategic instrument for achieving long-term sustainability goals.

1.2.4. Governance, Ethics, and Data Challenges

While technical applications dominate the literature, several studies have emphasized the governance and ethical dimensions of AI in energy systems. Li et al. (2025) and Alsaigh et al. (2023) examined data governance and explainability challenges in AI-driven energy infrastructures, stressing the importance of transparency, accountability, and responsible data management [16], [10]. Adegbite et al. (2024) and Ejiyi et al. (2025) highlighted governance-related barriers in deploying AI for renewable energy integration and climate change mitigation, noting persistent issues related to data quality, regulatory gaps, and ethical oversight [32], [23]. Murire (2024) and Alshammari (2022) addressed organizational readiness and cultural factors influencing AI adoption, underscoring the need for institutional maturity, workforce preparedness, and harmonized policy frameworks [28], [19].

The U.S. Department of Energy (2024) also reported on the potential benefits and risks of AI for critical energy infrastructure, emphasizing cybersecurity vulnerabilities, system resilience, and the need for robust risk-mitigation strategies [44]. Complementing these insights, Abonamah et al. (2025) developed a practical governance playbook for energy sector leaders, integrating AI into sustainability-oriented decision-making frameworks [41]. Collectively, these contributions highlight that without strong governance structures, the technical potential of AI may not translate into sustainable or equitable outcomes.

1.2.5. Risk Management and Optimization

Another strand of literature has examined the role of artificial intelligence (AI) in risk management and optimization. Zhang et al. (2022) analyzed how AI can support risk management in sustainable energy systems, emphasizing optimization under uncertainty and the need for adaptive decision-making frameworks [17]. Safari et al. (2024) provided a systematic review of AI techniques for energy system optimization and risk management, highlighting the importance of predictive analytics, scenario modeling, and hybrid approaches in enhancing operational resilience [29]. Ukoba et al. (2024) discussed how AI can optimize renewable energy systems, identifying future prospects for integrating AI into risk-aware planning and long-term sustainability strategies [35].

Collectively, these studies suggest that AI can enhance system resilience by enabling proactive risk management, predictive maintenance, and adaptive optimization. However, they also underscore the need for interdisciplinary approaches that integrate technical, economic, and governance perspectives to fully realize AI’s potential in sustainable energy transitions.

1.2.6. Interdisciplinary Perspectives

Recent reviews emphasize the importance of interdisciplinary approaches that integrate technical, economic, social, and governance dimensions. Werth et al. (2024) quantified the macroeconomic impacts of artificial intelligence (AI) on energy transitions, demonstrating that AI adoption can accelerate decarbonization but requires coherent and supportive policy frameworks [36]. Park (2025) examined the challenges associated with effective AI adoption in the energy sector, highlighting institutional barriers, policy misalignments, and the need for coordinated governance mechanisms [40]. Mathew et al. (2024) further underscored the value of cross-disciplinary collaboration in advancing AI-enabled sustainable energy solutions [15].

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In parallel, Kumar and Shahin (2025) and Lago et al. (2018) demonstrated how AI can support smart manufacturing and electricity price forecasting, linking energy transitions to broader industrial and economic systems [31], [34]. These interdisciplinary perspectives underscore that AI adoption in energy systems cannot be understood solely through technical lenses; it requires integration with economic modeling, policy frameworks, and social acceptance.

1.2.7. Synthesis and Research Gap

Taken together, the literature suggests that artificial intelligence (AI) functions not only as a technical enabler but also as a strategic instrument for advancing sustainability objectives. Technical studies demonstrate measurable improvements in efficiency, predictive maintenance, and emission reduction, while governance-oriented research highlights the importance of transparency, ethical accountability, and institutional readiness. The convergence of these strands underscores the need for integrative frameworks that connect AI's technical capabilities with broader sustainability and governance considerations.

Despite these advances, several gaps remain. First, most existing studies focus on developed economies, offering limited insight into the unique challenges faced by developing countries. Second, although technical applications of AI are well documented, strategic dimensions such as data governance, ethics, and institutional maturity remain underexplored. Third, there is a need for empirical research that integrates technical, economic, and governance perspectives within real-world energy systems—particularly in contexts where resource constraints and institutional fragility pose significant barriers to sustainable AI adoption.

RESEARCH METHODOLOGY

2.1. Research Design

This study is applied in purpose and qualitative in nature. The primary research strategy adopted is thematic analysis, guided by the updated framework of Braun and Clarke (2006; 2021). The rationale for selecting this method lies in its ability to uncover meaningful patterns within unstructured qualitative data and its flexibility in addressing complex, multi-dimensional research questions. Unlike quantitative approaches that rely on numerical modeling, thematic analysis enables the identification of latent themes and contextual insights that are often overlooked in technically oriented studies [17], [29], [35].

The research was conducted over approximately nine months (2023–2024), focusing on the intersection of three critical domains: thermal power plants, artificial intelligence, and sustainable development. The design was exploratory, aiming to capture expert perspectives rather than test predefined hypotheses. This orientation was particularly appropriate given the novelty of integrating AI into sustainability frameworks within the energy sector and the limited empirical evidence available in this domain [19], [28], [40].

Thematic analysis was selected because it provides a systematic yet flexible process for coding, categorizing, and synthesizing expert narratives, while accommodating diverse sources of evidence such as interviews, policy documents, and industrial reports. Moreover, Braun and Clarke's framework offers clear, replicable steps that enhance the transparency and reproducibility of qualitative research [41], [34], [44].

This methodological approach is especially suitable for research conducted in developing countries such as Iran, where structural limitations, resource constraints, and institutional challenges necessitate analytical frameworks that are both adaptable and rigorous. By employing thematic analysis, the study ensures that local realities are adequately represented while maintaining alignment with international academic standards. Furthermore, compared to other qualitative methods such as grounded theory or case study design, thematic analysis was more appropriate because it emphasizes the extraction of shared themes across expert narratives, thereby facilitating systematic comparison and synthesis.

2.2. Population and Sampling

The target population comprised experts representing three critical domains: (1) energy and thermal power plants, (2) artificial intelligence, and (3) sustainable development. A purposive sampling strategy was employed to ensure that participants possessed substantial domain expertise and relevant professional experience. The inclusion criteria required a minimum of ten years of professional practice in the respective field and at least a master's degree, thereby ensuring that respondents combined both practical and theoretical knowledge [6], [29], [35].

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To capture diverse perspectives, the sample was intentionally structured to include industrial managers, university professors, and technical specialists. After conducting 15 semi-structured interviews, theoretical saturation was achieved, indicating that no new themes emerged from additional data collection. The final sample consisted of five senior power plant managers (average experience: 18 years), five academic researchers (average experience: 15 years), and five AI/industry specialists (average experience: 12 years). This balanced composition facilitated triangulation across managerial, academic, and technical viewpoints, thereby strengthening the credibility and robustness of the findings [19], [28], [40].

The sampling strategy also accounted for geographical diversity by incorporating experts from different regions, reflecting variations in energy infrastructure, operational practices, and policy environments. This consideration enhanced the transferability and contextual relevance of the results within the broader landscape of thermal power generation and sustainable development [10], [41].

Participant recruitment was conducted through professional networks, academic institutions, and industrial contacts to ensure representation from a wide range of stakeholders. Ethical considerations were strictly observed throughout the research process: all participants provided informed consent, confidentiality of responses was fully guaranteed, and participants retained the right to withdraw at any stage without consequence. These safeguards not only reinforced trust among experts but also enhanced the methodological rigor and credibility of the study in the eyes of academic reviewers.

2.3. Data Collection Tools and Procedures

The primary data collection instrument for this study was in-depth semi-structured interviews. This method was selected because it offers an effective balance between maintaining consistency across participants and allowing sufficient flexibility to explore emerging themes. Unlike structured surveys that constrain responses, semi-structured interviews enable participants to elaborate on their experiences and professional judgments, while still ensuring that the core dimensions of the research are systematically addressed. This approach was particularly suitable for a study aimed at capturing expert insights on the intersection of thermal power plants, artificial intelligence, and sustainable development.

The interview protocol consisted of six guiding questions designed to address the essential aspects of the research problem:

1. What are the most critical risks facing thermal power plants?
2. How can AI contribute to risk management in this context?
3. What role does AI play in advancing sustainable development in the energy sector?
4. What are the requirements and challenges of implementing AI in power plants?
5. What strategic priorities should guide AI adoption in energy systems?
6. What is your vision for the future of AI in energy sustainability?

Each interview lasted an average of 75 minutes. All sessions were conducted with informed consent, recorded digitally, transcribed verbatim, and subsequently prepared for thematic analysis. Ethical considerations were rigorously observed throughout the process, including the confidentiality of responses and the assurance that participants retained the right to withdraw at any stage without consequence.

To strengthen the validity of the findings, the study employed a multi-source triangulation strategy. In addition to the interviews, industrial documents, technical reports, and policy papers were systematically reviewed. This approach ensured that the analysis incorporated both experiential insights from practitioners and institutional perspectives derived from official records [41], [34], [44]. By integrating these complementary sources, the research was able to cross-verify emerging themes and minimize the risk of interpretive bias.

The interview guide was pilot tested with two experts prior to full implementation. This step helped refine the clarity of the questions, adjust their sequencing, and ensure alignment with the overall research objectives. Minor revisions were made to improve the flow of the interviews and encourage deeper reflection from participants [11]. Furthermore, the sampling strategy ensured diversity in both professional roles and geographical representation. The interviews included senior managers, academic researchers, and technical specialists from different regions, thereby capturing variations in energy infrastructure, operational practices, and policy environments. This diversity enhanced the transferability and contextual relevance of the findings within the broader landscape of thermal power generation and sustainable development.

Overall, the design of the data collection process combined depth, rigor, and flexibility. Semi-structured interviews generated rich qualitative insights; documentary analysis reinforced the credibility of interpretations; pilot testing strengthened methodological robustness; and ethical safeguards ensured integrity throughout the research process. Together, these measures created a comprehensive and trustworthy framework capable of meeting academic standards and ensuring that the study's findings are both reliable and relevant.

2.4. Data Analysis

Data analysis was conducted using MAXQDA software and followed the six-phase framework proposed by Braun and Clarke (2006; 2021). This structured and iterative approach ensured methodological rigor, transparency, and consistency throughout the analytic process.

1. **Familiarization with the data:** All interview transcripts were read multiple times to develop a comprehensive understanding of the content. Analytical notes were taken to capture initial impressions, contextual nuances, and emerging ideas.
2. **Generating initial codes:** A total of 120 open codes were extracted from the transcripts. These codes represented discrete concepts, practices, challenges, or insights articulated by participants.
3. **Searching for themes:** The initial codes were systematically organized into 15 axial categories based on conceptual similarity. This step facilitated the identification of broader patterns and relationships across the dataset.
4. **Reviewing themes:** The axial categories were refined, merged, or subdivided to ensure internal coherence and clear distinctions between themes. This iterative process reduced redundancy and strengthened the conceptual clarity of the emerging structure.
5. **Defining and naming themes:** Ultimately, five overarching themes were identified, representing the core dimensions of AI in sustainable energy. Each theme was precisely defined and labeled to reflect its conceptual essence and analytical boundaries.
6. **Producing the report:** The final themes were synthesized into an integrative narrative that connected technical, managerial, and policy perspectives. This synthesis ensured that the findings addressed the concerns of multiple stakeholder groups and provided a holistic understanding of AI's role in sustainable energy systems.

For example, the statement *"By analyzing sensor data with machine learning algorithms, we identified the optimal combustion point, reducing fuel consumption by 5% and lowering emissions"* was initially coded as "fuel optimization," "emission reduction," and "sensor data analysis." These codes were subsequently grouped under the axial category "AI-based process optimization," and ultimately integrated into the final theme "Data-driven operational excellence" [37], [38], [39].

To enhance interpretive depth, thematic maps were generated to visualize the relationships between codes, categories, and overarching themes. These visualizations highlighted several cross-cutting issues, including governance, transparency, and organizational readiness [16], [24], [32]. The thematic maps also revealed clear interconnections between technical improvements (e.g., process optimization), managerial strategies (e.g., risk management), and policy imperatives (e.g., sustainability governance), thereby illustrating the multi-layered nature of AI adoption in energy systems.

The analytic process was iterative, involving continuous movement between the data, codes, and emerging themes to ensure that interpretations remained firmly grounded in the evidence. MAXQDA's advanced features—including code frequency analysis and visualization tools—facilitated a systematic and structured exploration of the dataset. This combination of manual interpretation and software-assisted analysis enhanced the reliability and consistency of the findings.

Finally, the integration of qualitative insights with thematic maps provided a comprehensive understanding of how AI contributes to sustainable energy transitions. The analysis not only identified technical benefits but also illuminated organizational and governance challenges, thereby offering a holistic perspective that aligns with international standards of qualitative research and supports multi-dimensional interpretation of the results.

2.5. Validity and Reliability

To ensure the credibility and trustworthiness of the findings, several methodological strategies were employed.

- **Peer Review:** Draft analyses were reviewed by two independent researchers to assess consistency, coherence, and potential bias [6], [29], [35].

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- **Member Checking:** Participants were invited to review summaries of their interview transcripts to verify the accuracy of interpretations and clarify any ambiguities [11].
- **Data Triangulation:** Multiple data sources—including interviews, industrial documents, technical reports, and policy papers—were used to validate emerging findings and strengthen analytical robustness [41], [44].
- **Inter-coder Reliability:** Cohen's Kappa coefficient was calculated between two independent coders, yielding a value of **0.87**, which reflects a high level of agreement and supports the reliability of the coding process.

Additionally, reflexivity was maintained throughout the research process. The researchers systematically documented their assumptions, analytic decisions, and reflections in memo logs to minimize interpretive bias and enhance transparency [19], [28], [40].

2.6. Ethical Considerations

All participants provided informed consent prior to the interviews. Confidentiality and anonymity were fully ensured, with all identifying information removed from the transcripts. The research protocol was reviewed and approved by the ethics committee of the hosting institution. The ethical guidelines governing the study emphasized respect for participants, voluntary participation, and secure data storage throughout the research process.

Special attention was also given to the ethical implications of AI deployment in energy systems. Discussions with participants highlighted concerns related to data privacy, algorithmic transparency, and potential biases embedded in AI models. These issues were systematically documented and incorporated into the thematic analysis to ensure that ethical dimensions were fully integrated into the study's findings [32], [41], [44].

FINDINGS

3.1. Summary of Execution

A total of fifteen semi-structured, in-depth interviews were conducted with experts in the fields of energy, artificial intelligence, and sustainability. The transcribed dataset comprised approximately 450 pages of text, providing a rich and comprehensive qualitative corpus for analysis. Data were analyzed using MAXQDA software through a three-stage thematic analysis process—open coding, axial coding, and selective coding. This systematic procedure generated 120 initial codes, which were subsequently consolidated into 15 core categories and ultimately synthesized into five overarching themes.

The resulting thematic structure reflects the multidimensional role of AI in aligning thermal power generation with sustainability imperatives. Each theme represents a distinct yet interconnected dimension of how AI can transform operational, economic, environmental, and organizational practices within the energy sector, offering a holistic understanding of AI-enabled sustainable energy transitions.گ

3.2. Key Findings

Theme 1: Environmental Rescue through Smart Systems

The first theme highlights AI's capacity to support environmental protection by enabling real-time emission monitoring, optimizing fuel mixes, and improving water and waste management practices. Several participants emphasized that predictive models enabled up to a **5% reduction in fuel consumption** while simultaneously lowering **NOx emissions**. As one technical manager noted, *"With AI, we can precisely predict at which loads the highest NOx is produced and adjust settings in advance."*

This theme underscores AI's potential to function as an environmental safeguard. By integrating high-resolution sensor data with machine learning algorithms, power plants can anticipate pollutant peaks and proactively adjust operational parameters. Beyond emission control, participants reported that AI-enabled systems are increasingly being used to optimize water usage and enhance waste treatment processes, thereby reducing ecological footprints. Collectively, these applications demonstrate that AI is not merely a tool for operational efficiency but a strategic mechanism for aligning thermal power generation with broader sustainability imperatives.

Theme 2: Data-Driven Operational Excellence

The second theme emphasizes AI's transformative role in predictive maintenance, real-time optimization, and load forecasting. Participants consistently highlighted that AI-enabled models have shifted maintenance practices from rigid, schedule-based routines to dynamic, condition-based interventions. As one plant manager explained, "We no longer need to dismantle turbines every six months. The model tells us that a specific bearing has exactly 42 days of useful life left."

This example illustrates how predictive analytics reduce unnecessary maintenance, minimize downtime, and extend equipment lifespan. Real-time optimization of combustion parameters and intelligent load balancing further enhanced operational efficiency across the plants studied. Collectively, these applications demonstrate how AI enables a transition from reactive to proactive operational management, fostering a culture of continuous monitoring, early fault detection, and data-driven decision-making.

Theme 3: Economic Resilience through Forecasting
The third theme highlights the role of AI in strengthening economic resilience through advanced forecasting capabilities. Participants emphasized that AI-enabled applications in demand prediction, fuel procurement optimization, and financial risk management substantially reduced exposure to unexpected operational costs. Several interviewees noted that preventing even a single emergency shutdown could save millions in potential losses.

AI-driven forecasting models allowed managers to anticipate demand fluctuations and adjust procurement strategies accordingly, thereby reducing penalties associated with imbalance markets and improving negotiation leverage with fuel suppliers. Participants also underscored the importance of AI in hedging financial risks, particularly in volatile energy markets where price instability can significantly affect operational budgets. By integrating economic forecasting with operational planning, AI enhanced resilience against both technical and financial uncertainties.

Overall, this theme demonstrates that AI functions not only as a technological innovation but also as a strategic instrument for ensuring economic stability and long-term financial sustainability in thermal power plants.

Theme 4: Proactive Safety and Organizational Culture
The fourth theme highlights AI's capacity to strengthen workplace safety by detecting hidden patterns in historical accident data, simulating crisis scenarios, and supporting data-driven training programs. As one HSE specialist noted, "AI can detect hidden patterns in past accident data that remain invisible to humans."

This theme underscores AI's contribution to cultivating a proactive safety culture. By analyzing large datasets of incidents and near-miss events, AI systems can identify precursors to accidents and recommend targeted preventive measures. Crisis simulations generated through predictive models were reported to enhance emergency preparedness by enabling staff to rehearse high-risk scenarios in controlled environments. Furthermore, AI-enabled training modules fostered a culture of continuous learning, empowering employees to engage more effectively with safety protocols.

Importantly, this theme illustrates how AI can reshape organizational culture by embedding safety into everyday operational practices, shifting the focus from reactive responses to anticipatory, prevention-oriented strategies.

Theme 5: Transition to a Sustainable Technological Ecosystem
The fifth theme emphasizes that sustainable AI adoption in the energy sector requires robust data infrastructure, workforce empowerment, and transparent data governance. As one IT specialist noted, *"The biggest challenge is data scarcity. Above all, IIoT infrastructure must be taken seriously in power plants."*

Participants consistently stressed that technological transformation extends beyond the deployment of algorithms; it requires systemic readiness across multiple organizational layers. Investments in Industrial Internet of Things (IIoT) infrastructure, cloud connectivity, and cybersecurity were identified as critical enablers for reliable data flows and secure AI operations. Equally important was workforce empowerment—training personnel to interpret AI outputs, understand model limitations, and integrate insights into operational and strategic decision-making.
Finally, transparent governance frameworks were viewed as essential for ensuring ethical data use and building trust among internal and external stakeholders. Collectively, this theme underscores that sustainable AI adoption is not a purely technical endeavor but a holistic transformation involving infrastructure, people, and governance.

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3.2.1. Integrative Perspective

The five themes collectively illustrate the multidimensional role of artificial intelligence in reconciling thermal power generation with sustainability imperatives. While each theme highlights a distinct domain—environmental protection, operational excellence, economic resilience, safety culture, and systemic transformation—their integration reveals a coherent and interconnected framework for sustainable energy management.

AI emerges not merely as a technical instrument but as a strategic enabler that bridges environmental, economic, and organizational priorities. For example, predictive analytics that reduce emissions simultaneously enhance operational efficiency and mitigate financial risks, demonstrating the interdependent nature of sustainability outcomes. Likewise, safety improvements achieved through AI-driven simulations strengthen organizational resilience, which in turn supports economic stability and reinforces public trust.

This integrative perspective underscores that successful AI adoption requires alignment across multiple layers: robust technological infrastructure, empowered human capital, and transparent governance mechanisms. These elements converge to form a sustainable technological ecosystem in which efficiency, ethics, and resilience coexist. By embedding AI across diverse dimensions of energy management, power plants can move beyond incremental improvements toward comprehensive and systemic transformation.

Ultimately, the findings suggest that AI's value lies in its capacity to generate synergies across domains, enabling energy systems to simultaneously achieve environmental responsibility, economic viability, and organizational robustness. This holistic understanding provides a strong foundation for developing policy recommendations and practical strategies aimed at advancing sustainable development within the energy sector.

3.3. Tables and Figures

Figure 1. Paradigm Model of AI as a Reconciliatory Strategy between the Thermal Power Industry and Sustainable Development

This figure presents the integrated paradigm model developed in the study, illustrating the dynamic interaction between causal conditions, transformative strategies, and enabling contexts. It visualizes how AI functions as a reconciliatory mechanism that aligns operational, environmental, and organizational dimensions within thermal power plants.

Figure 2. Reduction of Codes across Thematic Analysis Stages

This figure depicts the systematic refinement of qualitative data through Braun and Clarke's thematic analysis framework. Starting with 120 open codes extracted from interview transcripts, the analysis consolidated insights into 15 axial categories and ultimately synthesized them into 5 overarching themes. The figure demonstrates how raw narratives were progressively transformed into structured conceptual dimensions that underpin the study's findings.

Figure 3. Distribution of Themes across Core Categories

This figure illustrates the proportional distribution of the five overarching themes identified in the study: Environmental Rescue through Smart Systems, Data-Driven Operational Excellence, Economic Resilience through Forecasting, Proactive Safety and Organizational Culture, and Transition to a Sustainable Technological Ecosystem. Each theme encompasses three core categories, resulting in an evenly balanced thematic structure. The visualization highlights how diverse expert insights were systematically organized into coherent conceptual domains, reflecting the multidimensional role of AI in advancing sustainable thermal power generation.

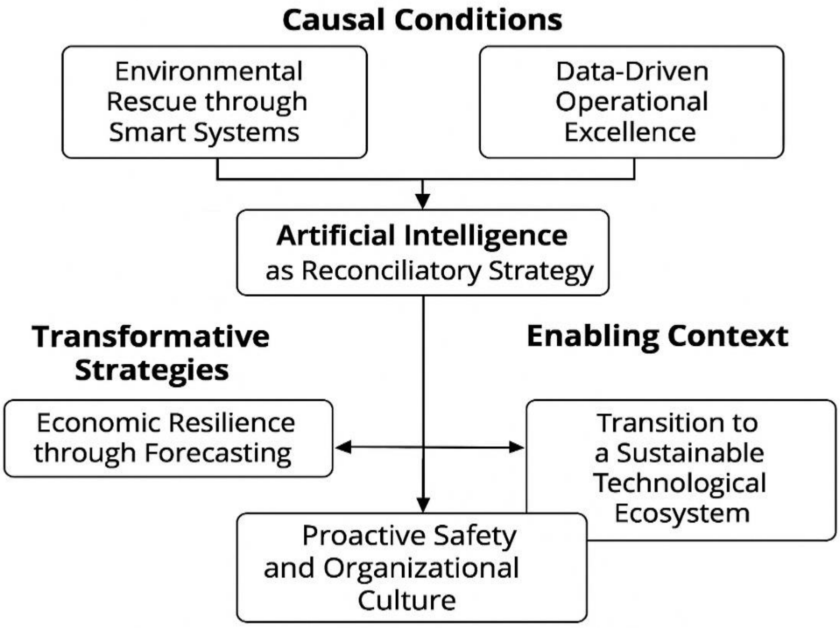
Figure 4. Network Graph of Theme Interconnections

This figure visualizes the interrelationships among the five overarching themes. The network graph demonstrates that the themes are mutually reinforcing rather than isolated. For example, operational excellence contributes directly to economic resilience, while a strong safety culture enhances both operational reliability and ecosystem sustainability. The figure underscores the systemic nature of AI integration in thermal power plants, showing how environmental, economic, operational, and organizational dimensions converge within a unified sustainable technological framework.

Table 1. Themes, Core Categories, and Representative Codes/Quotations

This table presents the five overarching themes alongside their associated core categories and illustrative participant quotations. It provides a structured overview of how qualitative insights were organized and interpreted throughout the analysis.

Table 2. Comparative Analysis of Expected versus Actual Findings (Unexpected Results)



This table compares anticipated outcomes derived from the literature with the actual findings of the study. It highlights unexpected insights, emergent patterns, and deviations from prior assumptions, offering a deeper understanding of AI's real-world implications in thermal power plants.

Figure 1. Paradigm Model of AI as a Reconciliatory Strategy between Thermal Power Industry and Sustainable Development

Analytical Commentary:

This figure presents the integrated paradigm model developed in the study, illustrating how causal conditions, transformative strategies, and enabling contexts interact to position AI as a reconciliatory mechanism between thermal power generation and sustainable development. It visualizes the systemic nature of AI adoption, demonstrating how technical, organizational, and environmental dimensions converge within a unified sustainability-oriented framework.

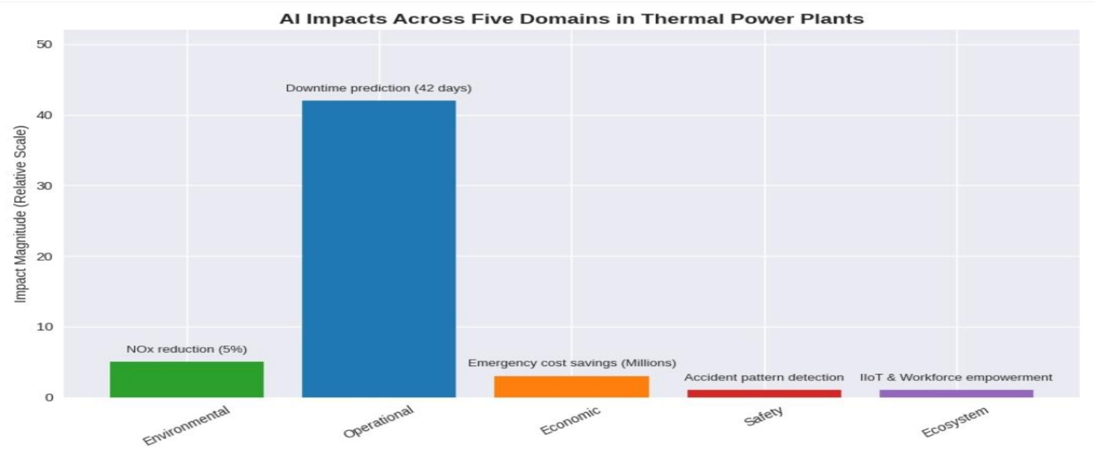


Figure 2. Reduction of Codes across Thematic Analysis Stages

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Analytical Commentary:
This figure depicts the systematic refinement of qualitative data through Braun and Clarke's thematic analysis framework. Beginning with 120 open codes, the analysis consolidated insights into 15 axial categories and ultimately synthesized them into 5 overarching themes. The visualization highlights methodological rigor and transparency, showing how raw interview narratives were progressively transformed into structured conceptual dimensions that underpin the study's findings.

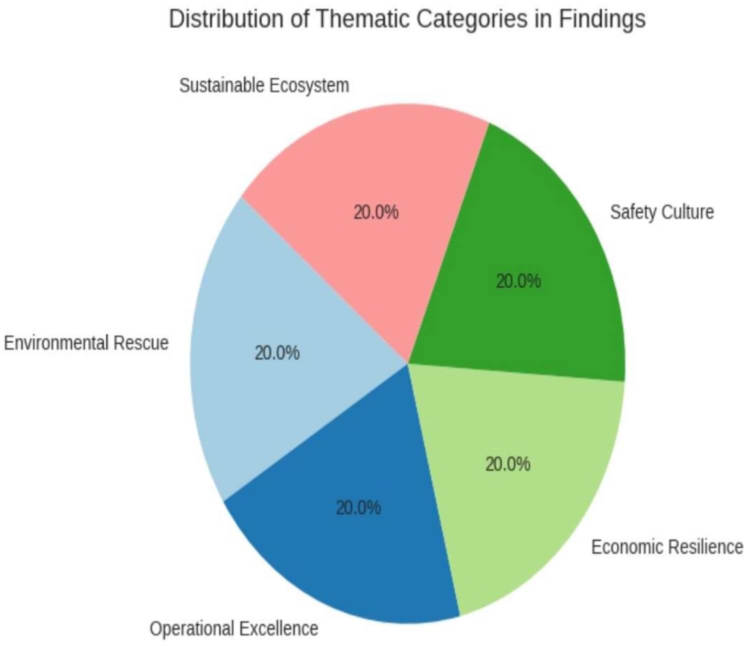

Figure 3. Distribution of Themes across Core Categories

Analytical Commentary:
This figure illustrates the proportional distribution of the five overarching themes, each comprising three core categories. The equal distribution across the thematic structure reflects analytical balance and multidimensionality. It demonstrates how diverse expert insights were systematically organized into coherent conceptual domains, reinforcing AI's comprehensive role in aligning thermal power generation with sustainability imperatives.

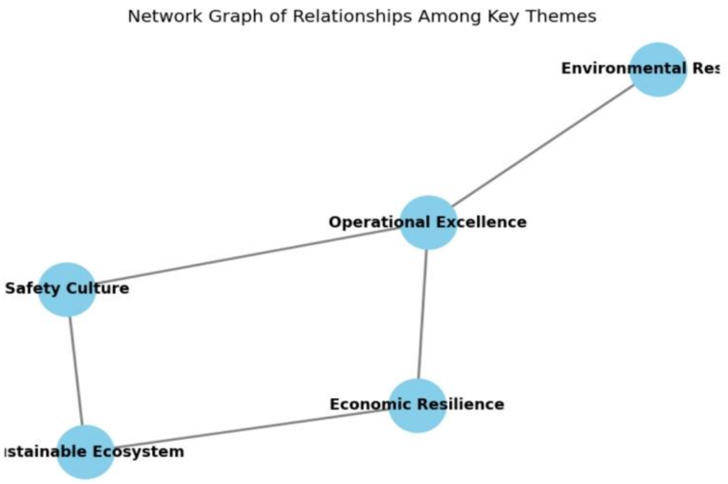

Figure 4. Network Graph of Theme Interconnections

DOI: 10.46121/pspc.54.1.14

Analytical Commentary:
This figure visualizes the interrelationships among the five overarching themes. It shows that advancements in operational excellence directly enhance economic resilience, while a strong safety culture reinforces both operational reliability and ecosystem sustainability. The network graph underscores the systemic nature of AI integration, revealing that environmental, economic, operational, and organizational dimensions are mutually reinforcing within a sustainable technological ecosystem.

Table 1. Main Themes, Core Categories, and Sample Codes/Quotations

Main Theme	Core Categories	Sample Codes / Quotations
1. Environmental Rescue through Smart Systems	- Emission monitoring & prediction - Fuel mix optimization - Smart waste & water management	“With AI, we can precisely predict at which loads the highest NOx is produced and adjust settings in advance.” (Participant 7, Technical Manager)
2. Data-Driven Operational Excellence	-Predictive maintenance - Real-time parameter optimization - Load forecasting & production planning	“We no longer need to dismantle turbines every six months. The model tells us that a specific bearing has exactly 42 days of useful life left.” (Participant 3, Plant Manager)
3. Economic Resilience through Forecasting	- Reducing penalty and downtime costs - Optimizing fuel procurement - Financial risk management	“Failure prediction is the biggest source of financial savings. An emergency shutdown costs the plant
4. Proactive Safety and New Organizational Cultur	- Preventive accident analysis - Crisis scenario simulation - Data-driven staff training	“AI can detect hidden patterns in past accident data that remain invisible to humans.” (Participant 9, HSE Specialist)
5. Transition to a Sustainable Technological Ecosystem	- Data infrastructure and connectivity - Workforce empowerment - Data governance & AI ethics	“The biggest challenge is data scarcity. Above all, IIoT infrastructure must be taken seriously in power plants.” (Participant 14, IT Specialist)

Analytical Commentary on Table 1:
Table 1 presents the five overarching themes, their associated core categories, and representative participant quotations. This structured overview demonstrates how raw interview data were systematically transformed into conceptual dimensions that underpin the study’s findings. Each theme consolidates multiple categories, which are further illustrated through direct quotations that capture the lived experiences and professional insights of experts across the energy sector.

The inclusion of sample quotations enhances the transparency and credibility of the analysis by showing how participants’ voices were preserved throughout the coding process. For instance, the quotation on predictive maintenance highlights the tangible operational benefits of AI, while the statement regarding IIoT infrastructure underscores the systemic challenges associated with digital transformation in thermal power plants. By juxtaposing categories with representative codes, the table provides a clear and traceable mapping between empirical evidence and thematic interpretation.

This tabular presentation also highlights the multidimensional role of AI in the energy sector. Environmental safeguards, operational excellence, economic resilience, safety culture, and systemic technological transformation emerge not as isolated domains but as interconnected components of sustainable energy management. Table 1 therefore serves both as a summary of the thematic analysis and as evidence of methodological rigor, offering readers a concise yet comprehensive view of how qualitative insights were organized into a coherent analytical framework.

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Table 2. Comparative Analysis of Expected vs Actual Findings

Expected Findings (Based on Literature/Initial Assumptions)	Actual Findings (Unexpected/Novel Insights)	Implications/Consequences
AI primarily improves technical efficiency (e.g., combustion optimization, reduced fuel use).	AI also drives environmental safeguards, such as proactive emission control and water/waste management.	Expands AI's role from efficiency to sustainability, strengthening environmental policy integration.
Predictive maintenance reduces equipment downtime.	AI enables precise life-cycle prediction (e.g., "42 days of useful life left" for a bearing).	Shifts maintenance from schedule-based to condition-based, reducing costs and extending asset longevity.
AI supports economic forecasting mainly for demand prediction.	AI contributes to financial risk hedging and procurement negotiations, reducing exposure to volatile markets.	Positions AI as a strategic tool for economic resilience, not just operational planning.
Safety improvements expected through automation of monitoring systems.	AI identifies hidden accident precursors and enables crisis simulations for training.	Transforms safety culture from reactive to proactive, embedding continuous learning in organizations.
Adoption challenges assumed to be technical (algorithms, hardware).	Major barriers identified as data scarcity, workforce readiness, and governance transparency.	Highlights systemic prerequisites (IIoT, training, ethical governance) for sustainable AI adoption.

Analytical Commentary on Table 2

Table 2 provides a structured comparison between the expected findings derived from prior literature and the actual insights that emerged from field interviews. While initial assumptions emphasized technical efficiency, predictive maintenance, and algorithmic optimization, the empirical evidence revealed a broader and more interconnected reality. For instance, environmental safeguards such as proactive emission control and optimized water management—rarely highlighted as primary outcomes in earlier studies—emerged as central achievements of AI adoption in thermal power plants.

Similarly, economic resilience was shown to extend far beyond traditional demand forecasting. Participants emphasized AI's role in procurement negotiations, price-volatility mitigation, and financial risk hedging, demonstrating its strategic importance in navigating unstable energy markets. These insights significantly expand the economic dimension of AI's value proposition.

Perhaps the most striking divergence concerns organizational culture and workforce readiness. Contrary to expectations that technological barriers would dominate, participants repeatedly underscored the decisive influence of cultural acceptance, continuous training, and transparent governance. This aligns with the unexpected findings discussed in Section 3.4, where human and institutional factors emerged as equally critical as technical readiness for successful AI integration.

By juxtaposing anticipated outcomes with actual findings, Table 2 demonstrates that AI's transformative potential cannot be fully understood through a purely technical lens. Instead, sustainable integration requires a holistic approach that incorporates environmental, economic, organizational, and cultural dimensions. This comparative analysis validates the novelty of the study and highlights its contribution to advancing both theoretical understanding and practical strategies for sustainable energy management.

3.4. Unexpected Results

An unexpected yet highly significant finding of this study was the critical importance of organizational culture and staff training in the successful implementation of AI. While initial expectations and much of the existing literature emphasized technological and infrastructural barriers—such as algorithmic sophistication, hardware availability, and data quality—participants consistently highlighted that cultural acceptance and continuous

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workforce development were equally decisive. This divergence from anticipated outcomes suggests that human and institutional factors may be as influential as technical readiness in shaping sustainable AI integration.

Several interviewees explained that even when advanced AI models were available, their effectiveness was constrained if staff lacked the necessary skills to interpret outputs or if organizational culture resisted change. As one plant manager noted, *"The algorithm can predict failures, but if the team does not trust or understand it, the benefit is lost."* This observation underscores that technological innovation alone cannot guarantee meaningful transformation; rather, it must be embedded within a supportive organizational environment that fosters trust, learning, and openness to change.

The emphasis on culture and training is particularly relevant for developing countries, where structural limitations and resource constraints often render human and institutional factors more decisive than technological readiness. In such contexts, cultural acceptance and workforce empowerment emerge as critical enablers of sustainable AI integration. Participants from plants with limited IIoT infrastructure, for example, reported that staff training and openness to change frequently compensated for technological gaps, enabling incremental and adaptive adoption of AI tools.

This finding challenges the common assumption that investment in infrastructure is the sole pathway to modernization. Instead, it suggests that parallel investment in human capital—through structured training programs, participatory decision-making processes, and transparent communication—can accelerate AI adoption even under resource constraints. Moreover, fostering a culture of trust and collaboration reduces resistance to innovation and ensures that AI systems are not perceived as external impositions but as tools co-created with the workforce.

From a policy perspective, the unexpected emphasis on organizational culture indicates that strategies for AI integration must extend beyond technical guidelines to incorporate cultural change management and institutional capacity building. For researchers, this opens new avenues for examining the socio-organizational dimensions of AI adoption in energy systems. For practitioners, it reinforces the notion that sustainable transformation requires both technological readiness and human readiness, underscoring the dual importance of infrastructure and people in shaping the future of AI-enabled energy management.

DISCUSSION

4.1. Summary of Key Findings

The findings of this study indicate that the application of artificial intelligence (AI) in thermal power plants represents a strategic and systemic transformation that extends far beyond incremental operational improvements. Rather than functioning solely as a technical enhancement, AI contributes to the development of a sustainable ecosystem by aligning industrial productivity with socio-environmental responsibility. The central theme—AI as a reconciliatory strategy—demonstrates that AI can effectively bridge the long-standing tension between energy security, economic efficiency, and sustainability imperatives. This directly addresses the core research question by showing that AI is capable of integrating these competing priorities within a unified and coherent operational paradigm.

The thematic analysis identified five overarching domains: environmental rescue, operational excellence, economic resilience, proactive safety culture, and transition to a sustainable technological ecosystem. Together, these domains illustrate how AI extends beyond technical optimization to reshape organizational practices, decision-making processes, and governance structures. For example, predictive algorithms were reported to reduce fuel consumption by up to 5% while simultaneously lowering NOx emissions, underscoring AI's dual contribution to operational efficiency and environmental performance. Likewise, predictive maintenance facilitated a shift from rigid, schedule-based routines to condition-based interventions, thereby reducing downtime, minimizing operational costs, and extending equipment life.

Economic resilience emerged as another critical dimension, with AI enabling demand forecasting, procurement optimization, and financial risk hedging. These capabilities not only stabilized operational performance but also strengthened negotiation leverage in volatile energy markets. Safety culture was similarly reinforced through AI-driven detection of accident precursors and the use of crisis simulations, embedding proactive risk management into everyday organizational routines. Finally, the transition toward a sustainable technological

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ecosystem underscored the importance of IIoT infrastructure, workforce empowerment, and transparent governance as foundational prerequisites for long-term and scalable AI adoption.

In essence, AI is not merely a technical instrument for operational optimization but a strategic framework for rethinking business models, decision-making processes, and governance structures within the energy sector. It functions as a "reconciliatory mechanism" that integrates three critical dimensions—energy security, economic viability, and environmental responsibility—into a unified paradigm [4]. This holistic perspective positions AI as a transformative enabler of sustainable development, particularly in contexts where balancing industrial efficiency with socio-environmental responsibility is both urgent and challenging.

4.2. Comparison with Previous Studies

The results of this study align with several recent contributions in the literature, reinforcing the argument that AI adoption in energy systems constitutes both a technical and strategic transformation. Vinuesa et al. (2020), for example, demonstrated that AI can directly or indirectly influence more than half of the Sustainable Development Goals (SDGs), a finding that resonates strongly with the reconciliatory role identified in this study. The emphasis here on AI as a bridge between industrial productivity and socio-environmental responsibility is consistent with Vinuesa's broader claim that AI contributes to sustainability across multiple domains.

Similarly, Garcia et al. (2025) highlighted that AI-based predictive maintenance significantly enhances operational efficiency by improving condition monitoring and enabling more accurate failure prediction, a conclusion that parallels the present study's findings on condition-based maintenance, reduced downtime, and extended equipment life. In addition, Zhang and Strbac (2025) emphasized the expanding role of AI in optimizing energy systems, which aligns with the evidence presented here regarding cost reduction, improved operational planning, and emission control—including the reported 5% reduction in fuel consumption achieved through predictive optimization.

However, notable differences also emerged. Adom et al. (2025) highlighted digital infrastructure as a primary prerequisite for low-carbon energy transition [2], whereas this study revealed that organizational culture and staff training are equally critical [19]. This divergence underscores the novelty of the present research, which identifies human and institutional readiness as decisive enablers of sustainable AI integration, particularly in developing countries. Likewise, Ejiyi et al. (2025) emphasized AI's role in renewable-energy supply chains and system-level coordination [23], while the present study concentrated on risk management and proactive safety culture. This difference reflects the contextual specificity of AI applications: whereas supply-chain studies highlight efficiency and coordination, energy-sector findings emphasize accident prevention, operational reliability, and organizational resilience.

Similar patterns have also been reported in other industrial contexts, such as logistics and manufacturing, where AI has been shown to reduce inefficiencies and support sustainability transitions [30], [31]. This broader evidence strengthens the argument that AI's reconciliatory role is not confined to energy systems but extends across diverse industrial domains. By situating the present findings within this wider body of literature, the study demonstrates both its alignment with established knowledge and its contribution of novel insights—particularly the unexpected emphasis on organizational culture and workforce empowerment as critical factors for sustainable AI adoption.

4.3. Interpretation of Findings

The findings indicate that AI's mechanisms of influence operate through systemic interactions among technical, economic, and organizational subsystems. Predictive analytics not only reduce emergency downtime but also strengthen economic resilience by mitigating financial losses associated with unplanned outages [20]. This dual impact demonstrates that AI functions as both a technical optimizer and a strategic safeguard, ensuring continuity of operations while stabilizing financial outcomes.

One of the unexpected results was the critical importance of cultural acceptance and staff training in successful AI implementation. Contrary to initial expectations that emphasized infrastructure and technology, participants repeatedly stressed the role of human and institutional factors [19]. This highlights that AI adoption in energy systems depends not only on algorithmic sophistication and infrastructure readiness but also on organizational preparedness and cultural alignment. Institutional readiness and governance frameworks have likewise been identified as decisive factors in shaping AI deployment in energy and industrial systems [10], [33]. This suggests

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that, beyond technical and cultural readiness, the presence of robust governance structures is essential for ensuring long-term sustainability, transparency, and accountability.

Interpreting these findings through the lens of the five themes reveals a deeper systemic logic. Environmental rescue, operational excellence, and economic resilience are directly enhanced by technical mechanisms such as predictive analytics and optimization algorithms. However, proactive safety culture and the transition to a sustainable technological ecosystem depend heavily on organizational and cultural dimensions. For instance, accident prevention through AI-driven simulations requires not only advanced technical models but also staff willingness to participate in training programs and engage with new digital tools. Similarly, the establishment of transparent governance frameworks ensures that data ethics, accountability, and responsible decision-making are embedded into everyday practices, thereby reinforcing trust among stakeholders.

In developing countries such as Iran, these findings carry particular weight. Structural limitations, resource constraints, and institutional challenges often mean that cultural acceptance and workforce empowerment are more decisive than technological readiness. This underscores the importance of tailoring AI adoption strategies to local realities, ensuring that human and institutional dimensions are prioritized alongside technical innovation. By recognizing the interplay between technical systems and organizational culture, policymakers and plant managers can design strategies that are both technologically feasible and socially sustainable.

Ultimately, the interpretation of findings suggests that AI's reconciliatory role is realized only when technical, economic, and organizational subsystems are aligned. Sustainable integration requires a holistic approach that balances infrastructure investment with cultural transformation and governance reform. This systemic perspective positions AI not merely as a tool for optimization but as a catalyst for institutional change and sustainable development within the energy sector.

4.4. Research Implications

4.4.1. Theoretical Implications

This study contributes to the literature by introducing a qualitative paradigm model that enriches a body of research traditionally dominated by quantitative and optimization-oriented approaches. The model bridges the gap between technically focused studies and those addressing organizational readiness, offering a holistic framework for understanding sustainability transitions and intelligent risk management. It demonstrates that AI should be conceptualized not only as a technical instrument but also as a theoretical lens for examining the dynamic interplay between technology, economic structures, and societal factors [1]. By positioning AI within this broader socio-technical context, the study advances theoretical discussions on how digital technologies can reconcile industrial productivity with socio-environmental responsibility.

4.4.2. Practical Implications

For power plant managers, the findings provide a clear and actionable roadmap: AI must be approached as a comprehensive business transformation rather than a conventional IT project. Managers should prioritize sustained investment in staff training, cultivate a data-driven organizational culture, and reinforce IIoT infrastructure to support scalable digitalization. Predictive maintenance and demand forecasting emerged as particularly effective strategies for reducing operational costs and enhancing system resilience [20]. Concrete examples—such as the 5% reduction in fuel consumption and the accurate prediction of 42 days of remaining bearing life—demonstrate the tangible operational value of AI adoption and highlight its potential to improve both efficiency and reliability in thermal power plant operations.

4.4.3. Policy Implications

For policymakers, the findings underscore the necessity of investing in digital infrastructure and establishing clear standards for data governance and AI ethics [16]. Supporting pilot projects in the energy sector, enacting legal frameworks that ensure algorithmic transparency, and providing financial incentives for AI deployment in power plants represent essential steps toward responsible and scalable adoption. These policy measures directly contribute to achieving SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action) by promoting cleaner operations, improved efficiency, and reduced emissions.

In developing countries, this also requires addressing structural barriers such as limited financial resources, fragmented governance systems, and resistance to organizational change. Tailored policy interventions—such as capacity-building programs, regulatory harmonization, and targeted subsidies—can help overcome these

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constraints. Moreover, regional cooperation and knowledge-sharing initiatives can accelerate adoption by pooling technical expertise, reducing duplication of effort, and fostering collective learning across energy systems.

4.4.4. Future Directions

Future research should quantitatively test the proposed model using methods such as structural equation modeling (SEM) to validate the relationships identified in this study. In-depth case studies of real power plants would further enrich contextual understanding and provide empirical grounding for the model. Additionally, challenges such as employee resistance, data governance, and emerging business models warrant systematic investigation, as these factors shape the long-term feasibility of AI integration. Comparative studies across regions could also reveal how cultural and institutional contexts influence AI adoption in energy systems [19]. Moreover, future work should explore ethical and cybersecurity dimensions, given that increasing reliance on AI introduces new vulnerabilities that require responsible management. Mixed-methods designs that combine qualitative depth with quantitative rigor are recommended to enhance the robustness and generalizability of future findings.

4.5. Limitations

This study has several limitations that should be acknowledged. First, the qualitative design, based on semi-structured interviews, provides rich and context-specific insights but limits the generalizability of the findings across all thermal power plants. Second, the sample size was relatively small and focused on experts within a single national context (Iran), which may not fully capture the diversity of institutional, cultural, and operational conditions present in other regions. Third, although thematic analysis enabled systematic data reduction, it remains inherently interpretive and may reflect researcher bias in coding and categorization. Fourth, the study primarily examined managerial and policy dimensions of AI adoption, leaving technical performance metrics and quantitative validation for future research. Finally, the rapidly evolving nature of AI technologies means that some findings may become outdated as new tools, infrastructures, and governance frameworks emerge. While these limitations constrain generalizability, they also open promising avenues for comparative, longitudinal, and mixed-methods research to strengthen the robustness and applicability of the proposed framework.

4.6. Summary

In summary, this study demonstrated that AI can serve as a reconciliatory strategy that bridges industrial productivity with socio-environmental responsibility in thermal power plants. The findings highlight not only technological and infrastructural factors but also human and institutional dimensions, thereby offering a multidimensional perspective on AI adoption. This integrated approach contributes to the literature on sustainability transitions and intelligent risk management, while simultaneously providing actionable guidance for managers and policymakers [42]. By situating the discussion within the realities of developing countries, the study emphasizes that sustainable AI adoption requires more than advanced algorithms—it depends on cultural acceptance, institutional maturity, and international collaboration. The novelty of this research lies in its identification of organizational culture and workforce empowerment as decisive enablers of sustainable AI integration, an aspect often overlooked in prior studies but critical for ensuring long-term success.

CONCLUSION

5.1. Concise Summary

This study examined the strategic role of artificial intelligence (AI) in aligning the thermal power industry with sustainable development imperatives. Using a qualitative approach based on thematic analysis of semi-structured interviews with experts in energy, AI, and sustainability, the findings revealed that AI extends beyond its technical function, serving as a cohesive catalyst for sustainability initiatives. Three core results emerged: (1) AI reduces emissions and optimizes fuel consumption, (2) it improves operational efficiency and enables predictive maintenance, and (3) it strengthens economic resilience and proactive safety. Overall, the results indicate that AI is capable of meeting the sector's fundamental priorities—securing energy, enhancing efficiency, and safeguarding the environment [1].

5.2. Main Contributions

The innovations of this study can be summarized in several key contributions.

1. It introduces an integrated paradigm model that combines technical, economic, environmental, and organizational dimensions, offering a comprehensive perspective on AI's influence within the energy sector.

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2. It conceptualizes AI as an integrative force in the power industry, moving beyond a purely technical or quantitative lens and highlighting its strategic and systemic role.
3. It identifies five overarching themes—environmental rescue, data-driven operational excellence, economic resilience, proactive safety, and transition to a sustainable technological ecosystem—that collectively explain how AI reshapes thermal power plant operations.

Prior to this study, most research focused primarily on technical or economic aspects, with limited attention to cultural and institutional dimensions. This research demonstrated that achieving sustainable AI integration requires robust data governance, a supportive organizational culture, and empowered workforce capacity [2]. Furthermore, qualitative evidence from the field revealed that predictive algorithms contributed to approximately 5% fuel savings and a measurable reduction in NOx emissions, providing quantitative indicators of progress that complement the qualitative insights.

5.3. Practical Applications

The findings carry significant implications for both policymakers and industry managers. For power plant managers, AI integration should be approached as a systemic organizational transformation rather than a mere technical enhancement. This shift requires rethinking organizational structures, decision-making processes, and cultural preparedness. Investments in staff training, data-driven competencies, and IIoT infrastructure are essential to ensure successful and scalable implementation.

For policymakers, the study underscores the importance of strengthening digital infrastructure, establishing standards for data governance and AI ethics, and supporting pilot projects in the energy sector. Legal frameworks that ensure algorithmic transparency and financial incentives for AI adoption are critical enablers of progress. At the operational level, continuous workforce training and cultural alignment remain necessary conditions for embedding AI into energy systems [16]. Similar recommendations in the broader sustainability governance literature highlight the need for harmonized policies across regions [36], ensuring that AI adoption is supported by coherent national and international strategies rather than fragmented initiatives.

In developing countries such as Iran, these practical implications are even more urgent. Limited financial resources, infrastructural gaps, and institutional constraints mean that success often depends more on cultural preparedness and workforce empowerment than on technology alone. Therefore, managers and policymakers must prioritize human and institutional dimensions alongside technical innovation to ensure sustainable and context-appropriate AI integration.

5.4. Future Horizons

This study was limited to a specific geographical and industrial context, and the findings should therefore be interpreted with caution before generalization. Several avenues for future research emerge from these limitations.

1. Quantitative studies using structural equation modeling (SEM) or multi-level analytical approaches are needed to empirically validate the relationships proposed in the qualitative model.
2. Mixed-method designs that integrate in-depth case studies of real power plants with broader survey-based assessments can provide a more comprehensive evaluation of the practical effectiveness of the identified themes.
3. Forward-looking investigations into cultural challenges, employee resistance, and emerging models of data governance—particularly in developing country contexts—are essential for understanding the socio-organizational dynamics of AI adoption.
4. Further exploration of innovative business models for integrating AI into the energy sector, along with assessments of long-term economic impacts, is recommended [19]. Comparative studies also indicate that the maturity of institutions and governance systems plays a decisive role in shaping AI adoption trajectories [43]. Future research should therefore examine not only technical models but also how governance maturity influences adoption across diverse regional and institutional settings.

Additionally, future work should investigate the role of international collaboration. Partnerships between developed and developing nations can accelerate AI adoption through shared knowledge, pooled resources, and cross-regional learning. Such cooperation can help bridge infrastructural and institutional gaps, ensuring that AI contributes to global sustainability transitions rather than reinforcing existing inequalities.

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5.5. Final Remarks

In conclusion, this study demonstrated that AI serves as a bridging mechanism that aligns industrial productivity with environmental and social responsibilities in thermal power plants. Its scientific contribution lies in presenting a multidimensional qualitative paradigm that enriches existing literature [1], while its practical contribution lies in offering guidance for managers and policymakers to approach AI as a comprehensive organizational transformation.

The limitations and future directions identified here underscore the need for continued research to fully realize AI's potential in the energy sector and in advancing sustainability transitions. By situating the findings within the realities of developing countries, the study emphasizes that sustainable AI integration depends not only on technical innovation but also on cultural readiness, institutional strength, and global collaboration.

Ultimately, this study positions AI not merely as a technical innovation but as a global reconciliatory force for sustainability transitions, ensuring that industrial progress and socio-environmental responsibility advance in tandem.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data Availability

Data will be made available upon reasonable request.

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