AI Governance for Sustainable Tech Adoption and Carbon Reduction in Smart Industries

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ABSTRACT

Rapid advancements in Artificial Intelligence (AI) and sustainable technologies are transforming smart industries, yet many organizations still struggle to establish governance mechanisms that ensure responsible adoption while contributing to carbon-reduction objectives. **This study aims** to examine how AI governance frameworks support sustainable technology adoption and promote carbon reduction across smart industrial environments. **Using a mixed-methods research design**, the study integrates a systematic literature review, expert interviews, and quantitative assessment of governance maturity to explore the relationship between governance structures, sustainability practices, and emission-reduction outcomes. The empirical data were collected through semi-structured expert interviews and a structured survey involving 150 professionals from manufacturing, logistics, and energy sectors, representing managerial, technical, and governance roles within smart industry environments. **The findings** reveal that AI governance significantly enhances the effectiveness of sustainable technology deployment, particularly through standardized accountability mechanisms, transparent decision-making models, and proactive risk-management protocols. Organizations with higher governance maturity not only adopt sustainable technologies more efficiently but also demonstrate measurable decreases in operational carbon intensity. These results suggest that robust AI governance serves as a critical enabler for sustainable industrial transformation, ensuring that AI-driven innovations align with environmental objectives and long-term strategic value. **The study concludes** that strengthening AI governance frameworks can accelerate responsible technology integration in smart industries, offering practical pathways for carbon reduction and sustainable competitiveness. Future research is encouraged to investigate cross-industry implementation models and develop governance metrics that better capture environmental impacts in evolving digital ecosystems.

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1. INTRODUCTION

The rapid advancement of AI has significantly transformed smart industrial environments through enhanced automation, real-time analytics, and data-driven decision-making. Smart industries increasingly rely on AI-enabled systems to improve operational efficiency, optimize resource utilization, and support strategic competitiveness [1]. Alongside this digital transformation, organizations face growing pressure to integrate sustainable technologies that address environmental concerns, particularly in response to global climate challenges and regulatory demands for reduced carbon emissions.

Sustainable development has therefore emerged as a strategic priority for smart industries seeking to balance technological innovation with environmental responsibility [2]. International frameworks, most notably the United Nations Sustainable Development Goals (SDGs), provide a global reference for aligning industrial growth with sustainability objectives. Within this context, AI-driven solutions such as energy optimization, predictive maintenance, and carbon monitoring systems demonstrate strong potential to support sustainable industrial practices [3]. However, the effectiveness of these solutions depends heavily on the presence of robust governance structures that ensure ethical, transparent, and accountable AI deployment.

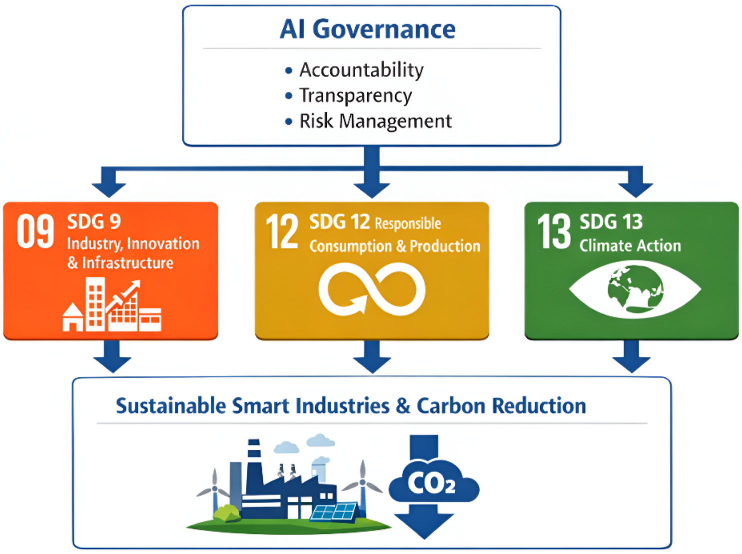

Figure 1. SDG Alignment of the Study

Figure 1 illustrates the alignment between AI governance and key Sustainable Development Goals (SDGs) that are most relevant to smart industrial transformation. The figure highlights SDG 9 (Industry, Innovation, and Infrastructure), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action) as the primary sustainability pillars supported by AI-enabled governance frameworks [4]. AI governance functions as an enabling mechanism that ensures accountability, transparency, and risk management in the adoption of sustainable technologies. Through this alignment, smart industries can systematically integrate innovation-driven processes while promoting responsible resource use and achieving measurable carbon-reduction outcomes [5].

Despite the growing importance of AI governance in supporting sustainability-oriented objectives, existing studies remain fragmented in explaining how governance maturity influences sustainable technology adoption and carbon-reduction performance within smart industrial environments [6]. Prior research has largely examined AI performance or sustainability initiatives independently, with limited empirical studies integrating governance structures with sustainability outcomes. Furthermore, few studies have systematically examined these relationships using quantitative modeling approaches such as structural equation modeling [7]. To address this gap, this study develops and empirically tests an integrated framework linking AI governance, sustainable technology adoption, and carbon-reduction performance through a mixed-methods approach.

2. RESEARCH METHOD

The research method is structured to systematically examine the role of AI governance in enabling sustainable technology adoption and enhancing carbon-reduction performance within smart industrial environments. A rigorous methodological framework is applied to ensure empirical validity, analytical consistency, and alignment with the study's conceptual model. Through the integration of structured data collection procedures, validated measurement instruments, and appropriate analytical techniques, the study provides a robust foundation for testing the proposed relationships among governance maturity, sustainability practices, and environmental outcomes.

2.1. Research Design

This study employs a mixed-methods research design that systematically integrates both qualitative and quantitative approaches to examine the role of AI governance in enabling sustainable technology adoption and carbon reduction in smart industries [8, 9]. The qualitative component focuses on gathering in-depth insights from industry experts, governance specialists, and sustainability practitioners to understand how governance structures, policies, and organizational capabilities shape responsible AI implementation. These insights provide contextual depth and uncover governance challenges that are not easily captured through numerical data.

The quantitative component complements this by using survey-based measurement to evaluate AI governance maturity, sustainability readiness, and carbon-reduction performance across smart-industry firms. Statistical analysis is applied to identify relationships between governance practices and sustainability outcomes, allowing the study to generate empirical evidence that strengthens the qualitative findings [10]. By combining these two approaches, the research design offers a holistic and methodologically robust framework for understanding how AI governance mechanisms contribute to sustainable industrial transformation

2.2. Literature Review Approach

The literature review adopts a systematic narrative approach by synthesizing scholarly publications from 2021 to 2025 to capture recent developments in AI governance and sustainable industrial transformation. Sources were drawn from Scopus, IEEE Xplore, ScienceDirect, and Google Scholar using keywords such as AI governance, sustainable technology, carbon reduction, smart industries, and digital transformation to ensure comprehensive coverage of current debates and practices [11, 12]. The review is organized around four key domains: AI governance frameworks (accountability, transparency, compliance, and risk management), sustainable technology adoption (energy-efficient solutions, clean technology integration, and AI-enabled monitoring), carbon reduction strategies (AI-driven optimization, emission tracking, and carbon accounting), and smart industry transformation (digitalization, automation, and Industry 4.0 integration), which together form the conceptual foundation for examining how governance maturity shapes sustainability outcomes in advanced industrial ecosystems.

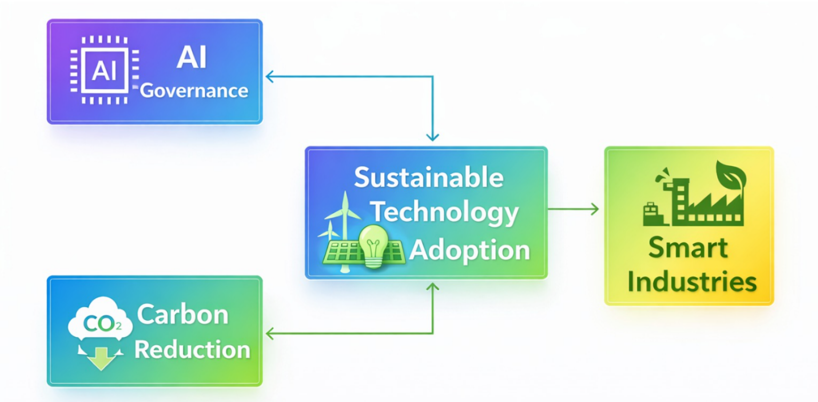

Figure 2. Conceptual Framework of the Study

Figure 2 presents the conceptual framework of this study, which explains the structural relationships among AI governance, sustainable technology adoption, and carbon-reduction performance in smart industrial environments. AI governance is positioned as the core institutional and managerial foundation that guides how

AI is designed, implemented, and monitored within organizations. It encompasses accountability mechanisms, transparency principles, compliance structures, and risk-management practices that ensure AI systems operate in alignment with ethical standards and sustainability objectives. Through these mechanisms, governance creates organizational clarity, reduces implementation uncertainty, and strengthens trust in AI-driven decision-making processes [13].

Within this framework, AI governance functions as an enabling driver that shapes the effectiveness of sustainable technology adoption. Organizations with higher governance maturity are better able to integrate energy-efficient technologies, digital monitoring systems, and AI-based optimization tools into their operational processes [14]. Sustainable technology adoption then acts as the key mediating pathway through which governance influences carbon-reduction performance, allowing firms to monitor emissions more accurately, optimize resource use, and implement predictive strategies that lower environmental impact. This sequential logic is empirically tested using Structural Equation Modeling (SEM). Quantitative data were analyzed using PLS-SEM with SmartPLS to assess measurement and structural relationships [15].

2.3. Data Collection Procedures

Data collection for this study employed two complementary techniques to capture both strategic insights and operational realities within smart industrial environments. The first technique involved conducting semi-structured expert interviews with professionals working in manufacturing, logistics, and energy sectors [16]. These participants were selected using purposive sampling based on their direct involvement in AI implementation, governance oversight, and sustainability management. The interviews explored challenges related to ethical AI deployment, organizational readiness for sustainable technology adoption, compliance mechanisms, and practical barriers to carbon-reduction initiatives [17]. This qualitative stage provided a deeper understanding of governance practices and contextual issues that influence technology-driven sustainability outcomes.

The second technique consisted of administering a structured survey to a broader group of practitioners, including managers, engineers, digital transformation specialists, and IT governance personnel across various smart industries [18]. A total of 150 valid responses were successfully collected and used for the quantitative analysis. The survey aimed to quantitatively measure key variables such as governance maturity, sustainable technology readiness, digital transformation progress, and carbon-reduction performance. Participants were reached through industry networks, corporate sustainability divisions, and professional associations. The combination of expert interviews and survey distribution enabled the collection of rich, multi-layered data that reflects both organizational strategy and operational execution [19].

2.4. Measurement Instruments

The survey instrument used in this study incorporated validated measurement scales adapted from previous research on AI governance, sustainability assessment, and digital transformation maturity [20]. Each construct was operationalized using multiple items measured on a five-point Likert scale, allowing respondents to indicate their level of agreement with statements related to governance structure, transparency mechanisms, compliance processes, sustainability integration, and carbon-tracking capabilities. These items were reviewed and refined through expert validation to ensure conceptual clarity, contextual appropriateness, and domain relevance [21]. In addition to the survey, an interview guide was developed for the qualitative phase to maintain consistency across interviews while allowing flexibility for participants to elaborate on their experiences and perspectives. Together, these instruments ensured that both qualitative and quantitative data were measured systematically and aligned with the study's objectives.

Table 1. Summary of Research Variables and Indicators

Variable	**Indicators (Examples)**
AI Governance	Accountability, transparency, compliance, risk control
Sustainable Technology Adoption	Energy efficiency, clean tech integration, monitoring
Carbon Reduction Performance	Emission tracking, carbon accounting, optimization index
Digital Transformation Maturity	Automation level, data usage, system integration

Table 1 summarizes the core constructs examined in this study and their corresponding indicators, which operationalize abstract theoretical concepts into measurable variables. Each construct is represented by a set of indicators that capture key dimensions of organizational governance, technological capability, and environmental performance within smart industrial contexts [22]. By specifying accountability, transparency, compliance, and risk control under AI governance, as well as energy efficiency, clean technology integration, monitoring systems, and carbon accounting practices, the table demonstrates how complex sustainability-oriented processes are translated into observable and quantifiable measures [23].

These indicators form the foundation of the survey instrument and enable a systematic quantitative assessment of governance maturity, sustainable technology adoption, digital transformation readiness, and carbon-reduction performance [24]. The structure of the table ensures coherence between the conceptual framework and empirical analysis, facilitating the testing of relationships among constructs using SEM. In this way, Table 1 not only clarifies the measurement design of the study but also strengthens the analytical linkage between theory and data, supporting the validity and rigor of the research findings.

2.5. Data Analysis Techniques

The analysis of qualitative and quantitative data followed a structured, multi-phase approach. Interview transcripts were analyzed using thematic analysis, which involved coding recurring themes related to governance implementation, sustainability alignment, ethical considerations, and carbon-reduction initiatives [23]. This method allowed for the identification of patterns that illustrate how governance practices influence sustainable technology adoption across different industrial contexts. The thematic insights also informed the interpretation of quantitative findings, ensuring analytical coherence between data sources.

Quantitative survey data were processed using statistical methods, including descriptive statistics to summarize participant characteristics and variable distributions, as well as reliability tests to verify instrument internal consistency [25]. SEM was then applied to examine the relationships among AI governance, sustainable technology adoption, and carbon-reduction outcomes. SEM was selected due to its ability to test complex, multi-variable relationships and evaluate the mediating effects of governance mechanisms on sustainability performance. The integration of qualitative and quantitative findings enhanced the robustness and explanatory power of the research conclusions [26].

2.6. Ethical Considerations

This study adheres to established ethical standards to ensure the protection of participants' rights, privacy, and data integrity throughout the research process. Ethical considerations were integrated across all stages of data collection, analysis, and reporting to maintain research transparency and academic integrity. Specifically, the ethical procedures implemented in this study include:

- Informed consent
  All participants received clear and comprehensive information regarding the objectives, scope, research methods, and expected use of the data prior to participation. Consent was obtained voluntarily before interviews and survey distribution to ensure participants' full awareness and understanding of their involvement.

- Voluntary participation and right to withdrawal
  Participation in this study was entirely voluntary. Respondents were informed of their right to decline participation or withdraw from the study at any point without any obligation, penalty, or negative consequence.

- Confidentiality and anonymity protection
  To safeguard participant privacy, all personal and organizational identifiers were removed and replaced with coded references. Interview transcripts and survey responses were anonymized during analysis and reporting to prevent direct or indirect identification of participants.

- Secure data management and storage
  All collected qualitative and quantitative data were securely stored using password-protected digital repositories and restricted access protocols. Data handling procedures were designed to minimize the risk of unauthorized access, loss, or misuse.

- Responsible data use and reporting
  Data were analyzed and reported exclusively for academic and research purposes. Findings were presented in aggregated form to ensure confidentiality and to avoid the disclosure of sensitive organizational or individual information.

- Transparency and ethical compliance
  The study followed recognized academic and institutional ethical guidelines, ensuring transparency in data collection, analysis, and dissemination. Ethical considerations were continuously monitored throughout the research process to maintain consistency with established research integrity standards.

In addition, this study follows ethical principles of transparency, accountability, and respect for participant autonomy. No personal or sensitive information was disclosed at any stage of the research process [27]. Ethical guidelines and best practices recommended by recognized academic and institutional review standards were strictly observed throughout data collection, analysis, and dissemination, thereby ensuring the credibility and trustworthiness of the research findings.

3. FINDINGS

The findings present the empirical outcomes derived from the integrated quantitative and qualitative analyses undertaken in this study. The results are structured to demonstrate the relationships among AI governance, sustainable technology adoption, and carbon-reduction performance within smart industrial environments. By combining statistical model evaluation with expert interview insights, the analysis provides comprehensive evidence supporting the proposed conceptual framework.

3.1. Descriptive Statistics of Respondents and Variables

The descriptive profile of the respondents and the key research variables is presented in this section. The survey involved professionals from smart-industry sectors, including manufacturing, logistics, and energy, who are directly engaged in AI implementation and sustainability initiatives [28]. The demographic distribution reflects a balanced representation across managerial, technical, and governance roles, ensuring that the data capture both strategic and operational perspectives. This diversity enhances the credibility of the findings, as respondents possess relevant experience in AI governance, digital transformation, and environmental performance monitoring [29].

Table 2. Respondent Profile and Descriptive Statistics

Category	Item	Frequency (N)	Percentage (%)
Gender	Male	78	52.0
	Female	72	48.0
Position	Manager / Supervisor	45	30.0
	Engineer / Technical Staff	60	40.0
	IT / Digital Transformation Specialist	30	20.0
	Governance / Sustainability Officer	15	10.0
Industry Sector	Manufacturing	58	38.7
	Logistics	47	31.3
	Energy	45	30.0
Years of Experience	1–5 years	42	28.0
	6–10 years	55	36.7
	>10 years	53	35.3

Table 2 summarizes the demographic characteristics of the respondents as well as the descriptive statistics of the main research variables. The gender distribution is relatively balanced, and the respondents are primarily drawn from managerial, engineering, and digital transformation positions across manufacturing, logistics, and energy sectors [30]. The experience profile indicates that most participants have more than five years of professional exposure, suggesting a mature understanding of organizational governance and sustainability practices.

In terms of variable distribution, the mean values of AI governance maturity, sustainable technology adoption, digital transformation maturity, and carbon-reduction performance are in the moderate to high range [31]. This indicates that most participating organizations have already initiated structured governance and sustainability efforts. However, the observed standard deviations suggest variability across firms, reflecting differences in implementation depth and strategic alignment. These descriptive patterns provide an important foundation for subsequent structural model analysis [32].

3.2. Measurement Model Evaluation (Reliability & Validity)

The reliability and validity of the measurement model were rigorously evaluated prior to testing the structural relationships among the research constructs to ensure the robustness and credibility of the empirical analysis. Internal consistency was assessed using Cronbach's Alpha and Composite Reliability (CR) as standard indicators of measurement reliability. The results indicate that all constructs exceed the recommended threshold of 0.70, demonstrating satisfactory internal consistency and confirming that the measurement items consistently represent their respective latent variables. These findings provide strong evidence that the indicators reliably capture the core constructs examined in this study, including AI governance, sustainable technology adoption, digital transformation maturity, and carbon-reduction performance [33]. Overall, the evaluation confirms that the measurement model meets established statistical criteria and is appropriate for subsequent structural model testing and hypothesis analysis.

Table 3. Reliability and Validity Results

Construct	Cronbach's Alpha	CR	AVE
AI Governance	0.872	0.901	0.645
Sustainable Technology Adoption	0.856	0.889	0.621
Digital Transformation Maturity	0.841	0.878	0.603
Carbon Reduction Performance	0.864	0.895	0.638

Table 3 presents the results of the reliability and validity assessment for all research constructs. Convergent validity was examined using Average Variance Extracted (AVE), with all constructs achieving values above the recommended threshold of 0.50, indicating that the indicators adequately explain the variance of their respective constructs [34]. Discriminant validity was further confirmed using the Fornell–Larcker criterion, demonstrating that each construct is empirically distinct from the others. Overall, these results indicate that the measurement model is statistically sound and appropriate for subsequent structural model and hypothesis testing [35, 36].

3.3. Structural Model and Hypothesis Testing

The structural model was analyzed using SEM to examine the relationships among AI governance, sustainable technology adoption, and carbon-reduction performance [37]. The results show that AI governance has a significant positive effect on sustainable technology adoption. Organizations with strong accountability frameworks, transparent processes, and effective risk-management mechanisms are more capable of systematically implementing sustainability-oriented technologies [38]. This indicates that governance maturity plays an important role in aligning digital transformation initiatives with environmental objectives.

Furthermore, sustainable technology adoption significantly improves carbon-reduction performance, confirming that AI-enabled sustainability initiatives generate measurable environmental benefits [39]. The mediating effect of sustainable technology adoption between AI governance and carbon reduction was also supported, suggesting that governance influences emissions indirectly through structured technology deployment [40]. Overall, these findings highlight governance as a key strategic enabler of sustainable industrial transformation.

3.4. Qualitative Insights from Expert Interviews

The qualitative findings from expert interviews enrich and contextualize the quantitative results. Participants emphasized that AI governance is not merely a compliance mechanism, but a practical framework that aligns digital innovation with sustainability objectives [41]. Clear governance structures were described as essential for reducing ambiguity in AI deployment, strengthening accountability in environmental reporting, and enhancing trust in AI-driven decision-making through improved data integrity, ethical standards, and risk management. These perspectives highlight governance as a strategic bridge linking technological capability with measurable environmental impact.

Furthermore, experts noted that organizations with mature governance frameworks are better equipped to integrate AI into carbon-tracking systems, energy-efficiency platforms, and predictive maintenance tools [42]. Strong governance supports coordinated implementation, consistent data practices, and clearer carbon-performance evaluation, while weak governance often leads to fragmented adoption and limited sustainability outcomes. Overall, these qualitative insights reinforce the SEM findings by demonstrating how governance maturity shapes practical AI adoption and carbon-reduction performance in smart industries.

3.5. Result and Discussion

The integration of quantitative and qualitative findings demonstrates a clear alignment between statistical evidence and practitioner perspectives. Both data sources consistently confirm that AI governance maturity plays a crucial role in driving sustainable technology adoption and improving carbon-reduction performance [43, 44]. The SEM analysis provides empirical validation of these relationships, highlighting their significance and structural pathways, while the interview findings offer practical explanations of how governance mechanisms operate within organizations through structured coordination, accountability systems, and performance monitoring practices. This methodological triangulation enhances the overall credibility and depth of the study by combining analytical rigor with contextual insight. Collectively, the findings provide a comprehensive understanding of how governance, technological implementation, and sustainability outcomes interact within smart industrial environments [45], reinforcing the strategic importance of structured AI governance in supporting long-term environmental transformation.

Figure 3. Integrated Findings Framework

Figure 3 presents a synthesized overview of the key quantitative paths and corresponding qualitative themes derived from the mixed-methods analysis. The table shows that the positive effect of AI governance on sustainable technology adoption identified in the SEM results is reinforced by interview themes emphasizing accountability, transparency, and structured decision-making [46]. Similarly, the relationship between sustainable technology adoption and carbon-reduction performance is supported by qualitative evidence highlighting the role of AI-enabled monitoring, energy-efficiency systems, and emission-tracking practices.

Overall, the integrated results demonstrate that smart industries achieve greater environmental impact when AI innovation is supported by transparent governance frameworks, standardized procedures, and ethical accountability [47, 48]. The combination of governance discipline and digital capability enables firms to translate AI potential into measurable sustainability performance. This integrated evidence underscores the strategic importance of aligning AI governance with sustainability objectives in digitally transformed industrial ecosystems [49].

4. MANAGERIAL IMPLICATIONS

The findings of this study highlight that managers can significantly enhance supply chain resilience by integrating machine learning based risk prediction tools into their operational decision making. Organizations should adopt predictive analytics to monitor real time fluctuations in supplier performance, logistics stability, and market uncertainty. This enables managers to shift from reactive responses to proactive mitigation, allowing them to allocate resources more efficiently and prepare contingency plans before disruptions escalate. The implementation of data driven models also encourages standardized risk assessment practices across departments, which improves communication flow and ensures that risk indicators are consistently interpreted.

Furthermore, managers must invest in building technological readiness and analytical capabilities within their teams. This involves providing training on machine learning applications, improving data quality governance, and establishing cross functional units dedicated to digital supply chain monitoring. Without these enablers, predictive models may produce inaccurate assessments or fail to be adopted effectively. Managers should also evaluate the ethical and transparency aspects of automated predictions to maintain trust in decision support systems and ensure compliance with organizational policies.

Finally, the adoption of machine learning based risk prediction fosters strategic advantages by enabling firms to simulate multiple risk scenarios and choose the most cost effective responses. Managers can use model outputs to refine supplier diversification strategies, optimize inventory buffers, and identify early warning signals across global supply networks. By institutionalizing these digital capabilities, organizations can achieve sustained operational resilience and gain a competitive edge in highly volatile supply chain environments.

5. CONCLUSION

This study introduces a conceptual framework that integrates machine learning based predictive analytics into supply chain risk management. The novelty of this framework lies in its structured alignment of data inputs, modelling techniques, and risk mitigation pathways, which collectively provide a more systematic approach to understanding how real time data can improve risk anticipation. Unlike traditional qualitative or retrospective methods, the proposed framework demonstrates the potential of predictive algorithms to generate early warning signals that enhance operational preparedness.

The findings emphasize that machine learning can strengthen decision making by enabling continuous risk monitoring, scenario based analysis, and more precise assessments of supply chain vulnerabilities. Through the synthesis of existing literature, this study identifies key factors that influence the effectiveness of risk prediction models, including data quality, technological readiness, and organizational adoption. These insights highlight the growing relevance of digital capabilities in building supply chain resilience, particularly in environments characterized by uncertainty and disruption.

Future research should focus on empirically validating the proposed framework through case studies, pilot implementations, or quantitative modelling. Researchers may also explore the integration of advanced techniques such as deep learning, multimodal data fusion, or real time IoT enabled monitoring to expand the predictive capabilities of supply chain systems. Additionally, future studies could examine cross industry differences and ethical considerations associated with automated prediction to develop more comprehensive guidelines for digital risk governance.

6. DECLARATIONS

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6.2. Author Contributions

Conceptualization: SP; Methodology: NR; Software: RA; Validation: DC and SP; Formal Analysis: NR and RA ; Investigation: DC; Resources: SP Data Curation: DC; Writing Original Draft Preparation: RA and NR; Writing Review and Editing: SP and DC; Visualization: RA; All authors, SP, RA, DC, and NR, have read and agreed to the published version of the manuscript.

6.3. Data Availability Statement

As part of our commitment to transparency, the dataset used in this study is openly available via the Zenodo Repository https://zenodo.org/records/18871257

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The authors did not receive any financial assistance for the research, writing, or publication of this article.

6.5. Declaration of Conflicting Interest

The authors declare that there are no conflicts of interest, financial competition, or personal relationships that could have affected the outcomes of this study.

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