Proceedings of the 2nd World Congress on Industrial Engineering and Operations Management
Windsor, Canada, October 14-16, 2025

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/WC02.20250185
Published: October 14, 2025

AI-Enabled End-to-End Visibility in Global Supply Chains: Predictive Approaches for Risk Mitigation in Manufacturing

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Abstract

Artificial intelligence (AI) and blockchain technology have become game-changing tools that can solve most of the underlying supply chain management challenges and improve end-to-end visibility in global supply chains by providing predictive approaches for risk mitigation in manufacturing. The present study attempts to quantify the link between AI-enabled visibility and important supply chain performance metrics by concentrating on predictive methodologies and offers evidence that can be used to influence the adoption of new innovative technologies. The findings revealed a statistically significant correlation between industry sector and the belief that AI risk scores accurately detect delayed shipments or products ($\chi^2(8, N = 50) = 67.39$, $p < .001$). The results of the ANOVA demonstrated that the regression model accounted for all of the variance in the dependent variable. From a substantive perspective, the findings show how crucial AI-driven risk management solutions are to facilitating seamless data flow integration amongst different supply chain systems. The results suggest that when risk ratings are precise, timely, and operationally sound, integration across ERP, WMS, TMS, MES, and supplier portals is fully achieved.

Keywords
Supply Chain Integration, Supply Chain Resilience, Supplier Networks, Lead Time, Operational Efficiency.

1. Introduction
In today's world of networked economies and global trade, supply chains have become more complex and interlinked, but this complexity has also increased their exposure to a variety of potential disruptions such as natural disasters, political upheaval, sudden shifts in consumer demand, and supplier financial collapses, which may disrupt the smooth flow of goods, services, and information along the supply chain. Effective supply chain management (SCM) requires ensuring the fluid, continuous, and cost-effective flow of resources and products at every level (Aljohani, 2023; Daios et al., 2025). Presently, due to the involved complexities, supply chains have become a major source of worry for many businesses, governments, and consumers, and also receive greater press coverage (Belhadi et al., 2024). Businesses now have an absolute need of maintaining an end-to-end visibility as supply chains grow more dynamic and consumer expectations keep rising (Kumawat, 2024; Onotole et al., 2022). Supply chain agility is the capacity of a business to swiftly and efficiently adapt its processes and operations to unexpected disruptions. In the face of disruptions, which may occur unexpectedly and without warning, maintaining consumer satisfaction and maintaining business continuity become vital (Belhadi et al., 2024). The concept of open innovation supports an innovative approach that proposes businesses ought to explore a range of approaches to manage their supply chains and include both internal and external ideas in order to develop and effectively utilize appropriate technology (Khedr & S, 2024; Lebhar et al., 2023). By putting the idea of open innovation into practice, businesses actively work with a range of external players, including consumers, competitors, academics, and businesses in unrelated industries, to promote innovation (Khedr & S, 2024; Zhang & Cheng, 2023). The fundamental idea behind open innovation is that not all of

the information required for innovation can be found within a company's own limits; as a result, it is critical for businesses to look for and get knowledge from other sources.

At the moment, a vast majority of conventional supply chain risk management strategies have been reactive in nature, often relying on post-event analysis and historical data to address disruptions that have already taken place (Lebhar et al., 2023). In order to remain efficient and resilient in such a context, companies need to switch from reactive risk management to proactive risk mitigation which requires a paradigm shift that takes advantage of the merging of two disruptive innovations, predictive analytics and machine learning (Belhadi et al., 2024; Daios et al., 2025; Singh et al., 2024). The application of artificial intelligence (AI) and related technological innovations can enhance end-to-end visibility by transitioning to prescriptive and predictive visibility from reactive monitoring. Conventional visibility technologies frequently use descriptive analytics, which only record past events, leaving companies to react after disruptions have already happened. However, AI models such as anomaly detection, machine learning-based risk rating, and time-series forecasting that enable businesses to predict disruptions before they happen (Lebhar et al., 2023). As a result, sophisticated and predictive data analytics are now a key part of SCRM decision-making, and it is increasingly pertinent to use AI in SCRM by utilizing certain potent methods like machine learning (ML), deep learning (DL), and natural language processing (NLP) (Al-Sadaan & Berger, 2021). The newly developed AI-based models and techniques can detect SC threats by extracting useful insights from social media data and online textual content (Chu et al., 2020). The unexplored field of risk management among the many text mining applications may prove to be a fruitful area for further study (Kumar et al., 2021). Therefore, the new SCRM transformation that leverages AI approaches can assist companies in maintaining or achieving continuous development in the face of unpredictable circumstances and offer practical insights for improvement of supply chain management and its subfields (Canhoto and Clear, 2020, Soni et al., 2020). Similar to this, possible quality deviations or capacity shortages may be predicted using production yield trends and IoT sensor data before they affect operations further down the line. Artificial intelligence (AI) systems provide preemptive measures like redistributing capacity, accelerating shipments, or modifying safety stock levels ahead of the interruption by producing predicted risk warnings and the corresponding likelihood scores.

Manufacturers face critical risk mitigation challenges that directly disrupt the supply chain system. Presently, there is a lack of solid, quantifiable proof that predictive visibility afforded by AI lowers the frequency and intensity of disruptions in global supply chains. Upstream and downstream signals are frequently not integrated into a single predictive framework by current visibility solutions, which frequently stay compartmentalized and concentrate either on logistics or demand forecasting. The timeliness and precision of the predictive alerts are further weakened by data latency, incompleteness, and heterogeneity, whether from sensor data, ERP transactions, or logistical milestones which further limits the tools' usefulness for proactive interventions. Furthermore, on-time-in-full delivery, lead-time variability, and inventory efficiency have not been directly linked to advances in predictive visibility, such as signal coverage, latency, and accuracy, using a standardized, empirically verified framework. Although most AI-driven visibility systems are employed in pilot projects or specific use cases, there is no scientific evidence that the systems reliably lower risk and boost performance on manufacturing and related supply chain links. The vast majority of research and applications rely upon anecdotal accounts or performance indicators that are specific to a single instance and might not be applicable to global industrial supply chains. Furthermore, not enough empirical research has been done regarding the relationship of the quality of visibility signals, specifically, data coverage, latency, and accuracy, to quantifiable operational outcomes like inventory turnover, lead-time variability, on-time-in-full delivery, and schedule adherence. Without such evidence, businesses find challenging to justify the significant expenditures on AI-powered predictive visibility systems. As such, the present study aims to provide data-driven insights into how AI-enabled end-to-end visibility aids in risk reduction in global industrial supply chains by answering the question of whether using AI-based predictive risk score on supply chain data, both historical and present, improves manufacturing risk mitigation results in a measurable way. The study attempts to quantify the link between AI-enabled visibility and important supply chain performance metrics by concentrating on predictive methodologies and offers evidence that can be used to influence the adoption of new innovative technologies.

1.1 Objectives

The objectives of the research have been divided down into a single primary objective and several minor objectives that direct the study's scope.

Primary Objective

- To examine the predictive role of artificial intelligence in enabling end-to-end visibility within global manufacturing supply chains to mitigate risks.

Specific Objectives

- To explore the extent to which AI-driven predictive models improve disruption detection, demand forecasting, and response mechanisms across global manufacturing supply chains.
- To examine how AI-enabled systems integrate fragmented data streams from suppliers, logistics providers, and manufacturers into a unified visibility framework.
- To assess the advantages, disadvantages, and potential areas for development of AI-enabled predictive visibility techniques in comparison to conventional supply chain risk management techniques.

2. Literature Review

As global supply chains become more complicated, scholars are becoming more interested in how manufacturing networks may become more resilient, transparent, and flexible. Even though traditional supply chain management frameworks perform well in settings that are generally stable, they have been shown to be ineffective when dealing with the unforeseen disruptions brought on by disasters like pandemics, geopolitical conflicts, and climate-induced shocks. Notwithstanding the significant progress in research on AI applications in inventory management, logistics, and procurement, a thorough understanding of how AI may offer end-to-end visibility across the entire supply chain ecosystem remains lacking. This highlights the need for a critical assessment of recent studies, with particular attention to how well AI-enabled prediction techniques handle visibility issues and lower risks in manufacturing supply chains. Aljohani (2023) investigated the symbiotic relationship between supply chain agility, machine learning, and predictive analytics through a combination of theoretical discussion and empirical data in improving risk mitigation and supply chain agility. According to the author, AI predictive analytical capabilities helps systems perform better by learning from data and identifying patterns, correlations, and anomalies that would not be visible through traditional analytical methods. Also, Aljohani (2023) reports that the majority of the fundamental supply chain management problems can be resolved by blockchain technology and artificial intelligence (AI), which have emerged as game-changing solutions. Supply chains can benefit from the decentralized, immutable ledger system that blockchain offers by securely recording all transactions and operations and minimizes risks like fraud and counterfeiting, ensures data integrity, and facilitates real-time tracking.

In their study, Belhadi et al. (2021) investigated how artificial intelligence-driven innovation can be used to improve supply chain resilience and performance by enhancing end-to-end visibility to mitigate risks in manufacturing based on the on the organizational information processing theory (OIPT). According to Belhadi et al. (2021), AI has a short-term direct effect on improving end-to-end visibility in supply chain and recommends that its capabilities should be exploited by companies to ensure supply chain resilience through early detection and mitigation of risks. A similar empirical investigation by Lebahr et al. (2023) explored the benefits and challenges of adoption of AI in mitigating risks in supply chain systems and reported that it might have a bigger impact by acting as an invention technique that transforms the way that innovation is done in supply chain especially in relation to detection and mitigation of risks. Lebahr et al. (2023) further highlight the critical role of AI in ensure flexibility and control of supply chain operations and conclude that the related models and techniques have proven their usefulness in risk mitigation in manufacturing process. Deiva Ganesh & Kalpana (2022) conducted a systematic review on the future of AI in supply chain risk management and explored its role in mitigation of risks that can disrupt the seamless flow of goods and services. According to their review, AI can be used to improve SC resilience by offering predictive approaches for mitigating risks and disruptions to increase transparency through ongoing monitoring and lessening the impact of unexpected interruptions, AI can improve SC resilience. The review emphasizes how AI has brought about a paradigm shift to enhance SC decision-making by utilizing automated tools that can utilize data and expertise. Also, Deiva Ganesh & Kalpana, (2022) reported that AI solves problems faster, more accurately, and with a greater number of inputs as compared to traditional methods. In the same vein, as reported by Nweje & Taiwo (2025), AI provides end-to-end insight by employing advanced analytical capabilities and massive datasets to improve decision-making, streamline logistics, and predict disruptions. The findings highlight the need for business to retain end-to-end visibility in global supply chains by providing predictive ways for manufacturing risk reduction through technical innovation and efficient use of the powerful synergy produced by blockchain and artificial intelligence.

The use of AI and ML solutions to help transform the risk management process was examined by Lynn et al. (2019) who reported that the majority of industries are changing their production planning methods from forecasting to prediction, manual to automated operations, and reactive to proactive, as also reported by Toorajipour et al. (2021). The findings by Daios et al. (2025) are also supported by a review by Khedr & S (2024) applying machine learning (ML) and deep learning (DL) artificial intelligence algorithms streamlines classification procedures and identifies important traits, which greatly improves supplier assessment. The authors further posit that the use of ML and DL has also aided in demand forecasting, risk prediction and mitigation, supply chain resilience and profitability, inventory cost reduction through precise estimations, and logistics and transportation optimization through enhanced delivery routes and reduced damage (Daios et al., 2025; Khedr & S, 2024). Additionally, these strategies advanced production planning by improving scheduling accuracy and managing workflow restrictions. Zhang & Cheng (2023) also offered a comprehensive analysis of the role of AI in risk mitigation in international supply chains by ensuring product traceability and authenticity, and reported that showed AI-enabled authentication systems slashed verification times from 47.3 minutes to an average of 2.8 seconds while improving accuracy by 15.7–26.0% in comparison to traditional techniques. Similar findings were reported by Orcun Sarioguz (2025) who noted that AI-powered production forecasting generates incredibly accurate estimates that improve resource allocation by leveraging global events, demand variations, output measures, and a wealth of previous data. By optimizing logistics and inventory levels to meet exact production requirements, inventory and supply chain optimization can adopt AI-powered production forecasting to achieve significant cost reductions through real-time tracking of inventory, delays, and changing demands.

Shaji, (2024) investigated the application of AI in intelligent manufacturing for increased productivity quality and insights. According to the results, Shaji (2024) reported that predictive analytical tools analyze sensor data collected from components and equipment using artificial intelligence to predict maintenance requirements before malfunctions happen which efficiently reduces costly downtime and makes it easier to schedule repair at the best time. Also, the author reported that quality optimization makes use of computer vision and deep learning techniques to find little product flaws early and make the required corrections to enhance quality control which significantly prevents any disruptions and ensures proper risk mitigation in supply chain systems. The findings are supported by Ratra & Seth (2025) who modeled an AI-driven hybrid edge-cloud architecture for real-time big data analytics and scalable communication in retail supply chains, and reported that the model shows significant savings, more consistent alignment between supply and demand, and fewer supply chain problems. According to Ratra & Seth (2025), early adopters of AI in manufacturing across a variety of industries have reported significant benefits, such as 20–50% increases in productivity, 10–30% improvements in product quality, 15–40% increases in operational efficiency, and millions of dollars in cost savings from waste elimination, excess inventory, suboptimal supply chain flows, and machine downtime. The findings by Ratra & Seth (2025) and Shaji (2024) show that industrial intelligence, competitiveness, profitability, and sustainability could all be greatly enhanced by AI-powered innovations when applied across global supply chains. Similarly, a study by Vivek Prasanna Prabu (2024) reported that AI and ML technology systems improves service levels, lowers operating expenses, and makes end-to-end visibility easier by revealing hidden trends in big datasets, allowing for dynamic inventory planning, maintenance scheduling, supplier risk assessment, and route optimization. However, the authors note that it is not entirely a rosy affair by highlighting existing challenges associated with data integration, system interoperability, model explainability, and workforce readiness. They further highlight the need to address associated ethical challenges such as transparency, fairness, and sustainability.

3. Methods

The primary objective of the present research study is to examine the predictive role of artificial intelligence in enabling end-to-end visibility within global manufacturing supply chains to mitigate risks by providing data-driven insights into how AI-enabled end-to-end visibility aids in risk reduction in global industrial supply chains. To achieve the intended primary objective, the study adopts a quantitative survey research methodology to collect data from industrial companies that operate global supply chains. The study respondents include supply chain managers, logistics coordinators, and operations executives that have a direct hand in implementing AI solutions in their companies. The purpose of the survey tool is to collect statistical data on key constructs such as the degree of adoption of AI, visibility metrics and perceived outcomes of risk mitigation such as reduced supply disruptions, lead time variability, and demand-supply discrepancies. The study's sample consists of manufacturing companies that operate in global or multinational supply chains, and are particularly relevant to the study since they are exposed to a variety of supply chain risks, including demand swings, natural disasters, logistical bottlenecks, and geopolitical disruptions, and AI-enabled solutions are increasingly being used to mitigate these risks. The study adopts a stratified random selection technique to ensure sample representation from a variety of industries, including consumer goods, electronics, automobiles, and medicines considering supply chain issues and AI adoption levels can vary greatly throughout industries, necessitating stratification. To ensure statistical robustness and accuracy in testing the hypotheses, power analysis is performed to establish the sample size to allow for broad generalizations for capturing sectoral variances through appropriate representation and sample size.

The three primary variables operationalized in the study include end-to-end visibility, risk mitigation results, and AI adoption. The indicators of interest were the degree of AI integration into supply chain predictive modeling apps, real-time analytics, and decision-making which are used to measure the adoption of AI. The end-to-end visibility is operationalized by measuring the level of supply chain transparency, data system integration, information timeliness and correctness, and real-time supplier and logistics network monitoring. Reductions in supply chain interruptions, increased lead-time predictability, improved demand forecasting, and the capacity to proactively handle possible disruptions are examined to evaluate the results of risk mitigation to guarantee that intangible concepts are converted into quantifiable information suitable for statistical analysis. Every step of the research process was undertaken in adherence to ethical standards and the participant privacy and confidentiality was protected by ensuring that no personally identifiable or organizational data is disclosed in the reporting of results. Also, the research design and procedures were reviewed and authorized by the appropriate institutional ethics committee, guaranteeing compliance with established ethical guidelines, and all participants were provided with informed consent before collecting data, ensuring that they understood the purpose of the study and their right to withdraw at any time.

4. Data Collection

The selected participants received a structured online questionnaire electronically, which was utilized to collect primary data. The three main constructs measured by the questionnaire included risk mitigation results, end-to-end supply chain visibility, and AI adoption levels. A five-point Likert scale, ranging from "strongly disagree" to "strongly agree," was utilized to assess respondents' degree of agreement with each statement after each construct had been categorized into quantifiable variables. Statistical techniques including descriptive and inferential analysis was used to analyze the collected data. The demographic characteristics of the respondents, as well as the baseline degrees of AI adoption, visibility, and risk mitigation techniques, was summarized using descriptive statistics. Inferential analysis was used to test the proposed correlations between the variables, and the strength and direction of the correlations was determined using correlation analysis, and the predictive potential of AI adoption and visibility with respect to risk mitigation results was confirmed using multiple regression analysis. Statistical tools including Excel and Statistical Package for Social Sciences (SPSS) were used for statistical analyses because they offer strong capabilities for analyzing statistical survey data. The study employed regression modeling to measure how much AI-enabled visibility contributes to variances in risk mitigation effectiveness, and ANOVA testing can be used to examine differences between industry sectors. By ensuring a thorough and statistically supported analysis, the adopted data collection and analysis methods allow the study to yield insights that are supported by evidence.

5. Results and Discussion

5.1 Numerical Results

A total of 50 participants took part in the study by answering the questionnaire to determine whether how AI-enabled end-to-end visibility aids in risk reduction in global industrial supply chains by answering the question of whether using AI-based predictive risk score on supply chain data, both historical and present, improves manufacturing risk mitigation results in a measurable way. Out of the 50 participants, the automotive sector and pharmaceuticals sector had the highest representation (22% each), followed closely by electronics (20%), consumer goods (18%), and industrial equipment (18%). The relatively balanced distribution ensures that no single industry dominates the findings which ensures the validity of the findings. In relation to the respondent’s area of operation, the largest proportion of participants were from supply chain management roles (46%), followed by those working in manufacturing operations

(34%), and logistics functions (20%). In terms of the approximate number of global suppliers, the largest proportion of companies (44%) reported having between 10 and 49 suppliers globally, followed by 22% with 50–199 suppliers, and 20% with fewer than 10 suppliers, as shown in Table 1 below.

Table 1. Distribution of companies in terms of approximate number of global suppliers

Approximate Number of Global Suppliers					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	10–49	22	44.0	44.0	44.0
	50–199	11	22.0	22.0	66.0
	Less than 10	10	20.0	20.0	86.0
	More than 200	7	14.0	14.0	100.0
	Total	50	100.0	100.0	

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A smaller but significant proportion (14%) represented large-scale supply networks with more than 200 global suppliers. Also, a majority of organizations (68%) reported using AI tools currently, while 32% said they have not yet incorporated AI into their supply chain operations. When asked whether AI whether AI systems were being used to prioritize and automate response actions within supply chain operations, a vast majority of the respondents (90%) acknowledged that their AI systems help prioritize and automate responses, while only 10% reported that AI does not play this role. The results show that artificial intelligence (AI) in supply chain management is actively incorporated into operational decision-making procedures in addition to being extensively used. Nine out of ten businesses use AI to automate and prioritize responses, which points to a major change from conventional reactive supply chain strategies to more proactive and flexible ones. The participants were also asked whether AI is widely applied in production-related forecasting tasks and the results showed that 41 organizations (82%) reported using AI to predict production yield and quality deviations, while only 9 organizations (18%) indicated no such usage. The findings show that one of the main uses of AI in supply chain operations is predictive analytics and businesses should prioritize implementing AI where it can result in quantifiable efficiency, less waste, and enhanced product reliability, as more than four-fifths of respondents use it to anticipate yield and identify possible quality deviations. The results on application of AI in production-related forecasting tasks are shown in Table 2.

Table 2. Distribution of companies in terms of using AI to predict production yield and quality deviations.

We use AI to predict production yield and quality deviations.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	9	18.0	18.0	18.0
	Yes	41	82.0	82.0	100.0
	Total	50	100.0	100.0	

A Pearson Chi-Square test was performed to determine the relationship between industry sector and the perception that AI risk scores reliably identify delayed shipments/items. The results showed a statistically significant association, $\chi^2(8, N = 50) = 67.39$, $p < .001$. The significant finding implies that different industries have varying levels of AI risk score dependability. Practically speaking, some businesses like consumer goods or industrial equipment might demonstrate poorer reliability in AI risk scores, while others like pharmaceuticals and autos) may view them as more reliable in forecasting shipment delays. The Pearson-Chi-Square test results between industry sector and the perception that AI risk scores reliably identify delayed shipments/items are shown in Table 3.

Table 3. Chi-Square results between industry sector and the perception that AI risk scores

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	67.385[a]	8	.000
Likelihood Ratio	80.173	8	.000
N of Valid Cases	50		

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On the dependent variable, integration of data flows across enterprise systems (ERP, WMS, TMS, MES, and supplier portals), an analysis of variance (ANOVA) was performed to assess the predictive capacity of three independent variables: whether risk scores produced by artificial intelligence (AI) models reliably identify shipments or items likely to be delayed, whether such risk scores are delivered with sufficient lead time to facilitate mitigation, and whether the scores are embedded into formal decision workflows. ANOVA findings showed that the regression model explained all of the variance in the dependent variable, with a Total Sum of Squares (SST) of 83.620, a Regression Sum of Squares (SSR) of 83.620, and a Residual Sum of Squares (SSE) of 0.000. This result suggests that the predictors as a whole accounted for 100% of the variation in data flow integration (R2 = 1.000). From a substantive standpoint, the results demonstrate how important AI-powered risk management tools are for promoting smooth data flow integration among various supply chain systems. The findings imply that integration across ERP, WMS, TMS, MES, and supplier portals is completely accomplished when risk scores are accurate, timely, and operationally entrenched. The ANOVA results are shown in Table 4.

Table 4. ANOVA Results

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	83.620	3	27.873	.	.[b]
	Residual	.000	46	.000		
	Total	83.620	49			
a. Dependent Variable: Data flows are integrated across ERP, WMS, TMS, MES, and supplier portals.						
b. Predictors: (Constant), Risk scores are embedded into a formal decision workflow, Risk scores produced by our AI models reliably identify shipments or items that will be delayed. Risk scores are delivered with enough lead time to enact mitigation measures.						

5.2 Graphical Results

A cross-tab analysis was performed to examine the association between industry sector and perceptions of whether risk scores are delivered with sufficient lead time to enact mitigation measures. The findings showed clear trends across industries with all eleven respondents (n = 11) in the automotive sector highly agreed that risk scores are provided on time, and all nine respondents (n = 9) in the industrial equipment sector similarly showed consistency. Responses from the consumer goods industry, on the other hand, were more mixed, ranging from disagreement to agreement, indicating only a moderate level of confidence in the promptness of risk score delivery. On the other hand, there was a polarized trend in the electronics sector, with some respondents objecting and others agreeing, suggesting that opinions within the industry differ. Also, there is a balance between moderate and strong confidence, as seen by the pharmaceutical sector's split distribution, which was centered on neutrality and strong agreement. These results imply that perceptions of risk score timeliness are influenced by industry-specific differences with automotive and industrial equipment seem to have more dependable and established systems that allow for proactive mitigation, whereas consumer goods and electronics show more variability and potential implementation issues. Experiences in the pharmaceutical industry are mixed, which may be a result of variations in operational environments or organizational procedures. All things considered, the findings highlight how crucial it is to modify risk management plans to meet the demands of certain industries in order to guarantee that AI-driven risk scores continuously offer actionable lead times in all supply chain settings. The distribution of the participants' responses in terms of whether risk scores are delivered with sufficient lead time to enact mitigation measures are shown in Figure 1.

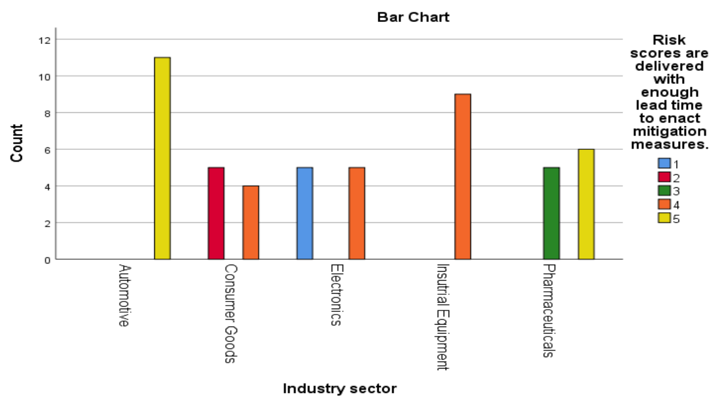

Figure 1. Industry sector and perceptions of whether risk scores are delivered with sufficient lead time to enact mitigation measures.

A cross tabulation was conducted to explore the relationship between the approximate number of global suppliers an organization works with and perceptions of whether AI-generated risk scores reliably identify shipments or items likely to be delayed. The findings showed that different supplier categories have different sectors. Responses were divided among firms with 10–49 suppliers, with ten strongly agreeing, six indicating agreement, and six strongly objecting, revealing a wide range of perspectives within this group. The trustworthiness of AI-generated risk rankings was viewed more favorably by organizations with 50–199 suppliers, as most of them agreed (n = 5) or strongly agreed (n = 6). Organizations with less than ten suppliers, on the other hand, expressed less confidence and five respondents strongly disagreed, five agreed, and none strongly agreed, indicating pessimism in suppliers' networks. It's interesting to note that while all seven firms with over 200 suppliers chose agreement, none chose strong agreement, suggesting that AI reliability is acknowledged but not fully supported. The distribution of the relationship between the approximate number of global suppliers an organization works with and perceptions of whether AI-generated risk scores reliably identify shipments or items likely to be delayed is shown in Figure 2.

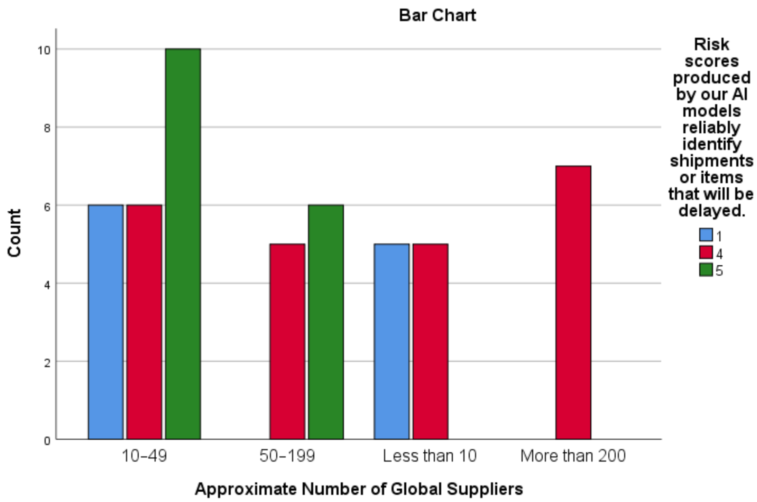

Figure 2. Distribution of responses on the basis of global suppliers.

Overall, these findings show that the perceived reliability of AI-based risk scores varies with the size of the supplier base, with very large supplier networks (>200) exhibiting moderate but consistent agreement, small networks (<10) displaying greater skepticism, and medium-sized supplier networks (50–199) reporting the highest levels of confidence. This implies that the size of supplier networks may have an impact on how businesses perceive and trust AI solutions' ability to predict shipment delays.

6. Conclusion

The present research attempts to address the question of whether applying an AI-based predictive risk score to supply chain data, both historical and current, enhances manufacturing risk mitigation outcomes in a quantifiable manner in order to offer data-driven insights into how AI-enabled end-to-end visibility helps with risk reduction in global industrial supply chains. The study focuses on predictive approaches in an effort to quantify the relationship between AI-enabled visibility and key supply chain performance measures and provides evidence that can be used to promote the adoption of new and innovative technologies. According to the findings, predictive analytics uses statistical algorithms, historical data, and machine learning techniques to predict possible future events or trends and help systems perform better by learning from data and identifying patterns, correlations, and anomalies that would not be visible through traditional analytical methods. Furthermore, the majority of the fundamental supply chain management problems can be resolved by blockchain technology and artificial intelligence (AI), which have emerged as game-changing solutions. Production yield trends and IoT sensor data can also be used to anticipate potential quality deviations or capacity shortages before they have an impact on operations later on. By generating projected risk warnings and the associated likelihood scores, artificial intelligence (AI) systems enable proactive actions such as transferring capacity, speeding up shipments, or adjusting safety stock levels, all of which are critical risk mitigation strategies.

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