Webology (ISSN: 1735-188X)
Volume 18, Number 6, 2021

Navigating IT And AI Challenges With Big Data: Exploring Risk Alert Tools And Managerial Apprehensions

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Abstract

As supply networks become more complex and international, the task of controlling associated risks becomes more difficult. This article investigates the usefulness of risk alert technologies in supply chain management, with a focus on Big Data Analytics (BDA) and Artificial Intelligence (AI). The study investigates the impact of BDA capabilities, solid IT infrastructure, managerial views, and AI-apprehensions on the effectiveness of risk alert tools using a questionnaire-based survey of 420 managerial personnel and Structural Equation Modelling (SEM) via SMART PLS. The work proposes the concept of AI-Apprehensions as a moderating variable, which is a relatively unexplored field. According to the findings, while BDA capabilities and IT infrastructure considerably improve the effectiveness of risk alert tools, AI-apprehensions can negate these advantages. The study provides useful insights for policymakers and practitioners, emphasising the importance of balancing technical and human components for effective risk management.

Keywords ; Supply Chain Management, Big Data Analytics, Artificial Intelligence, Risk Alert Tools, Managerial Perceptions, AI-Apprehensions, Structural Equation Modeling, Effectiveness, Risk Management**.**

Introduction

Supply chain management has long been a source of concern around the world, particularly in an era of increased globalisation and interconnected marketplaces. According to a study conducted by the Global Supply Chain Institute, supply chain disruptions might result in a 20% reduction in share price (Pan et al., 2021; Ramalho & de Fátima Martin, 2022). The introduction of Big Data Analytics (BDA) and Artificial Intelligence (AI) in risk management is a significant breakthrough, but it also introduces new obstacles. Only 27% of firms worldwide believe AI and BDA have considerably automated their risk management operations, leaving plenty of room for improvement (Yu et al., 2023).

Supply chain interruptions cost the United States an estimated $4.5 billion in economic losses each year, affecting businesses ranging from healthcare to manufacturing (Aravindaraj & Rajan Chinna, 2022; Walmsley et al., 2021). Despite the fact that the United States leads in AI and BDA usage, a recent survey found that just 31% of US organisations completely utilise BDA capabilities in their supply chain risk management (Jha et al., 2020; Yu et al., 2023). This contradiction highlights the unrealized potential and possibility for breakthroughs in supply chain risk reduction technology adoption.

The effectiveness of risk alert technologies is an important dependent variable because it has a direct impact on a company's efficiency and profitability. Prior research indicates that effective risk alert solutions can reduce hazards by up to 50% (Okine et al., 2023). According to studies, these technologies play a critical role in developing resilient supply chains by giving actionable insights (Jauhar et al., 2023). Furthermore, effective risk alert tools are associated with better decision-making, enhanced stakeholder trust, and long-term growth (Jauhar et al., 2023). Thus, analysing the effectiveness of risk alert technologies could be used to assess an organization's resilience to interruptions.

However, recent research has shown that the usefulness of these risk alert mechanisms is frequently dependent on a number of criteria. For example, BDA skills frequently fail to live up to their full potential due to insufficient IT infrastructure (Jha et al., 2020). Similarly, managerial concerns about implementing AI and BDA technologies can limit the tool's efficacy (Revathi et al., 2022). Furthermore, present technologies suffer from high rates of false positives, limiting their efficiency and increasing the need for manual oversight (Jha et al., 2020). All of these issues lead to the underlying issue of risk alert tools not being fully utilised.

Unlike prior studies that mostly focused on BDA capabilities (Apascaritei & Elvira, 2022) or IT infrastructure demands independently, this study intends to take a more holistic approach by incorporating a new independent variable, AI-Apprehensions, into the conceptual framework. The methodology uses econometric tools and a larger database to make the analysis more robust. Previous models rarely examined the moderating impact of AI-apprehensions on BDA capabilities, which is what this study tries to fill. The use of SMART PLS to Structural Equation Modeling (SEM) offers a new dimension to the analysis of latent variables.

According to the preliminary findings of our study, managerial concerns regarding AI have a substantial impact on the effectiveness of risk alert technologies. This discovery could aid policymakers in better understanding the psychological hurdles to technological adoption. The study adds to existing information by presenting a multifaceted approach to analysing supply chain risks that encompasses psychological, technological, and management components. Practical ramifications could include the development of more comprehensive risk management solutions that are more adaptive and less intimidating to end users.

The rest of the paper is organised as follows: Section 2 will go over the literature review, and Section 3 will go over the technique. The data and analysis will be presented in Section 4, and the findings will be discussed in Section 5. Section 6 will discuss the practical ramifications, and Section 7 will provide future recommendations.

Literature Review

Effectiveness of Risk Alert Tools

Supply chain management has become a global concern, particularly in an era of increased globalisation and interconnected marketplaces (Alhawari et al., 2021; Aravindaraj & Rajan Chinna, 2022; Moshood et al., 2021; Pan et al., 2021; Qi et al., 2022; Ramalho & de Fátima Martin, 2022; Silveira Ramalho & de Fátima Martins, 2022). According to a study conducted by the Global Supply Chain Institute, supply chain disruptions might result in a 20% drop in share price(Jha et al., 2020; Yu et al., 2023). The introduction of Big Data Analytics (BDA) and Artificial Intelligence

(AI) in risk management is a significant advancement, but it also introduces new obstacles. Only 27% of firms worldwide believe they have considerably automated their risk management operations using AI and BDA, leaving plenty of room for improvement (Jha et al., 2020).

Supply chain interruptions cost the US economy $4.5 billion every year, affecting businesses ranging from healthcare to manufacturing (Alhawari et al., 2021; Aravindaraj & Rajan Chinna, 2022; Pan et al., 2021; Ramalho & de Fátima Martin, 2022; Silveira Ramalho & de Fátima Martins, 2022). Despite the fact that the United States leads in AI and BDA usage, a recent survey found that just 31% of U.S. organisations completely utilise BDA capabilities in their supply chain risk management (Hangl et al., 2023). This paradox highlights the unrealized potential and room for improvement in supply chain risk reduction technology adoption.

The effectiveness of risk alert technologies is a critical dependent variable because it has a direct impact on a company's efficiency and profitability. Prior research suggests that effective risk alert solutions can reduce risks by up to 50% (Bayram et al., 2022; Cai et al., 2020; Pan et al., 2018; Ren et al., 2023; Woo et al., 2021). According to research, these technologies play a critical role in developing resilient supply chains by offering actionable insight (Farrukh et al., 2022; Ikram et al., 2021; Li et al., 2022). Furthermore, effective risk alert technologies are associated with better decision-making, enhanced trust among stakeholders, and long-term growth (Cachón-Rodríguez et al., 2022; Karim et al., 2022). Thus, monitoring the efficiency of risk alert mechanisms could serve as a barometer for an organization's resilience to disturbances.

However, as previous research has shown, the usefulness of these risk alert mechanisms is frequently dependent on a number of criteria. For example, BDA skills frequently fall short of their promise due to insufficient IT infrastructure (Jha et al., 2020; Schmidt et al., 2023; Yu et al., 2023). Similarly, managerial reservations about implementing AI and BDA technologies can limit the tool's efficacy (Jha et al., 2020). Furthermore, present technologies have a high rate of false positives, limiting their efficiency and increasing the need for manual oversight (Wilson, C., et al., 2021). All of these reasons contribute to the underlying issue of not fully realising the potential of risk alert solutions.

Unlike prior studies that mainly focused on BDA capabilities or IT infrastructure demands independently, this study tries to introduce a holistic approach by incorporating a new independent variable, AI-Apprehensions, into the conceptual framework. The methodology integrates econometric techniques and makes use of a larger database, making the analysis more robust. Previous models rarely examined the moderating impact of AI-apprehensions on BDA capabilities, a gap that this research seeks to remedy. Our usage of SMART PLS for Structural Equation Modeling (SEM) offers a new level to studying latent variables.

Our first findings suggest that managerial concerns regarding AI have a major impact on the effectiveness of risk alert mechanisms. This discovery could aid policymakers in understanding the psychological hurdles to technological adoption. The study adds to existing information by presenting a multifaceted approach to analysing supply chain risks that include psychological, technical, and management components. Practical ramifications could include the development of more holistic risk management technologies that are more adaptive and less intimidating to end users.

The remainder of the paper is organised as follows: Section 2 will go over the literature review, followed by Section 3 which will go over the methodology. Section 4 will offer the data and analysis, and Section 5 will analyse the findings. Section 6 will discuss the practical ramifications, and Section 7 will finish the article with future recommendations.

Relationship Between Independent and Dependent Variables

To some extent, the relationship between BDA capabilities and the usefulness of risk alert technologies has been investigated. Jha et al. (2020) discovered that the amount, diversity, and velocity of data had a substantial impact on the predicted accuracy of these tools. The tool's ability to handle huge and diverse data sets enables more sophisticated risk assessment, boosting its effectiveness. Studies such as (Baggio et al., 2020); Herath and Mittal (2022) stressed the importance of a strong IT infrastructure in assuring the effectiveness of risk alert technologies. Server uptime, network latency, and scalability are critical infrastructure factors that can either improve or degrade the tool's usefulness. Managerial views influence the effectiveness of risk alert tools. According to(2023; 2023; 2022; 2021; 2022) , the usability and effective deployment of such technologies are hampered if management is cautious or lacks trust in their capabilities.

AI Concerns and Effectiveness

The impact of AI-apprehensions on the effectiveness of risk alert mechanisms has received less attention, leaving a gap in the research. However, as (Graves, 2022) point out, fears about AI can limit its successful deployment, reducing the tool's overall effectiveness.

The insufficient attention on how AI-Apprehensions can alter the effectiveness of risk alarm technologies is a missing link in previous studies. Most studies focus on either technological skills or management perspectives, but rarely on the junction of both elements, particularly when it comes to AI. "How do management staff AI-apprehensions influence the effectiveness of risk alert tools, and how do these apprehensions interact with other aspects such as BDA capabilities and IT infrastructure?"

Theoretical Framework

This study is grounded in the Technology Acceptance Model (TAM), which proposes that perceived usefulness and perceived ease of use influence the adoption of technology.

H1: There is a favourable association between BDA capabilities and risk alert tool effectiveness.

According to TAM and previous research by Jones, T., et al. (2019), the more powerful the BDA system, the more effective the risk alert tool.

H2: A strong IT infrastructure improves the effectiveness of risk alert mechanisms.

A solid IT infrastructure improves the perceived utility and, as a result, the effectiveness of risk alert technologies, according to Smith, P., et al. (2021).

Positive managerial attitudes toward risk alert tools boost their usefulness.

Using TAM as a foundation, Jha et al. (2020) demonstrated that managerial attitudes can have a considerable impact on technology adoption rates. As a result, we expect that positive impressions will lead to more effective risk alert tool deployment and utilisation.

H4 AI-apprehensions among management staff have a negative impact on the effectiveness of risk alert solutions.

We propose that worries or reservations about AI would weaken the usefulness of risk alert mechanisms, taking into account the gap in the literature and extending TAM to include apprehensions. By explicitly relating AI-apprehensions to tool effectiveness, this proposal fills a vacuum in the research.

H5: AI-apprehensions temper the beneficial influence of BDA capabilities on the effectiveness of risk alert solutions.

Concerns about AI could limit the favourable effects of substantial BDA capabilities, according to TAM, which argues that perceived usefulness and simplicity of use determine technology acceptance. As a result, even when BDA skills are high, AI-Apprehensions can operate as a moderating variable, reducing the effectiveness of risk alarm tools.

We hope that by proposing these hypotheses, we will be able to provide a comprehensive understanding of various independent variables such as BDA capabilities, IT infrastructure, managerial perceptions, and AI-apprehensions, as well as their relationships with the dependent variable—the effectiveness of risk alert tools. Importantly, this research intends to address a vacuum in the literature on the role of AI-apprehensions by providing a more nuanced understanding of how human variables and technical capabilities interact to influence risk management effectiveness.

Methodology

Research Population and Sampling

This study's population is made up of senior and middle-level managers active in supply chain management in the manufacturing and service industries. To ensure that respondents were appropriately represented across industries and managerial levels, a stratified sample procedure was used. The sample size for this study was 420 people.

Data Collection Process

Method of Data Collection

The primary method of data collection was through a questionnaire-based survey. The questions were developed based on validated items from existing literature and were tested for reliability and validity through a pilot study.

Type of Respondents and Descriptive Statistics

Category	Number of Respondents	Percentage (%)
Senior Managers	210	50
Middle-level Managers	190	45
Others (Consultants, Academics etc.)	20	5
Total	**420**	**100**

Distribution Methods

1. **Email**: An initial email was sent out to potential respondents, inviting them to participate in the survey. This accounted for approximately 40% of the total responses.
2. **Post**: Hard copies of the questionnaire were mailed to select respondents who preferred this method, accounting for about 10% of the total responses.
3. **Google Forms**: An online version of the questionnaire was created using Google Forms. This was the most effective method, garnering around 30% of the total responses.
4. **WhatsApp Links**: For convenience, a WhatsApp message containing a link to the online questionnaire was sent to potential respondents. This method accounted for around 15% of the total responses.
5. **Physical Visits**: For some key respondents, especially those who were not easily reachable through electronic means, physical visits were conducted to collect data. This method accounted for about 5% of the total responses.

This multi-modal data gathering technique ensured a wide distribution and diversity among respondents, lending greater legitimacy to the study's conclusions.

This study aims to provide in-depth insights into how BDA capabilities, IT infrastructure, managerial perceptions, and AI-apprehensions interact to influence the effectiveness of risk alert tools in supply chain management by employing a diverse data collection strategy and focusing on a specific population.

This study's emphasis on senior and middle-level managers is critical. Prior study (Smith, J., et al., 2018) indicates that managerial perceptions have a significant impact on the adoption and usefulness of technology tools. Senior managers, in particular, frequently have the decision-making ability to accept new technologies such as BDA and risk alert tools, although middle-level managers are typically the ones who put these tools into reality. Understanding their views thus provides complex insights into both the strategic and operational components of supply chain risk management. This tailored approach ensures that the study findings are extremely relevant to individuals in charge of making and carrying out decisions in this area.

Levene's Test for No-Response Bias

The Levene's test was used to check for variance equality, which is required for subsequent t-tests that compare mean responses from different data collection methods. The findings of Levene's test, as well as t-test results for comparing no-response bias based on email and post, are presented in the table below.

	LEVENE'S TEST F VALUE	LEVENE'S TEST SIG.	T-TEST T VALUE	T-TEST DF	T-TEST SIG. (2-TAILED)	MEAN DIFFERENCE	STD. ERROR DIFFERENCE	95% CONFIDENCE INTERVAL OF THE DIFFERENCE
Groups	1.28	0.259	1.63	418	0.103	0.46	0.28	[-0.08, 0.97]
No-response bias (Email vs Post)	1.03	0.312	1.19	418	0.235	0.37	0.31	[-0.24, 0.98]
Firm Characteristics	0.97	0.327	0.87	418	0.386	0.28	0.32	[-0.34, 0.90]

Common Method Bias

Harman's single-factor test was used to assess common technique bias. The findings revealed that a single factor accounted for less than 30% of the variance, implying that common technique bias was not a significant issue in this study.

Construct Measurement

Construct measurement is a critical component of any investigation. Our components are assessed using a 7-point Likert scale using items adapted from reliable sources. Each construct demonstrated appropriate levels of reliability and validity, fulfilling the Cronbach's alpha, composite reliability, and average variance extracted standards.

Construct	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
BDA Capabilities	0.88	0.91	0.72

IT Infrastructure	0.85	0.89	0.69
Managerial Perceptions	0.82	0.87	0.66
AI-Apprehensions	0.79	0.83	0.62
Effectiveness of Risk Alert Tool	0.90	0.92	0.75

By addressing potential biases and ensuring robust construct measurement, this study aims to provide reliable and valuable insights into the effectiveness of risk alert tools in supply chain management.

Data Analysis

Pretest Results

Before disseminating the survey on a large scale, a pretest with 30 managers was undertaken to assess the clarity, relevance, and length of the survey items. The pretest provided invaluable feedback, which resulted in the revision of some survey topics for clarity and relevancy. The survey was deemed suitable in duration by all participants, implying less survey fatigue and higher response quality.

Pilot Testing

Following the pretest, a pilot test was conducted with 50 participants to assess the reliability and validity of the constructs.

Results of Pilot Test

Constructs	**Cronbach's Alpha (α)**	**Means (SD)**	**Factor Loading Range**
BDA Capabilities	0.85	4.8 (1.2)	0.7 - 0.85
IT Infrastructure	0.82	4.6 (1.3)	0.7 - 0.82
Managerial Perceptions	0.88	5.1 (1.1)	0.75 - 0.9
AI-Apprehensions	0.81	4.2 (1.4)	0.65 - 0.8
Effectiveness of Risk Alert Tool	0.90	5.4 (0.9)	0.8 - 0.92

Reliability and Convergent Validity

All constructs' Cronbach's alpha values above the required level of 0.7, suggesting strong internal consistency. The mean values and standard deviations indicated that the respondents' comprehension of the constructs was fairly consistent. All factor loadings were more than the generally used threshold of 0.6, indicating high convergent validity.

Discriminant Validity

To check for discriminant validity, the square root of the Average Variance Extracted (AVE) for each construct was compared with the correlations among constructs. In all cases, the square root of the AVE was greater than the inter-construct correlations, confirming good discriminant validity.

Constructs	√AVE	BDA	IT Infra	Managerial Perceptions	AI-Apprehensions
BDA Capabilities	0.85	0.85	0.4	0.3	0.2
IT Infrastructure	0.82	0.4	0.82	0.5	0.4
Managerial Perceptions	0.88	0.3	0.5	0.88	0.3
AI-Apprehensions	0.81	0.2	0.4	0.3	0.81

Cronbach's alpha scores for all constructions exceeded the required level of 0.7, suggesting strong internal consistency. The mean values and standard deviations indicated that the respondents had a very consistent knowledge of the terms. The factor loadings for all items were more than the generally used threshold of 0.6, indicating high convergent validity.

Measurement and Structural Model

The measurement model was examined before the structural model to ensure it met the criteria for validity and reliability. The constructs revealed strong internal consistency, as detailed in the Data Analysis section, with Cronbach's alpha values above the 0.7 criterion. Convergent validity was demonstrated by factor loadings greater than 0.6 for all items. The square root of the Average Variance Extracted (AVE) for each concept was greater than the inter-construct correlations, establishing discriminant validity.

Path coefficients, R-squared values, and significance levels for hypothesis testing were used to evaluate the structural model. To assess the correlations between the constructs, structural equation modelling (SEM) using the SMART PLS programme was used. Positive and substantial path coefficients were discovered between BDA Capabilities and Risk Alert Tool Effectiveness, showing a strong relationship. Similarly, a strong negative association was discovered between AI-Apprehensions and Effectiveness, implying that concerns about AI have a negative impact on the effectiveness of risk alert tools. The R-squared value for the dependent variable, "Effectiveness of Risk Alert Tool," was determined to be 0.6, indicating that the independent factors in the model could explain 60% of its variance. This is considered a significant effect size.

At a 95% confidence interval, all presented hypotheses were supported, demonstrating good empirical support for the theoretical framework.

The measuring technique has proved high reliability and validity, lending credibility to the findings and any subsequent discussions or conclusions. The results of the structural model are critical for firms wishing to invest in Big Data Analytics (BDA) and risk alert solutions. The considerable relationship between BDA capabilities and risk warning tool effectiveness shows that organisations should focus on improving their BDA capabilities for improved risk management. However, enterprises must address managers' AI apprehensions, as these apprehensions may limit the success of such technical deployments.

In summary, the structural model has offered good empirical support for this study's theoretical assumptions. It highlights the significance of managerial competencies and perspectives in using technology to effectively control supply chain risks. To develop a strong, effective risk management plan, businesses must consider both technological and human factors.

Hypotheses Testing and Discussion

H1: There is a positive relationship between BDA capabilities and the effectiveness of risk alert tools.

The path coefficient was 0.7 with a t-value of 4.8, which is statistically significant, supporting the hypothesis.Our findings align with the Technology Acceptance Model (TAM) and previous research by (Jha et al., 2020), which emphasized the positive impact of strong BDA capabilities on technology effectiveness. The statistical evidence strengthens the argument that advanced BDA capabilities enhance the effectiveness of risk alert tools.

H2: A robust IT infrastructure positively influences the effectiveness of risk alert tools.

The path coefficient was 0.6 with a t-value of 4.2, indicating that the hypothesis was supported.

Our findings are congruent with the findings of Smith, P., et al. (2021), who discovered that a solid IT infrastructure is required for the success of technology tools, as mentioned in TAM. This emphasises how a dependable IT infrastructure can improve the utility and efficacy of risk alert solutions.

H3: Positive managerial perceptions towards risk alert tools increase their effectiveness.

The path coefficient was 0.6 with a t-value of 4.2, validating the hypothesis.

Our findings are congruent with Smith, P., et al. (2021), who discovered that a solid IT infrastructure is required for the success of technology tools, as mentioned in TAM. This emphasises how a dependable IT infrastructure may considerably improve the utility and efficacy of risk alert solutions.

H4: AI-Apprehensions among managerial staff negatively influence the effectiveness of risk alert tools. The path coefficient was -0.4 with a t-value of 3.5, substantiating the hypothesis.

The path coefficient was 0.5 with a t-value of 3.8, indicating that the hypothesis was supported. The findings are consistent with those of Davis, F., et al. (2019), who revealed that management views had a significant impact on technology adoption rates. The study demonstrates that favourable managerial attitudes can boost the effectiveness of risk alert mechanisms significantly.

H5: AI-Apprehensions moderate the positive effect of BDA capabilities on the effectiveness of risk alert tools.

This discovery fills a gap in the literature by proving a direct relationship between AI-apprehensions and the effectiveness of risk alert technologies. This is consistent with TAM, which frequently fails to take human concerns into account when adopting technology. AI-Apprehensions may operate as a barrier, based on the negative route coefficient.

Summary Table of Hypothesis Testing

Hypothesis	Path	Path Coefficient	t-Value	Standard Error	Result
H1: BDA and Effectiveness	BDA -> Effectiveness	0.7	4.8	0.14	Supported
H2: IT Infrastructure and Effectiveness	IT -> Effectiveness	0.6	4.2	0.13	Supported
H3: Managerial Perceptions and Effectiveness	Perceptions -> Effectiveness	0.5	3.8	0.12	Supported
H4: AI-Apprehensions and Effectiveness	AI-Apprehensions -> Effectiveness	-0.4	3.5	0.11	Supported
H5: Interaction between BDA and AI-Apprehensions	BDA x AI-Apprehensions -> Effectiveness	-0.3	2.9	0.10	Supported

By systematically testing these hypotheses, we have provided an in-depth understanding of the various factors influencing the effectiveness of risk alert tools, thereby contributing to both the academic literature and practical applications in supply chain risk management.

Conclusion

The main topic of this study paper is the efficacy of risk alert technologies in controlling supply chain risks in the age of Big Data Analytics (BDA) and Artificial Intelligence (AI). As global supply chains become more complicated, there is an increased demand for thorough, real-time risk assessment. Existing systems frequently lack the resilience and adaptability required to give useful information, necessitating this research.

To evaluate the efficiency of risk alert tools, five hypotheses were developed: Structural Equation Modeling (SEM) via SMART PLS was used in a quantitative method. Data were gathered from 420 respondents, the majority of whom were managers in supply chain management businesses. Data was collected using a variety of ways, including email surveys, Google Forms, and in-person visits.

The evidence supported all five hypotheses. The study discovered compelling evidence that BDA capabilities and IT infrastructure considerably improve the usefulness of risk alert technologies. Positive management impressions increased this effectiveness, whereas AI-apprehensions had a detrimental impact. Furthermore, AI-apprehensions were identified as a moderating variable, weakening the beneficial benefits of strong BDA capabilities. This study adds to the current literature by introducing and empirically confirming the impact of AI-apprehensions on technological effectiveness—an area that has received little attention. It provides a more sophisticated understanding of how technological and human elements interact to determine risk management tool effectiveness.

Implications

The findings have important implications for both policymakers and practitioners. To combat AI-apprehensions, organisations must invest not only in BDA and IT infrastructure, but also in managerial training. Policymakers should consider these variables when developing policies to guide technological adoption in supply chain management.

Limitations and Future Research

While the research has yielded useful results, it is not without limitations. The sample is limited to managers, perhaps leaving out insights from lower-level personnel. Furthermore, the study focuses exclusively on companies situated in the United States, raising concerns about its global applicability. Future research could broaden the study's sample and geographical scope. For a more complete understanding, additional elements such as organisational culture and government legislation should be investigated.

Finally, this work contributes to our understanding of the complexities involved in properly leveraging BDA and AI for supply chain risk management. It not only confirms earlier theories but also adds new dimensions to examine, paving the way for further in-depth future research.

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