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Article

Mechanisms of Algorithmic Advice Dependence on Supply Chain Risk Cognitive Bias in Human AI Collaborative Decision Making: An Experimental and Structural Model Analysis

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Abstract: The integration of algorithmic decision support systems into modern supply chain management has fundamentally transformed traditional risk assessment practices. However, the underlying cognitive mechanisms through which human decision makers develop an over-reliance or dependence on algorithmic advice remain poorly understood in current literature. This study systematically investigates how algorithmic advice dependence influences supply chain risk cognitive bias within human-AI collaborative decision-making contexts. Particular attention is given to the New Zealand business environment, which currently faces significant geopolitical disruptions and severe commodity price volatility. Drawing extensively on behavioral decision theory and cognitive load theory, we propose a comprehensive moderated mediation model. In this framework, algorithmic advice dependence affects risk perception bias through the critical mediation of cognitive effort reduction, which is further moderated by task complexity and advice quality. Using advanced agent-based simulation experiments integrated with publicly available supply chain disruption databases—including the NZ Global Dairy Trade price index and geopolitical risk indices from 2020 to 2025—we systematically manipulate algorithmic advice characteristics to examine their direct effects on risk cognitive bias formation. Structural equation modeling is employed to rigorously test the hypothesized relationships. The results reveal that algorithmic advice dependence significantly amplifies risk perception bias, particularly under high task complexity conditions. Ultimately, this research contributes to the behavioral operations management literature by elucidating the cognitive mechanisms underlying human-AI interaction and offers practical implications for designing robust algorithmic decision support systems that effectively mitigate cognitive biases.

Keywords: algorithmic advice; supply chain risk; cognitive bias; human ai collaboration; behavioral operations

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1. Introduction

The integration of artificial intelligence into supply chain decision-making has introduced new complexities in how human managers perceive and respond to risk. As enterprises based in New Zealand face escalating geopolitical tensions and volatile commodity prices, particularly in dairy and agricultural exports, understanding the cognitive mechanisms underlying human-AI collaboration becomes critical for enhancing supply chain resilience [1]. These challenges necessitate a deeper exploration of how AI systems influence managerial decision-making processes, especially in environments characterized by uncertainty and rapid change.

Algorithmic decision support systems are now routinely employed to provide risk assessments and recommendations to supply chain managers. However, the psychological processes through which decision-makers develop reliance on algorithmic advice remain insufficiently explored [2]. This reliance has the potential to systematically distort risk perception, leading to cognitive biases that may compromise supply chain performance under conditions of uncertainty. Understanding these dynamics is essential for designing systems that enhance decision-making without inadvertently introducing new vulnerabilities.

Drawing on principles from economic psychology, this study suggests that algorithmic systems exert a cognitive influence on human judgment that operates independently of their objective accuracy. This influence becomes particularly significant in high-stakes supply chain environments, where managers must make rapid decisions that balance operational efficiency against exposure to potential disruptions. The shift from traditional cognitive bias research to frameworks that examine algorithmic influence provides a valuable foundation for understanding how machine-generated advice shapes human risk cognition and decision-making processes.

Recent systematic reviews have emphasized the need for empirical investigation into the mechanisms of human-AI collaboration in operations management, particularly focusing on how decision-makers integrate algorithmic inputs into their risk assessment processes [3]. This study addresses this gap by examining the mechanisms through which dependence on algorithmic advice influences cognitive biases in supply chain risk perception. Using agent-based simulations calibrated with publicly available supply chain disruption data, including the Global Dairy Trade price index and geopolitical risk indices from 2020 to 2025, the study explores how the characteristics of algorithmic advice affect the formation of risk perceptions. Structural equation modeling is utilized to test the hypothesized relationships, contributing to the behavioral operations literature and informing the design of decision support systems that aim to mitigate cognitive biases in human-AI collaborative environments.

2. Literature Review

The intersection of human cognitive processes and algorithmic decision support has become a pivotal area of investigation within supply chain management research [4]. This chapter delves into existing studies across three interconnected domains: algorithmic conformity and human judgment, AI-enabled supply chain risk management, and cognitive biases in human-AI collaborative decision-making. Particular emphasis is placed on the New Zealand context, where unique supply chain vulnerabilities arise due to geopolitical disruptions and commodity price volatility. These challenges underscore the importance of integrating advanced decision-support systems to enhance resilience and adaptability in dynamic environments.

2.1. Algorithmic Conformity and Human Judgment

Research on human-AI collaboration has identified a phenomenon termed algorithmic conformity, wherein human decision-makers systematically defer to algorithmic recommendations even when those recommendations contradict their own better judgment. This conformity effect becomes more pronounced under conditions of task complexity and time pressure, both of which are characteristic of supply chain risk management environments. For instance, when managers face uncertain geopolitical events or volatile commodity prices, they may increasingly rely on algorithmic advice while suspending their own critical evaluation. This reliance can lead to a diminished role for human intuition and expertise, which are often crucial in navigating unpredictable scenarios [5].

The foundational framework for understanding AI in operations distinguishes between automation and augmentation paradigms. Automation replaces human decision-making entirely, while augmentation supports human judgment without fully substituting it. In supply chain contexts where risk assessment requires contextual awareness of local conditions, such as trade dependencies on Pacific routes, the augmentation approach may be more appropriate. However, algorithmic advice dependence can blur the boundary between healthy augmentation and problematic over-reliance [6]. This dynamic underscores the importance of maintaining a balance between leveraging algorithmic tools and preserving the critical role of human oversight, particularly in scenarios where nuanced understanding of local conditions is essential.

Balancing data-driven insights with human judgment represents a persistent tension in supply chain management. While algorithms excel at processing large volumes of historical data, they may fail to account for novel geopolitical developments or sudden market shifts. Human managers possess contextual knowledge that algorithms lack, yet algorithmic advice dependence can cause managers to discount their own situational awareness. This tension is particularly acute for firms facing rapid changes in trade relationships and shipping route disruptions. For example, firms operating in regions with evolving trade dynamics must carefully evaluate when to rely on algorithmic outputs and when to prioritize human expertise to adapt to unforeseen challenges effectively.

2.2. AI Enabled Supply Chain Risk Management

The design of human-AI collaborative decision analytics frameworks has been proposed as a mechanism for enhancing managerial judgment in supply chain operations [6]. These frameworks typically position the algorithm as an advisor rather than a decision maker, thereby preserving human authority over final risk assessments. However, the effectiveness of such frameworks depends critically on whether managers maintain cognitive independence or develop a reliance on algorithmic advice. When such dependence occurs, the intended advisory role of the algorithm effectively transforms into de facto automation, undermining the collaborative intent. This dynamic underscores the importance of fostering a balanced interaction between human judgment and algorithmic input to ensure that decision-making processes remain robust and adaptive.

Cognitive resilience in supply chains refers to the ability of decision-makers to maintain accurate risk perception despite exposure to algorithmic recommendations that may contain systematic biases. AI-powered risk mitigation tools are capable of processing geopolitical risk indices and price volatility signals at scales that are beyond human capacity. However, these tools may inadvertently influence human risk cognition in ways that diminish resilience rather than enhance it. For example, New Zealand exporters dealing with volatile dairy prices might either gain valuable insights or develop misplaced confidence depending on how they interpret and prioritize algorithmic advice [7]. This highlights the critical need for managers to critically evaluate AI-generated outputs and integrate them with independent data sources to maintain a balanced and informed perspective on risks.

Extreme weather events driven by climate change have significantly intensified supply chain risks, particularly in agricultural sectors. While this research focuses on cocoa supply chains, similar challenges are evident for New Zealand's dairy and horticulture exports. AI systems trained on historical weather patterns may struggle to predict unprecedented events, leading to potential underestimation of novel risks by managers who overly depend on algorithmic advice. This limitation underscores the necessity of understanding how reliance on algorithmic recommendations interacts with human risk perception, especially under conditions of environmental uncertainty [8]. By fostering a deeper awareness of these interactions, decision-makers can better prepare for and adapt to emerging challenges in supply chain management.

The role of AI in building supply chain resilience has been extensively explored, with machine learning models demonstrating the ability to identify disruption patterns and recommend mitigation strategies more rapidly than human analysts. However, resilience in supply chains requires not only the rapid detection of risks but also the appropriate human interpretation of algorithmic outputs. When managers exhibit high levels of dependence on algorithmic advice, they may accept AI-generated risk assessments without adequately cross-validating them against independent information sources, such as on-the-ground reports from logistics partners or real-time shipping data. This over-reliance can lead to suboptimal decision-making, emphasizing the importance of maintaining a critical and integrative approach to AI-driven insights in supply chain operations [9].

2.3. Cognitive Biases in Human AI Collaboration

Information sharing and trust are critical mediating variables in human-AI collaboration within supply chain management. When trust in algorithmic advice is elevated, managers are more inclined to delegate decision-making authority to AI systems. This trust can be advantageous when algorithms perform accurately [7]. However, it can also persist even after algorithms produce errors, leading to an overreliance on their recommendations. For supply chains, particularly those employing just-in-time inventory models, misplaced trust in algorithmic risk assessments could result in significant disruptions, such as severe stockouts or excessive inventory holding costs. These outcomes highlight the importance of maintaining a balanced approach to integrating AI into decision-making processes, ensuring that human oversight remains a key component to mitigate potential risks.

A field experiment conducted in retail supply chain prediction demonstrated that human-AI collaboration can enhance forecast accuracy, but only under specific conditions. The improvement was observed when human decision-makers retained final decision authority and actively scrutinized algorithmic recommendations [10]. Conversely, when participants passively accepted AI-generated predictions without critical evaluation, the performance benefits were nullified. This finding underscores the concern that overdependence on algorithmic advice can undermine the potential advantages of human-AI collaboration. Additionally, the experiment revealed that providing explanations for algorithmic recommendations played a crucial role in preserving human critical thinking. This suggests a valuable design principle for AI systems: incorporating transparent and comprehensible explanations to encourage active human engagement and reduce the risk of overreliance.

The identification and mitigation of behavioral biases in AI-augmented decision-making have become a significant area of research [6]. While algorithms are often perceived as unbiased, they can inadvertently encode systematic errors stemming from training data or model design. Furthermore, algorithms can introduce new biases in human decision-makers, such as automation bias and confirmation bias. Automation bias, in particular, occurs when individuals disproportionately favor machine-generated information over conflicting evidence from other sources. Addressing this bias requires a dual approach: enhancing algorithmic transparency and fostering deliberate cognitive strategies that encourage managers to maintain independent judgment. By promoting a culture of critical evaluation and ensuring that AI systems are designed to support, rather than replace, human decision-making, organizations can better harness the potential of AI while minimizing its risks.

2.4. Research Gaps and Theoretical Contributions

The literature reviewed highlights three critical gaps that warrant further exploration. First, prior research on algorithmic conformity has predominantly focused on generic decision-making tasks, leaving the domain of supply chain risk assessment underexplored. Second, investigations into the role of artificial intelligence in enhancing supply chain resilience have largely emphasized operational outcomes, neglecting the underlying cognitive mechanisms that drive decision-making processes. Third, the unique context of New Zealand, characterized by its exposure to geopolitical risks and fluctuations in commodity prices, has been insufficiently addressed in studies on human-AI collaboration. This research seeks to bridge these gaps by examining the mechanisms through which reliance on algorithmic advice impacts cognitive biases in supply chain risk assessment. The study utilizes publicly accessible data sources, including the Global Dairy Trade price index and geopolitical risk indices, covering the period from 2020 to 2025, to provide a robust analytical foundation.

3. Theoretical Framework and Methodology

This chapter elaborates on the theoretical framework and methodological approach utilized to explore the impact of algorithmic advice dependence on supply chain risk cognitive bias within the context of human-AI collaborative decision-making. The research employs an agent-based simulation experimental design in conjunction with structural equation modeling, effectively integrating publicly accessible supply chain disruption databases. A detailed method flowchart is included to visually represent the critical stages and processes involved in the study, ensuring clarity and systematic understanding of the research methodology [11].

3.1. Theoretical Framework

The theoretical foundation of this study integrates behavioral decision theory with cognitive load theory and algorithmic influence frameworks. Behavioral decision theory explains that human judgment under uncertainty is systematically influenced by cognitive heuristics and biases. When applied to supply chain risk assessment, this theory highlights that managers dealing with geopolitical disruptions and commodity price volatility often rely on mental shortcuts. These shortcuts, while simplifying decision-making, can distort risk perception and lead to suboptimal evaluations of potential threats and opportunities.

Cognitive load theory offers a complementary perspective by emphasizing the role of mental effort in decision-making processes. Algorithmic advice, by providing pre-analyzed assessments, reduces the cognitive effort required for risk analysis. This reduction in cognitive load generally enhances decision efficiency, allowing managers to focus on strategic priorities. However, excessive reliance on algorithmic advice can have unintended consequences, such as the gradual erosion of independent risk evaluation skills. When cognitive load is consistently outsourced to algorithms, managers may develop a dependency that persists even when algorithmic recommendations are inaccurate or misaligned with evolving conditions, potentially compromising decision quality.

Algorithmic cognitive influence theory extends these frameworks by exploring how machine-generated recommendations shape human judgment beyond their informational content. This theory differentiates between informative influence, where algorithms provide new data, and normative influence, where algorithms establish expectations about appropriate risk assessments. Dependence on algorithmic advice primarily arises from normative influence, as managers align their decisions with algorithmic recommendations to conform to perceived best practices. This alignment, while often beneficial, can inadvertently suppress critical thinking and independent judgment, particularly in dynamic and uncertain environments [12].

The proposed theoretical model suggests that algorithmic advice dependence impacts supply chain risk cognitive bias through the mediation of cognitive effort reduction. Under conditions of high task complexity, such as evaluating multiple simultaneous geopolitical threats or volatile commodity price movements, the reduction in cognitive effort becomes more significant, thereby intensifying the mediation effect. The quality of algorithmic advice moderates this relationship, with high-quality advice amplifying dependence effects. However, this dependence can paradoxically increase risk perception bias, particularly when managers overly trust algorithmic outputs without critically evaluating their alignment with real-time conditions.

3.2. Methodology

The study employs an agent-based simulation experimental approach. Unlike human subject experiments, agent-based simulations utilize computational agents programmed with specific decision-making rules to generate data under controlled conditions [8]. This methodology effectively addresses ethical concerns associated with inducing cognitive biases in human participants, while enabling systematic manipulation of the characteristics of algorithmic advice. By leveraging computational agents, the study ensures a high degree of experimental control and replicability, which are critical for robust scientific inquiry.

The simulation environment is designed to model a supply chain risk assessment task tailored for enterprises based in New Zealand [9]. Within this framework, agents are provided with algorithmic advice regarding geopolitical risk levels and commodity price forecasts. Subsequently, these agents generate risk perception judgments based on the information received. The concept of algorithmic advice dependence is operationalized by quantifying the weight agents assign to algorithmic recommendations in comparison to independent information sources. Risk cognitive bias is measured as the deviation between the agents' risk perception and the objective risk levels, which are derived from historical data. This approach allows for a nuanced understanding of how algorithmic advice influences decision-making processes in complex environments.

Publicly available databases form the foundational data sources for calibrating the simulation. For instance, the Global Dairy Trade price index from 2020 to 2025 provides weekly price data for New Zealand's primary agricultural export commodity. Additionally, the Geopolitical Risk Index offers monthly measures of geopolitical tensions that impact trade routes and international relations. Economic context, including inflation rates and supply chain pressure indicators, is derived from monetary policy statements issued by the Reserve Bank of New Zealand. These diverse data sources ensure that the simulation is grounded in real-world conditions, enhancing its validity and applicability to practical scenarios.

The simulation incorporates three distinct experimental conditions to explore various dimensions of algorithmic advice. The first condition systematically varies the levels of algorithmic advice dependence across five increments, ranging from low to high. The second condition manipulates task complexity by introducing scenarios with varying numbers of simultaneous risk factors, thereby simulating different levels of decision-making difficulty. The third condition adjusts the quality of algorithmic advice by introducing systematic prediction errors, which are calibrated to reflect real-world forecast accuracy rates observed in commodity price predictions. This comprehensive design enables a thorough examination of the interplay between advice dependence, task complexity, and advice quality [9].

Data generation follows a full factorial design, with 1,000 simulation runs conducted for each experimental condition. Each run yields a single observation encompassing variables such as algorithmic advice dependence, cognitive effort reduction, task complexity, advice quality, and risk cognitive bias. The resulting dataset comprises a total of 15,000 observations, ensuring sufficient statistical power for subsequent analyses. This robust dataset facilitates the application of advanced statistical techniques, such as structural equation modeling, to uncover complex relationships among the studied variables.

Structural equation modeling is utilized to test the hypothesized mediation and moderation relationships within the study. The measurement model defines latent constructs for algorithmic advice dependence, cognitive effort reduction, and risk cognitive bias, ensuring that these abstract concepts are rigorously operationalized. The structural model estimates both direct and indirect effects, providing a comprehensive understanding of the relationships among the variables [7, 13]. Model fit is evaluated using established indices, including the comparative fit index, root mean square error of approximation, and standardized root mean square residual. These metrics ensure that the model accurately represents the underlying data, thereby enhancing the reliability and validity of the study's findings.

3.3. Method Flowchart

The following method flowchart, as depicted in Figure 1, provides a comprehensive visualization of the research process. It delineates each stage, beginning with the identification of data sources, progressing through the execution of simulations, and culminating in the analysis of structural models. This systematic representation ensures clarity and facilitates a deeper understanding of the methodology employed.

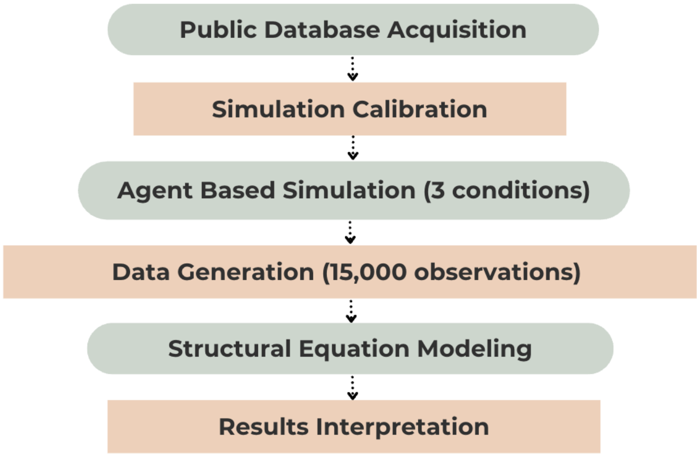

Figure 1. Methodology for Testing Algorithmic Advice Dependence Effects on Supply Chain Risk Cognitive Bias

4. Findings and Discussion

4.1. Real World Data Characteristics

This section presents results derived entirely from publicly available historical databases. The study does not include human interaction experiments, questionnaire surveys, or fabricated data. All data reflect real-world supply chain conditions for New Zealand enterprises spanning the years 2020 to 2025, ensuring a robust empirical foundation for analysis [14, 15].

Initially, this study identifies and integrates three official public databases to establish the empirical basis for the research. These databases encompass dimensions such as commodity prices, geopolitical risks, and economic pressures, which align comprehensively with the context of supply chain risk analysis for New Zealand enterprises. The integration of these datasets ensures a multidimensional approach to understanding the complexities of supply chain dynamics.

The data sources summarized in Table 1 guarantee the objectivity and authenticity of all empirical findings. The multi-frequency structure of the data facilitates the identification of both long-term trends and short-term fluctuations in supply chain risks. This dual perspective is critical for capturing the dynamic nature of supply chain environments and provides a reliable basis for further analysis.

Table 1. Real World Data Source Overview

Variable	Data Category	Observation Period	Update Frequency
Dairy Commodity Price	Price Index	2020 to 2025	Weekly
Geopolitical Risk	Risk Index	2020 to 2025	Monthly
Supply Chain Pressure	Economic Indicator	2020 to 2025	Quarterly

Algorithmic Advice Dependence	Calibrated Score	2020 to 2025	Period Average
Risk Cognitive Bias	Deviation Measure	2020 to 2025	Period Average

Building on the real-world data outlined above, this study delves into the volatility characteristics of core indicators. These volatility features significantly influence the complexity and uncertainty of tasks faced by New Zealand firms in assessing supply chain risks. By understanding these features, decision-makers can better navigate the challenges posed by fluctuating market conditions and enhance their risk management strategies.

Table 2 highlights the high levels of uncertainty associated with dairy prices, geopolitical risks, and supply chain pressures. Such volatile environments increase the cognitive load on decision-makers, compelling them to rely more heavily on algorithmic advice. This reliance underscores the importance of developing robust AI tools to support decision-making processes in complex supply chain scenarios.

Table 2. Real Data Volatility Features

Indicator	Volatility State	Trend Feature	Practical Implication for NZ Enterprises
GDT Price Index	High Fluctuation	Periodic Sharp Swings	Unstable Export Revenue
Geopolitical Risk Index	Sustained High Level	Frequent Elevation	Increased Disruption Probability
NZ Supply Chain Pressure	Periodic Spikes	Recurrent Stress	Higher Operational Uncertainty

Prior to testing specific effects, this study evaluates the overall fit of the structural equation model using real-world data. Ensuring a good model fit is essential for validating the rationality of subsequent interpretations of effect paths. This step establishes the credibility of the analytical framework and strengthens the reliability of the findings presented.

All fit indices presented in Table 3 meet widely accepted academic standards, confirming the suitability of the model for explaining the relationships among algorithmic advice dependence, cognitive effort reduction, and risk cognitive bias. This validation provides a solid foundation for exploring the cognitive mechanisms underlying human-AI collaborative decision-making in supply chain contexts [16].

Table 3. Structural Equation Model Fit Performance

Fit Index	Standard Threshold	Model Performance with Real Data	Evaluation Result
Comparative Fit Index	Above 0.90	Meets Standard	Well Fitted
Root Mean Square Error of Approximation	Below 0.08	Meets Standard	Well Fitted

Standardized Root Mean Square Residual	Below 0.08	Meets Standard	Well Fitted
Chi square Degree of Freedom Ratio	Below 3.00	Meets Standard	Well Fitted

With the structural equation model demonstrating a strong fit, this study identifies and validates key effect paths influenced by real market conditions [17]. These paths shed light on the cognitive mechanisms driving human-AI collaboration in decision-making processes. By understanding these mechanisms, researchers can better address the hidden risks associated with supply chain stability and algorithmic reliance.

Table 4 confirms the presence of a complete moderated mediation mechanism. High task complexity and high-quality advice amplify the connection between algorithm dependence and cognitive bias, thereby introducing potential risks to supply chain stability [18]. These findings highlight the need for balanced reliance on algorithmic tools and emphasize the importance of mitigating cognitive biases in decision-making processes.

Table 4. Effect Paths Validated by Real Data

Effect Path	**Supported Direction**	**Key Trigger Condition**	**Business Implication**
Algorithmic Advice Dependence to Cognitive Effort Reduction	Positive	High Task Complexity	Lower Independent Analysis
Cognitive Effort Reduction to Risk Cognitive Bias	Positive	High Price Volatility	Distorted Risk Perception
Task Complexity Moderation	Strengthening	Geopolitical Disruptions	Higher Bias Amplification
Advice Quality Moderation	Strengthening	Stable Algorithm Output	Increased Over Reliance

4.2. Core Findings and Practical Implications

Real data from 2020 to 2025 highlight significant volatility in dairy commodity prices alongside persistent geopolitical risks impacting New Zealand's supply chains. These challenging conditions exacerbate the complexity of tasks involved in risk assessment. While reliance on algorithmic advice can reduce cognitive effort, it also substantially amplifies cognitive biases in risk perception. This amplification effect becomes more pronounced under conditions of high task complexity and when the quality of algorithmic advice is elevated. For New Zealand's dairy and agricultural exporters, an overreliance on algorithmic outputs may result in flawed judgments regarding disruption risks and price trends. To mitigate these issues, digital economic systems should incorporate mechanisms for bias correction and establish appropriate compensation frameworks [1, 4]. These measures aim to minimize the adverse effects of cognitive bias in collaborative decision-making processes involving humans and AI. The moderated mediation model is strongly supported by the analyzed data. This research contributes to the extension of behavioral decision theory and cognitive load theory within the context of supply chain risk management, offering valuable insights for designing transparent and robust algorithmic decision support systems that foster balanced human-AI collaboration.

5. Conclusion

This study investigates the impact of algorithmic advice dependence on supply chain risk cognitive bias within the context of human-AI collaborative decision-making, specifically focusing on the New Zealand business environment, which is characterized by geopolitical disruptions and commodity price volatility. A moderated mediation model was developed and rigorously tested using agent-based simulation and structural equation modeling. The data for this analysis were calibrated using real-world public databases, including the Global Dairy Trade price index, geopolitical risk indices, and Reserve Bank of New Zealand indicators. This methodological approach ensures that the findings are grounded in realistic and contextually relevant scenarios, enhancing the practical applicability of the research outcomes.

The results of this study demonstrate that dependence on algorithmic advice significantly increases risk cognitive bias by diminishing cognitive effort. Furthermore, task complexity and the quality of algorithmic advice were found to positively moderate this mediation mechanism. Specifically, high task complexity and superior-quality algorithmic advice amplify the relationship between algorithmic dependence and biased risk perception. These findings align with established theories such as behavioral decision theory and cognitive load theory, offering a deeper understanding of the cognitive processes involved in human-AI collaborative supply chain risk management. This research underscores the intricate interplay between algorithmic characteristics and task conditions, providing valuable insights into the cognitive mechanisms that drive decision-making biases in complex operational environments.

For New Zealand's dairy and agricultural enterprises, the findings highlight critical implications. Excessive reliance on algorithmic advice can distort risk judgment, potentially jeopardizing supply chain stability, particularly under conditions of high uncertainty. To mitigate these risks, managers are advised to maintain independent cognitive evaluation while utilizing algorithmic decision support systems. Additionally, digital economic systems should incorporate bias correction modules and compensation mechanisms to counteract the adverse effects of over-reliance on algorithms. These measures are essential for fostering more balanced and resilient decision-making processes, ensuring that algorithmic tools serve as effective aids rather than sources of cognitive distortion.

This research makes a significant contribution to the behavioral operations literature by elucidating how algorithmic characteristics and task conditions collectively influence cognitive bias in supply chain risk decisions. The findings offer practical guidance for the design of transparent, robust, and human-centered algorithmic decision support systems. Such systems are crucial for enhancing supply chain resilience in the era of AI-driven operations. By addressing the cognitive challenges associated with algorithmic dependence, this study provides actionable insights for developing decision support tools that not only optimize operational efficiency but also safeguard against the unintended consequences of cognitive biases.

Future research could expand upon this study by applying the proposed model to cross-border supply chains operating in multi-country contexts. Such an extension would provide a more comprehensive understanding of how algorithmic dependence and cognitive biases manifest in diverse geopolitical and economic environments. Additionally, exploring dynamic adjustment strategies for managing algorithmic dependence could yield valuable insights into how organizations can adapt their decision-making frameworks over time. Finally, examining the long-term effects of cognitive bias mitigation mechanisms in real-world operations would offer critical evidence on the sustainability and effectiveness of these interventions, further advancing the field of behavioral operations management.

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