

AI and Managerial Decision-Making under Supply Chain Uncertainty

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Abstract:

Artificial intelligence (AI) is increasingly used to support supply chain decision-making, yet little is known about how managers incorporate AI outputs into decision processes under uncertainty. This research-in-progress examines how AI assistance shapes managerial cognition and decision practices across Simon's intelligence, design and choice stages. Drawing on semi-structured interviews with 10 supply chain managers from manufacturing, logistics and retail sectors, the study identifies AI as a stage-differentiated cognitive amplifier. AI accelerates environmental scanning and information synthesis in the intelligence stage, expands scenario exploration and alternative generation in the design stage, and supports preliminary comparison in the choice stage. However, managers retain final judgment because of data reliability, contextual interpretation and accountability concerns. The study contributes a process-based account of human-AI complementarity and offers governance implications for responsible AI-enabled innovation management.

Keywords: artificial intelligence; supply chain management; managerial decision-making; human-AI complementarity; decision support; responsible AI

1 Introduction

Supply chain managers increasingly operate in environments marked by geopolitical disruption, demand volatility, material shortages and rapid technological change. In this context, artificial intelligence (AI) is becoming part of everyday managerial work in supply chain management. AI-enabled analytics and large language models are used to gather information, compare alternatives and support operational planning. This reflects a wider shift in digital innovation management, where digital technologies reshape not only tools and outputs but also the organisation of innovation work and distributed agency (Yoo et al., 2010; Nambisan et al., 2017). Yet most AI discussions still emphasise adoption, efficiency or automation, rather than how AI affects the cognitive process through which managers move from problem recognition to action.

This paper focuses on this under-examined decision-process problem. In supply chain settings, AI can quickly summarise market information, compare suppliers, draft action options and flag risks. At the same time, supply chain decisions are often made under disruption, incomplete information and time pressure (Tang, 2006; Pettit, Fiksel and Croxton, 2010; Ivanov and Dolgui, 2020). If managers rely on AI outputs without sufficient verification, organisations may face inaccurate information, blurred accountability and weaker managerial judgment. The issue is therefore not whether AI is useful, but how managers should combine AI outputs with human expertise across different decision stages.

The study therefore asks: How do AI tools influence managerial cognition and decision practices across the intelligence, design and choice stages of decision-making in supply chain management? By answering this question, the paper contributes to a more grounded understanding of digital innovation in managerial work, where AI is neither a neutral tool nor a full substitute for human expertise, but a contested cognitive partner.

2 Theoretical positioning

The study is anchored in Simon's (1960) decision-making model, which conceptualises managerial decision processes as comprising intelligence, design and choice. Although developed in an earlier managerial context, the framework remains analytically useful because it captures the fundamental cognitive structure of decision-making rather than the specific technologies used. In AI-enabled environments, this structure allows us to ask a precise process question: does AI support managers in the same way across all decision stages, or does its contribution vary by stage and task? The model also underpins decision-support and business intelligence research, making it appropriate for examining contemporary AI-enabled decision processes (Turban, Sharda and Delen, 2011).

Recent work on AI and management highlights this tension. AI may augment human cognition by supporting sense-making, pattern recognition and decision support (Davenport and Ronanki, 2018; Jarrahi, 2018; Raisch and Krakowski, 2021). At the same time, AI creates new management challenges because algorithmic work can reshape organising practices, while AI outputs may be autonomous, inscrutable and difficult to govern (Faraj et al., 2018; Berente et al.,

2021). Research on human-AI and hybrid intelligence further suggests that value emerges when human contextual judgment and machine analytical capacity are deliberately combined rather than treated as substitutes (Dellermann et al., 2019; Shrestha, Ben-Menahem and von Krogh, 2019). In supply chains, AI and big data analytics have been examined mainly as tools for operations analytics, risk monitoring and resilience (Choi, Wallace and Wang, 2018; Baryannis et al., 2019; Wamba et al., 2015). Less is known about the stage-by-stage managerial cognition through which AI advice is interpreted, challenged and translated into decisions.

This study addresses that gap by examining AI assistance as a stage-specific human-AI interaction process. This perspective also prevents the paper from treating AI as a single monolithic intervention. The same AI tool may have different implications depending on whether the managerial task is to recognise a problem, construct an alternative or commit to a course of action. A stage-based approach therefore makes the contribution more specific for innovation management scholarship, where the challenge is often to understand not only the adoption of technologies but also their transformation of work practices and capabilities.

3 Research design

A qualitative research design was adopted to capture managers' experiences of AI-supported decision-making. Data were collected through semi-structured interviews with 10 supply chain managers from manufacturing, logistics and retail sectors. Participants held middle-to-senior management roles and had direct experience using AI tools, including large language models and AI-enabled decision-support systems, in supply chain decision tasks.

The interview protocol was structured around Simon's decision stages. Questions examined how managers used AI to gather and interpret information, generate alternatives, compare options, handle conflicting advice and decide whether to accept, modify or reject AI outputs. Thematic analysis was used because it enables systematic identification of patterns across qualitative data while retaining sensitivity to context (Braun and Clarke, 2006). The coding process combined theory-guided coding around intelligence, design and choice with open coding of emerging themes related to trust, verification, data access and accountability.

The sampling strategy was purposive: participants were selected because they were involved in supply chain-related decisions and had direct experience using AI tools in those decisions. Although the dataset remains modest, it is appropriate for research-in-progress because the purpose is to identify emerging decision-process mechanisms rather than to claim statistical generalisation. To enhance transparency, codes were compared across participants and repeatedly checked against the three-stage framework, while allowing additional themes such as data security, prompt dependence and over-reliance to emerge from the data.

4 Findings: How AI Supports Different Stages of Supply Chain Decision-Making

The findings suggest that AI does not influence managerial decision-making in a uniform way. Across the interviews, managers described AI as most useful for accelerating information gathering, exploring possible courses of action, and supporting preliminary comparison of alternatives. However, they also emphasised that AI outputs required human verification, contextual interpretation, and final managerial judgment. In this sense, AI acted as a stage-specific decision support tool rather than an autonomous decision-maker.

This pattern can be understood as a form of stage-differentiated cognitive amplification: AI strengthened different parts of the decision process in different ways, while managers retained responsibility for assessing data reliability, organisational fit, and decision accountability.

In the intelligence stage, managers used AI to accelerate environmental scanning, data synthesis and early problem identification. Participants described AI as useful for rapidly summarising supplier information, market trends, price changes and possible disruption signals. This finding extends prior work on big data analytics in operations management by showing how AI supports not only analytical capability but also managerial sense-making before a formal decision is made (Choi, Wallace and Wang, 2018; Wamba et al., 2015). However, managers also stressed that AI outputs could be outdated, speculative or based on unclear assumptions. Therefore, AI improved speed and breadth, but its value depended on human verification of data quality, sources and organisational relevance.

In the design stage, AI supported the generation of alternatives and the reframing of supply chain problems. Managers used AI to explore substitute suppliers, alternative sourcing approaches, logistics options and what-if scenarios. This expanded the solution space and made it easier to consider multiple courses of action under time pressure. Yet participants rarely treated AI-generated alternatives as directly actionable. The quality of AI suggestions depended heavily on prompt precision, domain knowledge and the manager's ability to provide contextual constraints. When internal data such as ERP, inventory levels, supplier history or production capacity were unavailable to AI tools, recommendations remained generic. AI therefore worked best as an exploratory aid that stimulated managerial thinking, not as an autonomous design engine.

In the choice stage, reliance on AI declined. Managers used AI to compare options, summarise trade-offs and conduct preliminary checks, but they resisted delegating final decision authority. Final choices still depended on professional

experience, cross-functional negotiation, supplier relationships, organisational priorities and accountability for consequences. This finding resonates with AI decision-making research showing that human and AI decisions differ in interpretability, accountability and contextual understanding (Shrestha, Ben-Menahem and von Krogh, 2019). AI was therefore treated as advisory input rather than as an authoritative decision-maker.

A notable pattern across all three stages was that managers did not simply accept or reject AI. Instead, they engaged in negotiated reliance. They used AI when it improved speed, structure or breadth, but reasserted human control when decisions involved confidential data, supplier relationships, resource commitments or reputational risk. This reliance is important because it shows that managerial agency remains active even when AI tools are deeply embedded in the decision process. The managers' practical question was not 'Can AI decide?' but 'Which part of this decision can AI safely improve?'

The findings also suggest that AI's limitations are not only technical but organisational. Several participants highlighted that the most valuable supply chain data are embedded in internal systems or protected by confidentiality rules. As a result, externally accessible AI tools can provide plausible reasoning but lack the enterprise-specific data required for final decisions. This gap between public or generic AI knowledge and internal organisational knowledge is a central barrier to deeper AI-assisted decision-making.

Table 1 Stage-specific role of AI in supply chain managerial decision-making

Stage	Main AI role	Observed value	Required managerial safeguard
Intelligence	Scanning, synthesising and identifying early signals	Faster information gathering; broader situational awareness	Verify data currency, sources and assumptions
Design	Generating options, scenarios and problem framings	Broader solution space; faster alternative generation	Provide precise prompts and internal context; assess feasibility
Choice	Comparing options and clarifying trade-offs	Quicker preliminary comparison and documentation	Retain human accountability; escalate high-risk decisions

5 Discussion and contribution

These findings make two contributions to innovation management. First, they shift attention from AI adoption outcomes to AI's processual effects on managerial decision-making. Rather than asking only whether AI improves efficiency, the paper shows where AI supports, constrains or complicates managerial cognition. This extends digital innovation research by clarifying how AI changes the process architecture of managerial work, not merely the technological infrastructure of innovation (Yoo et al., 2010; Nambisan et al., 2017).

Second, the study extends Simon's decision-process model into contemporary AI-enabled innovation settings. The model remains useful because AI does not remove the intelligence-design-choice logic; instead, it redistributes cognitive work across the stages. In the intelligence stage, AI broadens and accelerates information processing. In the design stage, AI expands exploratory thinking but remains dependent on human framing. In the choice stage, AI supports comparison but does not assume responsibility. This stage-based account provides a more precise view of human-AI complementarity than generic claims that AI either replaces or assists managers.

This argument has implications for the broader innovation management community. Many organisations are currently experimenting with generative AI through bottom-up managerial use rather than fully designed systems. The study suggests that such experimentation can create value, but only when accompanied by governance mechanisms that address verification, decision rights and accountability (Berente et al., 2021). It also enriches supply chain resilience research by showing that resilience depends not only on data visibility or predictive analytics, but also on managers' ability to judge when AI-generated options are reliable, actionable and strategically appropriate (Tang, 2006; Pettit, Fiksel and Croxton, 2010; Ivanov, 2020).

6 Practical implications and next steps

For practice, the study suggests that organisations should not design AI governance as a single rule for all decisions. Instead, governance should recognise stage-specific use. In the intelligence stage, organisations need source verification routines and clear expectations about checking AI-generated information. In the design stage, managers need prompt literacy, domain knowledge and access to safe internal data environments where AI can be used without exposing confidential information. In the choice stage, organisations should clarify decision rights, escalation thresholds and accountability rules, especially when AI advice conflicts with managerial experience or when decisions have high operational consequences.

The study also has implications for capability development. Supply chain managers require not only technical familiarity with AI tools, but also the ability to evaluate, challenge and contextualise AI outputs. Responsible AI use therefore

depends on preserving managerial judgment, not bypassing it. Three practical principles follow. First, organisations should create verification protocols for AI-supported intelligence work, including source checks and comparison with internal data. Second, they should train managers to use AI as a design partner by formulating high-quality prompts, specifying constraints and evaluating alternative scenarios. Third, they should maintain explicit human sign-off for consequential supply chain choices.

For firms developing internal AI systems, the results indicate a design priority: AI tools should be connected to reliable internal knowledge bases while protecting confidential information. Without secure access to relevant enterprise data, AI remains useful for broad scanning but limited for deep supply chain decisions. Future work will refine the emerging stage-based model, compare AI use across decision complexity levels and develop stronger implications for responsible AI governance in innovation-intensive organisations. This direction is aligned with research on AI management, hybrid intelligence and supply chain risk analytics, all of which emphasise the need to integrate technical capability with organisational control and human expertise (Dellermann et al., 2019; Baryannis et al., 2019; Berente et al., 2021).

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Areas for feedback and development

The authors seek feedback on three areas. First, is the stage-based framing sufficiently useful for explaining AI-assisted decision-making, or should the emerging model also distinguish decision complexity, organisational level or data sensitivity? Second, how can the paper sharpen its theoretical contribution to innovation management beyond applying Simon's model to AI-enabled supply chain decisions? Third, what governance concepts would best support the journal version of this work, particularly around accountability, over-reliance and the preservation of managerial judgment in AI-assisted innovation contexts?

This final page is included to support the Research-in-Progress discussion format and to help the assigned discussant and session participants provide targeted feedback. Thank you.