

Condé, Lansiné; Münch, Christopher

Article — Published Version

Resilient by Design: Exploring the Social Abilities and Actor-Network Roles of Artificial Intelligence in Supply Chain Management

Journal of Business Logistics

Provided in Cooperation with:

John Wiley & Sons

Suggested Citation: Condé, Lansiné; Münch, Christopher (2025) : Resilient by Design: Exploring the Social Abilities and Actor-Network Roles of Artificial Intelligence in Supply Chain Management, Journal of Business Logistics, ISSN 2158-1592, Wiley, Hoboken, NJ, Vol. 46, Iss. 4, <https://doi.org/10.1111/jbl.70032>

This Version is available at:

<https://hdl.handle.net/10419/329777>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by/4.0/>

ORIGINAL ARTICLE OPEN ACCESS

Resilient by Design: Exploring the Social Abilities and Actor-Network Roles of Artificial Intelligence in Supply Chain Management

Lansiné Condé  | Christopher Münch 

Friedrich-Alexander-Universität Erlangen-Nürnberg, Nuremberg, Germany

Correspondence: Lansiné Condé (lansine.conde@fau.de)**Received:** 21 November 2024 | **Revised:** 20 May 2025 | **Accepted:** 30 June 2025**Funding:** The authors received no specific funding for this work.**Keywords:** actor–network theory | artificial intelligence | autonomous actor | social abilities | supply chain resilience

ABSTRACT

Despite its substantial potential to enhance supply chain resilience (SCRes), artificial intelligence (AI) remains underexplored as an autonomous entity within supply chains (SCs), particularly in terms of its social capabilities and interactions within sociotechnical systems. Current literature has yet to address how AI can transform SC collaboration and network stability from a forward-looking perspective, creating a critical research gap. This study aims to address this gap by examining the social abilities introduced by AI and their implications for SCRes. The exploratory research design of this study is grounded in the actor-network theory and the Gioia method and includes 23 semi-structured interviews with experts. The findings reveal that AI actively influences decision-making processes, power dynamics, and trust among SC actors. By interacting with both human and non-human actors, AI emerges as a critical tool for redefining collaboration and network stability. While AI-driven SCs can enhance organizations' efficiency and adaptability, they also introduce challenges, including ethical considerations, responsibility allocation, and unintended consequences of algorithmic decision-making. This study contributes to the discourse on the embeddedness of AI in SCs by offering theoretical insights into its sociotechnical integration and managerial implications for its governance. Understanding AI as an active tool is crucial for designing resilient and future-proof SCs. The findings emphasize the need for organizations to develop strategies that balance the benefits and risks of AI, ensuring its responsible and effective deployment across SC networks.

1 | Introduction

Throughout the 21st century, disruptive digital technologies such as the Internet of Things, big data, blockchain, and artificial intelligence (AI) have emerged and gained significant attention as tools to enhance efficiency and performance in logistics and supply chain (SC) management (Wang et al. 2025). Min et al. (2019) highlight the potential of these technologies to optimize economic and environmental performance by supporting

strategic decision-making to improve organizations' long-term responsiveness (Richey et al. 2022).

Despite these technological advancements, many organizations continue to face a knowledge gap regarding disruptive technologies, particularly AI (Birkstedt et al. 2023; Martin and Parmar 2022), which has only recently garnered significant attention. While large corporations have begun to explore AI's potential, its adoption in small and medium-sized enterprises

This is an open access article under the terms of the [Creative Commons Attribution](https://creativecommons.org/licenses/by/4.0/) License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2025 The Author(s). *Journal of Business Logistics* published by Wiley Periodicals LLC.

remains scarce (Benbya et al. 2020). This knowledge deficit has led to a lack of motivation and limited investment from management, hindering the broader adoption of AI to enhance resilience in logistics and SC management (Klump and Zijm 2019) despite its recognized potential to positively impact the industry (Sanders et al. 2019).

Recent SC disruptions—such as the COVID-19 pandemic, blockages in critical shipping lanes, and geopolitical events like Russia's invasion of Ukraine—underscore the urgent need for more resilient SCs (Pujawan and Bah 2022; Swanson and Suzuki 2020; Wieland 2021). Due to the strong global integration of SCs, deglobalization and associated risk-mitigation strategies remain economically unfeasible (Attinasi et al. 2023). AI holds significant potential to mitigate SC risks and enhance resilience; however, research on its specific applications and implementations remains limited. Much of the literature focuses on past and current efforts, with a noticeable lack of forward-looking perspectives (Zamani et al. 2023).

Despite the theoretical potential of AI to enhance SC resilience (SCRes; Belhadi et al. 2022; Gupta et al. 2024; Modgil, Gupta, et al. 2022; Modgil, Singh, et al. 2022; Naz et al. 2022; Riahi et al. 2021; Zamani et al. 2023), actual implementation rates remain modest (Bui Trong and Bui Thi Kim 2020; Deiva Ganesh and Kalpana 2022; Riahi et al. 2021), and organizations face challenges in deploying AI-enabled SCs. AI is a relatively opaque concept for some of these organizations, which perceive it as a black box that entails operational complexities (Franzoni 2023; Schlögl et al. 2019). To address this issue, recent academic literature has explored AI from various perspectives and across diverse domains, offering strategic guidance for effective AI integration within SCs to foster resilience (Bechtsis et al. 2022; Dey et al. 2024; Moosavi et al. 2022; Thürer et al. 2020; Zamani et al. 2023). To drive forward-looking SC strategies, it is essential to make AI more accessible and easier to understand. This process begins with enhancing stakeholder familiarity with AI and articulating the transformative benefits of this disruptive technology (Hangl et al. 2022; Hasija and Esper 2022).

The positive relationship between AI utilization in SC management and performance outcomes has been well established (Dash et al. 2019; Hallikas et al. 2021; Mohsen 2023; Riahi et al. 2021). Prior research has highlighted opportunities for AI to act as a support mechanism in logistics and SC management. This includes tasks such as demand forecasting, inventory management, logistics optimization, and risk assessment (Atwani et al. 2022; Brinrup 2020; Dash et al. 2019; Riahi et al. 2021; R. Sharma, Shishodia, et al. 2022), as well as enhancing decision-making processes (Niranjan et al. 2021), facilitating real-time monitoring, and accelerating innovation cycles (Dash et al. 2019). Baldea et al. (2025) propose an alternative research approach to extend this perspective by adopting an automation-based framework for autonomous SC behavior supported by AI. The potential applications of this framework include optimized data-driven decision-making, real-time access to relevant information, and enhanced risk mitigation throughout the SC (Calatayud et al. 2019; Xu, Mak, Minaricova, et al. 2024; Xu, Mak, Proselkov, et al. 2024). However, the widespread implementation of these applications may be hindered by several

challenges, including limited trust in the technology, insufficient infrastructure, a shortage of skilled professionals, and the absence of a well-defined social dimension within AI systems (Kar and Kushwaha 2023; Kar et al. 2021). To support the effective and sustainable integration of AI into SC management, the social dimensions introduced by this disruptive technology must be analyzed to anticipate and assess its potential impacts on the surrounding environment (Khakurel et al. 2018; Rakowski and Kowaliková 2024).

This study contributes to the literature by addressing the research gap regarding the autonomous role of AI in enhancing SCRes, specifically examining the extent to which AI can use social abilities to bolster SC robustness. Additionally, the study aims to provide organizations with an informed outlook on anticipated changes associated with AI implementation across SC processes, including shifts in operational dynamics, interdependencies among stakeholders, and overall performance outcomes. It aims to support organizations' decision-making processes regarding the feasibility and potential return on AI adoption. Specifically, this study investigates the following research question:

What social capabilities can AI introduce to enhance SCRes?

An exploratory methodology was adopted to address this research question. Semi-structured interviews were conducted with 23 experts specializing in SC management and AI. The actor-network theory (ANT; Callon and Latour 1981), supported by the Gioia method (GM; Gioia et al. 2013), was employed to systematically examine the potential applications of AI within the SC.

The application of ANT as a theoretical foundation for analyzing technological implementation in corporate contexts has been validated across numerous studies and fields (Hald and Spring 2023). For example, it has supported the inclusion of information technology (IT) adoption in healthcare settings (Cresswell et al. 2010; Greenhalgh and Stones 2010), IT-enabled sustainability initiatives (Bengtsson and Ågerfalk 2011; Yurui et al. 2021), geographic information systems in local administration (Walsham and Sahay 1999), financial technology developments (Lee et al. 2015; Shim and Shin 2016), smart city frameworks (Söderström et al. 2014), and future-oriented innovations in agriculture (Berthet et al. 2018).

This study offers a dual contribution to academic research. First, it builds on prior research on AI-driven resilience by examining the role of AI within SCs, specifically focusing on six social dimensions introduced by AI during implementation. It bridges the existing research gap by presenting an exploratory approach to assessing the potential applications of AI across SC functions. Second, the study employs ANT as a methodological framework to investigate the dynamic relationship between AI and its organizational environment. This theoretical lens builds on the existing literature (e.g., Gams et al. 2019; Horvitz 2017) by examining human-technology interactions and the integration of AI systems within broader environmental contexts. This approach is used to address the challenges commonly encountered

by managers in AI implementation, underscoring the benefits of AI for enhancing SCRes (Dietzmann and Duan 2022; Sharma, Luthra, et al. 2022).

2 | Theoretical Background

2.1 | Supply Chain Resilience

The literature on SCRes dates back to the early 2000s (Blackhurst et al. 2011; Bode et al. 2011; Jüttner and Maklan 2011; Pettit et al. 2010; Rice and Caniato 2003; Sheffi 2007). Subsequent research has expanded on this foundational understanding by incorporating concepts such as agility, collaboration, and adaptability (Ambulkar et al. 2015; Chowdhury and Quaddus 2017; Melnyk et al. 2014; Safari et al. 2024; Scholten and Schilder 2015; Umar and Wilson 2024; Zhao et al. 2024).

SCs should be designed to exhibit low susceptibility to disruptions and recover quickly and cost-effectively. A lack of resilience in SCs can lead to significant financial losses, diminished stakeholder confidence, and imbalances between supply and demand, ultimately destabilizing production processes (Gupta et al. 2021; Ivanov et al. 2016; Pavlov et al. 2019; Pettit et al. 2019; Yoon et al. 2020). All SC disruptions share certain common characteristics: they arise from specific incidents, necessitate a rapid return to the initial state, and occur within a defined observation period (Wieland and Durach 2021). Ivanov (2021a, 2021b) distinguishes between design for efficiency and design for resilience. The former approach emphasizes that SCs should prioritize responsiveness and efficiency, aiming to maximize profit and minimize waste through optimal resource utilization. In contrast, the latter approach emphasizes the importance of resilient SCs that can effectively mitigate unexpected and substantial disruptions, enabling a rapid return to the initial state or, ideally, an improved state.

The literature identifies four distinct phases of SCRes: readiness, response, recovery, and growth strategies (Hohenstein et al. 2015). The readiness phase involves preparing for disruptive events, primarily by identifying and monitoring changes within organizational boundaries (Fahimnia and Jabbarzadeh 2016; Maitlis and Sonenshein 2010). The response phase focuses on executing preestablished strategies to mitigate disruptions (Stone and Rahimifard 2018). The recovery phase includes efforts to either rectify losses and return to a business-as-usual state (Brandon-Jones et al. 2014) or achieve the quickest possible transition to a desired future state (Fahimnia and Jabbarzadeh 2016; Ivanov 2021a, 2021b). The final phase, growth strategies, involves the implementation, adoption, and refinement of lessons learned by organizations to enhance preparedness for future disruptions (Dennehy et al. 2021; Hohenstein et al. 2015; Yan et al. 2023).

2.2 | Artificial Intelligence and Supply Chain Resilience in Supply Chain Management

The term AI was first introduced by McCarthy et al. (1955) during the Dartmouth Summer Research Project. They

envisioned machines capable of using language and solving problems traditionally associated with human intelligence (McCarthy et al. 1955). Haenlein and Kaplan (2019) define AI as the ability of a system to acquire knowledge by analyzing data from the external environment and applying it to achieve specific goals and tasks. Marvin Minsky, founder of the MIT Artificial Intelligence Lab, has described AI as “the science of making machines do things that would require intelligence if done by men” (Minsky 1968, v). These definitions encapsulate the core aspects of AI found in many other definitions in the literature (e.g., Barredo Arrieta et al. 2020; Leake 2001; Samoili et al. 2020; Wang 2019) and will guide the discussion of AI in this paper. Notably, there is no universally agreed-upon definition of AI yet (Legg and Hutter 2007; Nilsson 2009).

For the purpose of this study, the taxonomy of AI is adopted from Pournader et al. (2021), who categorize AI into three key domains: sensing and interacting (i.e., vision, speech recognition, and natural language processing), learning (i.e., machine learning), and decision-making (i.e., simulation and modeling, optimization, and planning and scheduling). This taxonomy aligns with the widely accepted definition of AI proposed by Kaplan and Haenlein (2019).

The specific application of AI in SC management, particularly in enhancing SCRes, remains an underexplored area of research. This research gap is increasingly highlighted in the literature, with several authors calling for concrete insights into the role of AI in strengthening resilience (Akter et al. 2022; Baryannis et al. 2019; Kassa et al. 2023; Pournader et al. 2021; Rodríguez-Espíndola et al. 2020).

Prior research underscores the transformative role of AI-driven technologies, such as machine learning and predictive analytics, in improving the accuracy of forecasting demand, optimizing inventory management, and enhancing real-time SC visibility (Choi et al. 2018; Riad et al. 2024). These advancements enable organizations to anticipate, mitigate, and recover from disruptions with increased efficiency (Modgil, Singh, et al. 2022). Further, AI has been used to foster transparency, facilitate tailored solutions, and refine procurement strategies to minimize the impact of SC disturbances (Singh et al. 2024).

In recent years, applications in SC management have increasingly transitioned from automated systems to fully autonomous systems (Baldea et al. 2025), reflecting advancements in AI-driven decision-making and operational capabilities (Xu et al. 2021). Various terms have been used to describe independent operating systems within SCs, including “agents” (Boyko et al. 2017; Cao et al. 2009; Ch. Meyer 2008), “autonomous SCs” (Xu, Mak, Minaricova, et al. 2024), and “self-thinking SCs” (Calatayud et al. 2019). Despite differences in terminology, these concepts converge on the idea of intelligent technologies (e.g., AI) that operate autonomously within dynamic environments (e.g., SCs) to achieve specific objectives (e.g., SCRes).

Autonomy has become increasingly significant due to the widespread adoption of Internet of Things technologies (Kumar et al. 2023; Madushanki et al. 2019; Tu 2018). Nitsche et al. (2023) explain that while automation and autonomy share the fundamental characteristic of executing processes without

direct human intervention, they differ fundamentally in their operational paradigms. The authors discuss how automated systems follow predefined rules established by human programmers, whereas autonomous systems exhibit the ability to act independently, adapt to novel situations, and deviate from their original programming when necessary (Wooldridge 2002; Wooldridge and Jennings 1995). This adaptive capability grants autonomous systems greater flexibility and self-management potential than automated systems.

To establish a unified theoretical foundation, this study employs the term “actor” to encapsulate these various concepts of autonomy. Actor-based models are widely utilized in domains such as financial technology (Pal et al. 2023) and data mining (Cao et al. 2009) to enhance efficiency and support decision-making processes. Such systems are particularly effective at managing complex, distributed structures under conditions of uncertainty (Boyko et al. 2017). They often integrate AI, machine learning, and big data analytics to optimize performance. Current research continues to refine actor-based model intelligence, improve the ability of these models to interpret user needs, and enhance their capacity for social interaction (Pal et al. 2023).

Although AI has traditionally been examined from an autonomous and technical standpoint, every technical system inherently possesses a social dimension (Channell and Volti 1991; Gieryn et al. 1994). This social aspect remains underexplored in the literature on autonomous SCs. This study examines AI from a social perspective, emphasizing its integration into existing networks as an independent actor that can enhance both societal impact and functionality. ANT provides a theoretical framework for analyzing the interactions between human and non-human actors. A detailed discussion of this approach is presented in Section 2.3.

2.3 | Overview of the Actor-Network Theory

Organizations are intricate systems that require the alignment and engagement of all stakeholders to ensure the successful implementation of new technologies (Gallivan 2001; Luo et al. 2006; Mateos-Garcia 2018). This study applies ANT as a theoretical framework to examine the multifaceted interactions between human and non-human actors throughout the technology implementation process (Latour 2005; Law and Hassard 1999). Grounded in a radical extension of the social constructivist approach typically used within science and technology studies, ANT emphasizes the influence of non-human actors in shaping social processes while challenging conventional distinctions between nature and society (Cresswell et al. 2010). Highlighting the distributed nature of agency, it asserts that both human and non-human entities operate within interconnected networks (Callon 1990).

ANT functions as both a theoretical framework and a methodological tool and is built upon three core principles (Callon 1984; Callon and Latour 1981, 1992). The first principle is agnosticism. ANT encourages the adoption of a neutral stance toward sociological questions about the actors involved. It avoids favoring any one perspective over another or excluding potential interpretations. Observers are advised to refrain from fixing actors’

identities until those identities are clarified definitively within the network. The second principle, free association, calls for observers to avoid imposing predefined categories or assumptions about the types and roles of actors. This allows for a flexible analysis free from traditional distinctions between natural and social phenomena. The third principle, generalized symmetry, requires the use of uniform language for describing and analyzing all processes, whether natural, social, or technical. This ensures consistency in the analysis of each type of actor or process within the network. Together, these three principles call for a redefinition of theoretical terminology, which is further discussed in the following paragraphs.

2.3.1 | Actors

ANT adopts a broad definition of the term “actor,” extending it beyond human entities. While any entity can be considered an actor, ANT acknowledges that not all actors possess the same capacity to act (Callon and Latour 1992). Consequently, this framework neither elevates non-human entities (e.g., objects, plants, animals) to the same status as humans nor reduces humans to the level of non-human entities (Callon and Latour 1992; Latour 1999). Instead, it challenges the anthropocentric assumption that humans are the sole initiators of action and highlights the active role that non-human entities play in shaping outcomes. Within the ANT framework, action is not the product of a single agent but the result of interactions among multiple entities.

In the ANT framework, an actor is defined as an entity driven to act by numerous others (Latour 2005). This perspective highlights that an actor’s ability to act is contingent upon the involvement of other entities, which may constrain, structure, influence, or modify one another; no single actor functions as the sole cause or autonomous subject of an action.

Rather than categorizing entities into natural, technical, or social domains, the ANT framework treats all variables as actors, adhering to the principles of agnosticism, free association, and generalized symmetry. Since ANT does not prescribe guidelines regarding the number, identity, or configuration of actors, the relationships between actors must be derived by analyzing relevant literature, empirical descriptions, or case reports.

Latour (2005) also introduces a distinction between actors and actants. Actors are protagonists explicitly defined by the researcher through descriptive figuration and possess specific characteristics, such as identity, form, and consistency. In contrast, actants are simpler, prefigured entities defined by their capacity to act, often excluding inert entities as uninteresting. The author rejects both objectivism and purely subjective interpretative approaches, instead advocating for an analysis that captures the complexity of actants, which include both human and non-human entities. This terminological distinction suggests that the same entity may be described differently in varying contexts, resulting in divergent interpretations of its role as an actor. This nuanced approach to defining actors and actants underscores the ANT framework’s emphasis on capturing the complexity and plurality of interactions within a network, eschewing rigid hierarchies or predetermined classifications.

2.3.2 | Networks

Actors in the ANT framework do not function autonomously but operate within actor-networks, which consist of interconnected actors. In this context, the term “network” is a theoretical construct representing the diverse linkages, connections, and relationships among actors. ANT employs a distinct definition of networks that diverges from traditional interpretations. Latour (2005) and Callon (1990) critique three traditional definitions, arguing that networks are not (a) merely technical connections (e.g., wires, trails, tubes); (b) purely intra-social relationships; or (c) postmodern metaphors for sociotechnical relationships.

Instead, ANT defines networks as dynamic assemblages of human and non-human entities that emerge through interactions. These interactions define the competencies, characteristics, functions, and roles of all participants. Thus, network formation involves two interrelated analytical processes: (a) the creation or modification of connections between actors and (b) the formation or reconfiguration of the actors themselves. This interplay underscores the mutual dependency between actors and networks. Actors are not independent of networks, nor do they hold inherent precedence over them. Rather than possessing fixed characteristics, intrinsic qualities, or autonomous capabilities, actors derive their identities and actions from their relationships with other actors. As Law (2008) notes, without networks, actors lack both identity and the potential for action. Conversely, networks cannot exist without actors, as their purpose is to reveal and allocate potential for actions to specific actors. Within the ANT framework, every actor is also an actor-network, and every network can function as an actor within other networks.

The concept of translation can be used to describe the process of network formation in ANT. Through the process of translation, the identities, programs, and competencies of actors are negotiated, transformed, and assigned (Callon 1980; Law 2008). Callon (1984) identifies four key interdependent steps in the translation process: (a) “problematization”, where the researcher identifies the problem and defines the potentially affected actors (206); (b) “interessement”, where various strategies are employed to align the actors’ interests with the problem and proposed solutions (207); (c) “enrolment”, where actors decide whether to accept the proposed roles and instructions for action (211), with efforts being focused on increasing actor acceptance and minimizing resistance; and (d) “mobilization”, which involves actors’ agreement and role acceptance if translation is successful, culminating in a stable network that defines the identities, capabilities, and roles of the actors in a binding manner (216). However, this stability is not permanent and can be dissolved or reconfigured at any time in response to new interaction or disruptions.

2.4 | ANT in Technological Research

Technology occupies a pivotal role in ANT due to its potential to reorient the framework through analysis or practical engagement. ANT redefines technology as an actor with distinct capacities for action rather than as a tool wielded by humans

(Callon 1980). A fundamental assumption of the ANT framework is that technological tools act in conjunction with other actors, both human and non-human. Thus, actions within an actor-network are not confined to specific locations but are distributed, displaced, and often dislocated (Latour 2005).

The agency of technology within networks is often overlooked, as it tends to become invisible when operating smoothly. The ANT framework describes this process of stabilizing, fixing, and integrating technology into routine practices as black boxing. A black box is conceptualized as an entity that is assigned explicit role specifications and predefined processes, encompassing all elements that have become objects of indifference due to their successful integration. The more elements—such as objects, methodologies, or conceptual frameworks—that are consolidated within a black box, the greater its utility as a foundation for further development (Callon and Latour 1981). However, black boxes are not immutable; their roles and functions can change, and technological tools can fail or break. The process of black boxing establishes a binding relationship among actors, thereby stabilizing these connections and facilitating translation. By closing black boxes, networks achieve a degree of consistency, resulting in the mechanization—i.e., the stabilization and institutionalization—of the network (Callon 1990). This mechanization enhances the predictability and calculability of interactions within the network, strengthening its overall resilience and coherence (Callon 1990).

3 | Research Methodology

3.1 | Rationale for the Exploratory Research Design

Given the nascent nature of AI in leveraging SCRes, the relatively underexplored research domain, and the limited number of experts with knowledge of both SC management and AI, this study adopts a qualitative, exploratory research design (Hlady-Rispal and Jouison-Laffitte 2014). The methodological approach is based on the GM, proposed by Gioia et al. (2013), which extends grounded theory and is particularly well-suited for inductive research. GM provides a systematic framework for developing new concepts while ensuring methodological rigor and preserving the creative potential inherent in qualitative inquiry. Its multi-step structure supports transparent data collection and analysis while facilitating theoretical development, making it well-aligned with the objectives of this study.

This methodological approach has been previously applied in research on AI and SCRes (e.g., Aarland 2024; Koponen et al. 2023; Musick et al. 2021; Russo 2024) and offers a framework that bridges macro- and micro-analyses (von Soest 2023). However, our systematic review of Scopus, Google Scholar, and ScienceDirect reveals the lack of studies examining the application of AI to enhance SCRes, particularly within the GM and ANT frameworks.

Data for this study were primarily collected through semi-structured expert interviews. This method provides a structured yet flexible framework that enables deeper exploration of critical areas of inquiry through follow-up and clarification

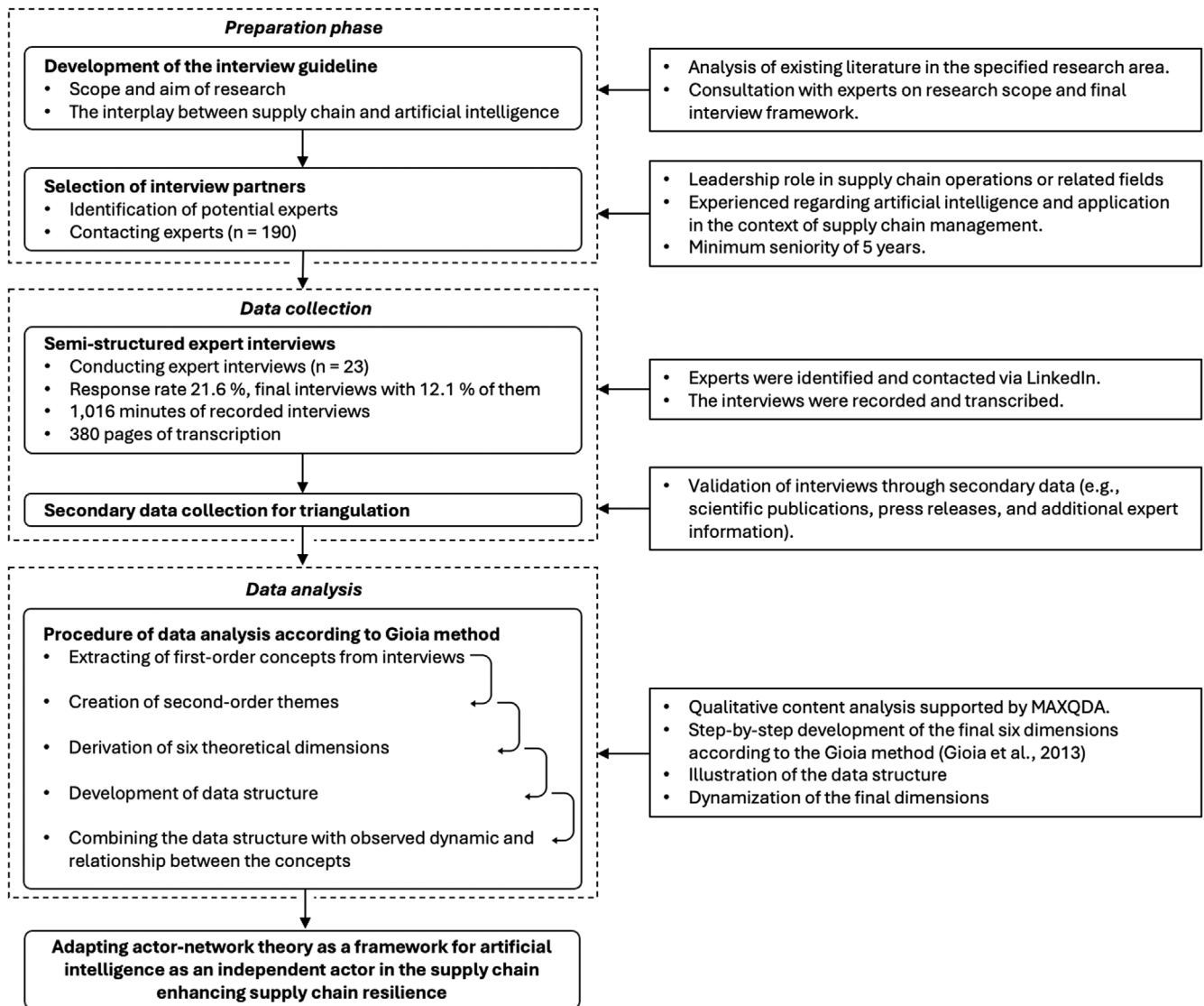


FIGURE 1 | Visualization of the research methodology procedure.

questions as needed (Adams 2015). To ensure rigor in data collection and analysis, the interviews were developed and conducted in accordance with established guidelines (Kallio et al. 2016), while integrating an analytical framework based on the GM (Gioia et al. 2013). This methodological alignment ensured a systematic and iterative research process, facilitating the identification of meaningful insights while maintaining transparency and reliability. The research design also allowed for a focused examination of key themes while remaining flexible enough to prioritize areas requiring further depth (Yin 2009).

3.2 | Preparation Phase and Data Collection

This study employed a systematic approach to ensure the precise sampling and collection of data relevant to the research focus (Eisenhardt and Graebner 2007), as illustrated in Figure 1. It adhered to a systematic approach following the methodological framework proposed by Kallio et al. (2016), who delineate a multi-step process for developing guidelines for the semi-structured

interviews. The process began with the identification of prerequisites to ensure the methodological appropriateness of the interviews. The second phase focused on acquiring the requisite expertise to conduct interviews with subject-matter experts. This was achieved through consultations with experts in the field and an extensive review of relevant literature. Building on this foundation, the third phase involved developing a well-structured and clearly formulated interview guide designed to elicit comprehensive and insightful responses from experts. The development of the interview questions drew on open-ended formats commonly used in the literature. Flexibility in the sequence of questions was maintained to allow interviewers to adapt to the natural flow of conversation while ensuring coherence throughout the interview process. The fourth phase comprised two pilot tests of the interview guide to assess its clarity and comprehensibility from an external perspective. Based on feedback, adjustments were made to two questions to improve their phrasing and precision and reduce ambiguity.

Expert selection was guided by clearly defined criteria. Participants were required to hold leadership roles in SC

TABLE 1 | Overview of the interviewees.

Expert	Academic degree ^a	Current role	Function	Years of experience	Knowledge of AI ^b
E01	Master's degree	Consultant, Supply Chain	External consultant	20	7
E02	Master's degree	Head of Purchasing	Head of department	19	7
E03	MBA	CEO	—	19	8
E04	N/A	Head of Customer Order Management	Head of department	27	8.5
E05	Bachelor's degree	Head of Procurement and Logistics	Head of department	19	6.5
E06	Master's degree	Managing Director	Data scientist	20	10
E07	Master's degree	Senior Consultant	External consultant	6	7
E08	Ph.D.	Expert Supply Chain Innovation	Internal consultant	8	7
E09	Ph.D.	Business Analytics and Optimization Consultant	External consultant	25	10
E10	Ph.D.	Business Unit Manager	Data scientist	21	6.5
E11	Master's degree	Consultant, AI & Supply Chain	External consultant	24	9
E12	Master's degree	CEO	—	22	8.5
E13	Ph.D.	Professor Supply Chain Management	—	21	7.5
E14	Ph.D.	Business Development Manager	Sales	24	7
E15	Apprenticeship	Head of Purchasing	Head of department	14	6.5
E16	Master's degree	Managing Director	Project manager	29	6.5
E17	Master's degree	Director, Logistics Strategy and Transformation	Head of department	28	8
E18	Ph.D.	Head of Purchasing	Head of department	26	3.5
E19	Ph.D.	Group Leader, Data Science	Head of department	8	6.5
E20	Master's degree	Director, Innovation, Digitalization, & AI	Research and development	24	5
E21	Ph.D.	Head of Sales	Head of department	16	8.5
E22	Apprenticeship	Consultant, Procurement Strategy	External consultant	38	8
E23	Ph.D.	Customer Success Lead	Production process	11	5

^aMaster's degree includes the German university degrees “Diplom-Ingenieur” and “Diplom-Betriebswirt.”

^bThe scale ranged from 1 (basic knowledge only) to 10 (expert). The category was based on the subjective perception of the interviewee. If the answer fell between two numbers, a half-step was used.

operations or related fields and possess extensive knowledge of AI applications in the context of SC management. A minimum of five years of seniority, either in research or industry, was also a prerequisite. To ensure a consistent regional perspective and minimize potential biases arising from regional differences in technological maturity, cultural factors, or economic conditions, only experts from Europe were interviewed (Richey et al. 2016).

A total of 190 potential experts were contacted via LinkedIn, yielding 41 responses (21.6%) and resulting in 23 completed interviews (12.1%) conducted between July and September 2024. Interviews continued until theoretical saturation was reached,

implying that no new significant insights emerged from additional interviews (Corbin and Strauss 1990). Table 1 presents an overview of the interviewees, including their professional backgrounds and experience levels.

The interview guideline was organized into two sections. The first section focused on general background information, such as the participants' professional roles and a self-assessment of their expertise in AI. The second section explored AI implementation in SCs, including perceived challenges, barriers, and crisis management strategies. The guideline was iteratively refined based on feedback from two pilot interviews, leading to adjustments in question phrasing to enhance clarity and precision.

TABLE 2 | Exemplary results of data analysis.

Interview excerpt	First-order concepts	ID of the concept
<p>“And you just have to have the right people, the right employees, who, let’s say, trust the whole thing to start with, who are open to new ideas, and who say, ‘Okay, we’ll test the whole thing and see what comes of it’” (E16)</p> <p>“That is one of those basic attitudes. I don’t think it has much to do with age but simply with the question: Am I open-minded and open to things or not? And I wouldn’t see that in demographic or age terms, but simply as a personal attitude” (E10)</p> <p>“But it is a fact that openness is not a question of age. No, it isn’t. And it is more a question of what you have experienced [...]. And then it is the case that you can very quickly enjoy rediscovering things for yourself” (E14)</p>	Open-mindedness	c2
<p>“Capturing the texts, feeding them back, analyzing them in terms of content, applying machine learning, utilizing data from other sources, then reconnecting them, and finally delivering the results on time” (E12)</p> <p>“I would say, primarily, integration. [...]. All the operational processes, meaning planning within the supply chain, are embedded in these systems, and then planning has to somehow integrate with them, pulling and feeding data back into the system” (E11)</p> <p>“It definitely needs to be integrated into the existing system landscape. It cannot be a standalone solution. Everything I generate from my e-procurement, from the SRM tool, or from any other system must be accessible through the tool, regardless of the purpose behind it. But fundamentally, it should be open to importing data via interfaces” (E05)</p>	Integration into/exchange with existing systems	c38

A total of 1016 min of interview data were recorded, with an average interview duration of 44 min, resulting in 380 pages of transcription. One interview was conducted via telephone, while the remaining 22 were held on Zoom or Microsoft Teams. All interviews were audio-recorded and transcribed verbatim to ensure data integrity and accuracy. Participants were assured complete anonymity throughout the research process.

3.3 | Data Analysis

Data analysis followed a structured coding process inspired by the GM (Gioia et al. 2013) and qualitative content analysis, supported by the MAXQDA software. In the first phase, first-order concepts were identified directly from the data (Van Maanen 1998). Each response was initially treated as a distinct category, preserving the respondents’ original language to ensure empirical grounding. This process was independently conducted by two researchers, who then collaboratively refined the coding scheme through discussion and iterative adjustments until consensus was reached (Beth Harry et al. 2005). Given the emphasis on interpretative alignment rather than statistical agreement, inter-coder reliability was not quantified (Saldana 2015), which is a common practice in qualitative studies (e.g., Münch et al. 2022; Pauli et al. 2025).

In the second phase, the first-order concepts were consolidated into second-order themes by abstracting and synthesizing key insights. The researchers adopted the perspective of knowledgeable agents, linking expert statements with theoretical

constructs and broader conceptual frameworks. This iterative approach involved continuous interaction between the empirical data and relevant literature to ensure that emerging themes were theoretically informed. Theoretical sampling was applied to constantly refine categories and concepts as new data became available (Glaser and Strauss 1970).

Once established, the second-order themes were further aggregated into higher-level dimensions—referred to in this study as social abilities—which summarize the key theoretical insights derived from the data (Gioia et al. 2013). Tables 2 and 3 present exemplary results of the data analysis process, including first-order concepts, second-order themes, and aggregate dimensions. The final phase of analysis involved the construction of a data structure to visually map the transformation of raw interview data into abstract theoretical dimensions. This structured visualization enhanced the transparency and rigor of the analytic process (Pratt 2008; Tracy 2010). Conceptual diagrams were developed to illustrate the relationships among categories using boxes and arrows, which facilitated an intuitive understanding of the findings (Nag et al. 2007).

To enhance the credibility of the findings, data triangulation was performed by integrating multiple sources and verification methods. All experts were asked a consistent set of questions, aligning with the principles of synchronic primary data source triangulation (Pauwels and Matthyssens 2004). Additionally, secondary data—including industry reports, company records, and archival documents—were analyzed to cross-validate the insights derived from the interviews (Denzin 2017). This approach ensured that the identified

TABLE 3 | Overview of dimensions, second-order themes, explanations, and corresponding first-order concepts.

Dimension	Second-order theme	Explanation	Corresponding first-order concepts
Inevitability	Fulfillment of expectations	The expectation is inherently linked to a foundational comprehension of AI principles	c1; c2
	Indispensable framework	The deployment of AI is presently imperative, and it is projected to become a critical prerequisite for market viability in the future	c3; c4
	Different levels of urgency	The urgency of implementation is contingent upon country-specific factors and organizational size	c5; c6
	Step-by-step implementation	AI-driven support is provided to a varying extent, encompassing both deliberate and inadvertent utilization	c7; c8
Neutrality	Focusing on the big picture of SC	All available data are integrated impartially, free from external or subjective influence	c9; c10; c11
	Exclusion of divisional thinking	The consideration of area-based perspectives is excluded, with sole emphasis placed on objective data	c12; c13; c14; c15; c16; c17; c18; c19
Flexibility	Data output optimized for time and content	Precise and rapid results are provided within a short timeframe	c20; c21; c22
	Change capacity	The analysis of extensive datasets enables ongoing adjustment to dynamic conditions	c23; c24
Vision	Objective, data-based decision-making	All relevant data are integrated systematically and objectively to facilitate expedited solution identification	c25; c26
	Scenario planning	Various scenarios are formulated based on the probabilistic assessment of their occurrence	c27; c28
	Creating open spaces	The reliability of results is ensured while maintaining the user's capacity for real-time intervention	c29; c30
	Analytical approach	Patterns are recognized, and decisions are strategically derived	c31; c32
Adaptability	Independent learning	Data are collected independently to support continuous learning	c33
	Possibility of constant information exchange	A mechanism for continuous information exchange exists between the user and the AI system	c34; c35
	Intelligence beyond the previously given data	The AI system identifies potential future issues and implements proactive measures to address them	c36; c37

(Continues)

TABLE 3 | (Continued)

Dimension	Second-order theme	Explanation	Corresponding first-order concepts
Reliability	System trust and access	The necessary level of trust in the AI system, along with its authorized access to all critical systems, is securely established	c38; c39
	Compliance with the legal framework	A comprehensive understanding of country-specific regulatory frameworks is acquired	c40; c41
	Eloquent and cosmopolitan	An appropriate communicative tone is adopted when interacting with individuals from diverse cultural backgrounds	c42; c43

themes and concepts were robust and reflective of both contemporary perspectives and historical context (Flick 2018). Overall, this systematic approach ensured that the study maintained methodological rigor while supporting a nuanced and contextually rich interpretation of AI implementation in SCs. The analytical process and resulting insights are further detailed in Section 4, accompanied by graphical representations to facilitate clarity and comprehension.

4 | Results

The analysis identified six social abilities influenced by the integration and application of AI in SCs: *inevitability*, *neutrality*, *vision*, *flexibility*, *adaptability*, and *reliability*. These abilities are explored in detail in the subsequent sections. Appendix 1 presents the coding scheme, demonstrating how the six abilities were derived from the data.

4.1 | Inevitability

Inevitability as a social ability refers to the notion that the integration of AI is essential for continued progress and success in today's market, particularly in the context of SCRes. This theme includes four main categories. The first category, *fulfillment of expectations*, is fundamentally linked to a basic understanding of AI principles and includes elements such as open-mindedness and ongoing education, both of which were frequently mentioned by experts. This includes recognizing the capabilities and limitations of AI systems, particularly the common misconception that AI can detect rare or random anomalies. For example, one interviewee expressed:

If you imagine a forecast from a logistics center, a very simple forecast, then our customers expect the AI to identify the days on which this logistics center is at its worst. So, typically, the outliers. Of course, it doesn't reveal exactly what causes these issues, nor can it, since they are simply driven by chance. Unless it's events like Black Friday or something.

But I don't need AI for that. So that means that here, too, the expectation is that the AI will actually find the irregularities. But what it actually finds are the regularities.

(E10)

The establishment of an *indispensable framework* is another critical aspect of the social ability of inevitability, underscoring the essential role of this technology. In the following statement, one participant noted that adopting AI is no longer optional but a necessary condition for long-term competitiveness:

In the medium term, AI is not a competitive advantage. That is, let me say, not using it is a competitive disadvantage. So, anyone who thinks they can do without it, have fun for the next ten years at most, but that's it.

(E16)

Regardless of this, another interviewee stated:

I believe that this is the case with many companies; they don't even realize that they are currently dying out. They only notice that their participation in growth is disproportionately low or that they are benefiting disproportionately from the momentum of the market.

(E06)

Interviewees cited *different levels of urgency* as a critical factor in the widespread adoption of AI, indicating that the size of the organization does not affect participation:

I think it is actually possible for everyone to participate. There are tools that are very expensive, but there is also a broad start-up scene that enables access to AI solutions through services. You don't have to develop everything yourself, you can also

use tools from the market and, as is usual, also from start-ups. And they are also happy to have customers. So not everything is correspondingly expensive.

(E17)

Similarly, another respondent noted the following:

I believe that even a small two-person craft business can benefit from this just as much as a billion-dollar corporation. The range is just so wide, there's definitely something for everyone.

(E15)

The final dimension of inevitability is described by the term *step-by-step implementation*, which is further supported by the concepts of previously unknown use cases and varying levels of potential support, as illustrated by the following statement:

The topic of the shortage of skilled workers is certainly a classic example of this. When we have problems filling positions and filling them suitably, it is certainly a method of providing support there, perhaps also of supporting people who may be unfamiliar with the subject matter to work in certain topics that they can only master with the help of AI as a supporting tool.

(E23)

4.2 | Neutrality

Neutrality as a social ability refers to the idea that AI remains focused on achieving defined objectives. In the context of SCRes, AI is unaffected by internal organizational sensitivities and consistently prioritizes the optimization of SCs and the enhancement of their resilience.

A key strength of AI is its ability to maintain impartiality while *focusing on the big picture of SC*, considering all influencing factors and remaining insulated from external pressures. One interviewee illustrated the value of AI's independence in forecasting by comparing it to human judgment within their organization:

At the end of 2022, the sales department optimistically predicted that 2023 would outperform the previous year, stating that it "can only get better." However, the AI model projected a decline and was ultimately correct. A similar pattern emerged at the end of 2023; due to lower performance, the sales team anticipated a poor outlook for 2024, whereas the AI model predicted improvement. Again, the AI was accurate. As the participant noted, AI "is simply more independent" and can produce reliable forecasts by drawing on historical data rather than subjective sentiment.

(E04)

A key component of neutrality is the *exclusion of divisional thinking*, where AI supports cross-functional decision-making by prioritizing outcomes over the interests of individual departments. One such area is the reduction of time-to-market for products:

This means, above all, that you have to be faster to reduce this time to market. That is actually the main challenge. I believe that this is pretty much the same for all other companies that also have a large research department. The cycles there are not as long as they are in our industry. But they will still have the challenge of simply shortening this time to market.

(E20)

Another area where the exclusion of divisional thinking comes into play is in supporting the legal department through the perceived omniscient knowledge of legal frameworks. One expert provided the following response regarding the specific domains in which AI can be applied:

Contract management. There are clearly also contract databases with alerts, etc. The question is, can you compare contracts with the existing tools today and identify differences? Can you say what has changed, etc.? I believe that an AI can say more clearly, "Watch out, here are two documents read out via OCR [Optical character recognition], please write down the differences, and depending on that, you can make an initial assessment: what is critical, what is not critical?" All of this can be taught and learned with a lawyer possibly in the background. So, there are many possibilities, and I believe there is added value, especially in the supply chain (i.e., where we are very contractual), that we have significant added value there.

(E18)

Further important applications involve route optimization or support and optimization of production processes, as following stated:

In matrix production, where products can flow through production in all possible ways. Yes, where not just one product group, but perhaps all products, can be manufactured by a system. Do you have such complex planning processes that a human would not be able to create a valid plan at all? These are scenarios where I say, "Let the AI decide as much as possible."

(E21)

4.3 | Flexibility

The social ability of flexibility is characterized by *data output optimized for time and content*, which underscores AI's ability

to adapt to changing conditions. For example, one of the interviewed experts and their employer integrate AI-driven tools into risk management processes, leveraging the technology's capability to systematically scan and analyze a vast array of external data sources. This automated data acquisition process enhances the accuracy and efficiency of risk assessment. Additionally, AI is employed in document management to facilitate the automated processing of invoices, as well as in predictive analytics to forecast delivery times, thereby optimizing operational efficiency and decision-making processes. The following statement was made in response to the question concerning the functional capabilities that AI must exhibit to gain acceptance by its immediate operational environment as an autonomous entity within the SC:

Yes, that's just very, very use case specific. On the one hand, we can measure accuracy; for example, in the context of lead time prediction, AI can be used to assess how frequently it determines or informs us in advance whether a delivery will arrive on time. In such cases, prediction accuracy can be measured effectively. If, for instance, the AI achieves an accuracy rate of 80%, this would generally be considered sufficient for operational teams to rely on and integrate into their workflows. However, if we are talking about using AI for data queries, like with ChatGPT, where the AI learns from our data models and then queries specific metrics, then an 80% accuracy is not sufficient, because I want a 99% accuracy in that case to ensure the model gives me the correct metric.

(E08)

Additional influencing factors for the user include reduced effort in obtaining information and the provision of faster, more detailed information within the same time frame when using AI:

It is a matter of time. So, when we use AI tools, for example, in the context of network simulation, such as constraint-based planning—where I may have limited production resources or limited stock availability—and now I use an AI application that is supposed to help me decide in day-to-day operations whether I should send the shipment to the customer from the German warehouse or the English one. With the AI solution, we often arrive at approaches that we wouldn't have come up with on our own.

(E17)

AI's *change capacity* in response to new situations is a key enabler of flexibility and includes the complex analysis of existing data:

We have a customer whose production plans are so complex that no human being could ever create a

valid plan. So, give it two days. Maybe they'll manage to create a workable plan in Excel, but in Excel. But by then, the world will have moved on.

(E21)

AI also allows for the iterative assessment of situations based on the most up-to-date information:

It achieves the performance, and it can, since it's a rolling process. This means the AI would continuously monitor the risk of supplier changes in the SC and then produce an alert when something changes, which simply cannot be managed with traditional methods.

(E12)

4.4 | Vision

Vision is the fourth social ability of AI identified in this study. This ability is grounded in four key dimensions that contribute to the sustainable implementation of AI across SC operations. First, AI must facilitate *objective, data-based decision-making*: As noted by an interviewee in response to a question concerning the fundamental prerequisites for the successful implementation of AI, this minimizes the need for ad hoc decision-making and instead promotes informed responses:

This means the system automatically notifies when the required quality will not be met. Then, someone with supply chain expertise and the ability to make calls steps in. But they do it in a data-supported and informed way. That's the difference. Unlike in the past, they don't have to react by saying, "Oh no, where do I get the data from, how do I gather everything, and what should I do now?" Instead, the proposal is already fully worked out in the system, and they simply decide, "That works for me," or "No, I know better." And then they override it, but they do so consciously.

(E14)

The second dimension is the potential use of AI for *scenario planning*. The presentation of a wide range of data-driven solutions and the communication of the associated uncertainties are both considered crucial. One participant responded to the question regarding the functional characteristics that AI must possess in order to be genuinely accepted as an autonomous control mechanism within the SC:

Being able to manage scenarios, for example. So, having a software, an AI, that develops scenarios, saying, "Here, I've analyzed [...] the situation." For that, of course, it needs data from the ERP [enterprise resource planning] system. Then, it presents possible

Scenarios 1, 2, 3, and 4, which may even have associated probabilities like, “I estimate scenario 2 will occur.” It then recommends actions such as increasing an order or making adjustments, followed by a prompt asking the user to confirm whether they want to proceed.

(E11)

Creating open spaces is an important aspect of the vision social skill, achieved by enabling freedom through trustworthy results while maintaining the theoretical authority of the user. An expert stated:

They must always feel like they still have control. That means, if they want to, they have the option to modify a suggestion. And if you provide both to the customer, then you're also building trust.

(E14)

The fourth dimension of the vision social skill is the adoption of an *analytical approach* to strategic decision-making and the optimal interpretation of results for the user, as discussed by an interviewee:

Optimized decision-making in the supply chain can be achieved by recognizing patterns in data volumes and then training and testing the models accordingly, so that you can make the best possible supplier selection and the best possible transport route, independently, based on the preceding parameters.

(E03)

4.5 | Adaptability

The social skill identified as adaptability refers to AI's capacity for *independent learning* and the ability to exhibit a level of *intelligence beyond the previously given data*. As one participant explained:

In my opinion, the system would have to have more human-like intelligent abilities because it has to be able to adapt to situations that cannot be taught in advance.

(E09)

To achieve this ability, the AI must be capable of making informed decisions, identifying potential weaknesses, and autonomously approaching the user to seek support when necessary. As another expert emphasized:

Then respond intelligently to the question: “What should we do with it?” And the real art is when the system independently recognizes whether it's a qualitatively good response or not. If it isn't, a human needs to review it.

(E14)

In addition, adaptability is closely linked to the *possibility of constant information exchange* between the user and the AI, specifically through real-time communication:

For example, when a tool is launched, it may initially operate like a chatbot, engaging in a dialogue with the user. After a simple login using personal credentials, the tool identifies the user and begins the interaction by offering suggested responses within the conversation. [...] So, what have I experienced this week, what key functions have I used? What keywords have I used? That also gives me feedback, so to speak, about my GenAI [generative AI] behavior. And maybe I can then think about whether I need or should change something. Or maybe compare myself with other colleagues if it's relevant in some way.

(E13)

4.6 | Reliability

The social ability identified as reliability encompasses the development of an optimal framework for utilizing AI as a sustainable operational tool within SC management. This ability includes three key considerations, the first of which is *system trust and access*. It is essential that AI systems be capable of independently acquiring all necessary data while integrating seamlessly into existing infrastructure to enable efficient data exchange. As one participant noted:

In any case, it must be integrated into the existing system landscape. It must not be a standalone solution, but everything that I generate in terms of relevant data from my e-procurement, from the SRM [supplier relationship management] tool, from whatever, I must be able to tap into it via the tool, with whatever purpose is behind it. But basically, it must be open to importing data via interfaces.

(E05)

The second essential consideration of reliability is *compliance with the legal framework*, including adherence to country-specific regulations. For example, one expert described using Microsoft Copilot for mergers and acquisitions, in combination with various large language models, to streamline the often complex process of navigating country-specific regulations, thereby enhancing efficiency and decision-making:

The greatest added value is, of course, increased efficiency, especially in the supply chain, ensuring that things are available on-site more reliably, faster, and cheaper. This is definitely very important because [...] products are becoming increasingly complex, regulations are becoming more complex, geopolitically it's getting more complex, and keeping track of everything is, I believe, extremely difficult. And that's where such tools can simply create

transparency. They are also legally required to provide transparency, which is why it has become so important nowadays.

(E07)

General legal compliance also plays an important role in reliability as a social skill for AI. As one participant pointed out, data protection and compliance with regulations like the EU AI Act are “an absolute must” (E01).

Another participant expanded on this idea, emphasizing that “what simply has to be guaranteed in any case is that it is functional, but it simply has to be legally compliant” (E02).

The final consideration of reliability pertains to the ability of AI systems to be *eloquent and cosmopolitan*, emphasizing the development of intercultural competency and awareness of regional particularities. For example, one expert utilizes an AI application to pre-screen emails for relevance and content, often accompanied by an AI-generated response suggestion. This process enhances efficiency by reducing the time required for email management. This AI skillset includes the ability to recognize country-specific nuances, such as appropriate salutations in written correspondence (e.g., emails), and facilitate effective communication across diverse cultural contexts:

If I use it as a communication tool, I am using the technology, but I’m not sending a technical message;

rather, I’m communicating as a person. The sender must be able to tell that it came from me as a person. I have this as an anecdote, but the other way around, I sometimes see customers reply to me and they have obviously used ChatGPT but have not refined the prompt, so that I immediately see that they have simply generated a response to my email, and it doesn’t feel very appreciative. And that’s exactly why I try to avoid it the other way around, by always refining and manually adapting these texts, never taking the text 100%.

(E23)

4.7 | Dependencies of Social Abilities

Figure 2 illustrates the final step in the GM procedure, which involves linking the six social abilities that AI contributes to SCs and their interrelationships.

The foundation of the simplified conceptual framework is the ability of inevitability, which is driven by the necessity of using AI to achieve predefined objectives and ensure a highly resilient SC. This ability is characterized by varying levels of urgency and the necessary institutional and technological infrastructure. An impartial perspective, free from sectoral bias, is critical, as is maintaining a high degree of flexibility to facilitate rapid adaptation of the SC to dynamic conditions.

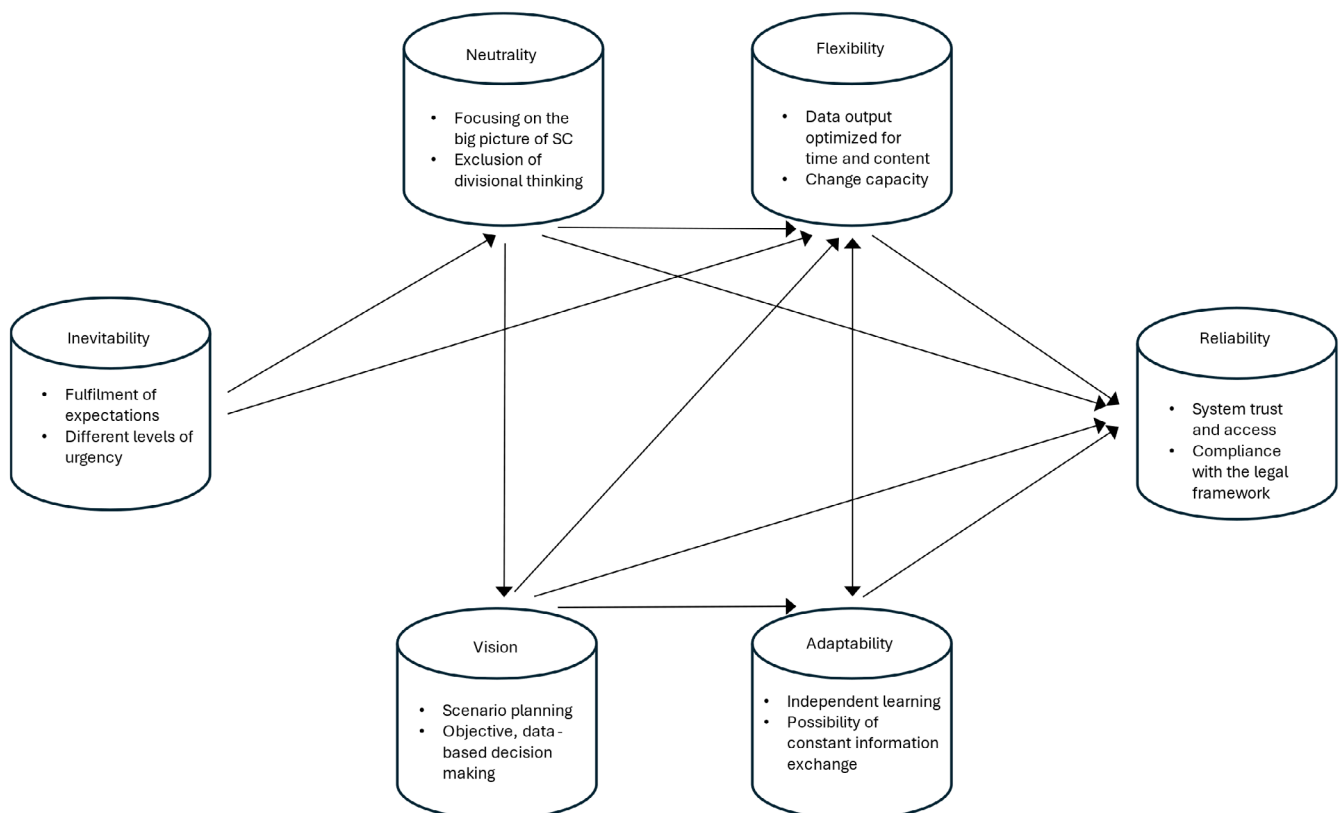


FIGURE 2 | Simplified illustration of the interdependencies among the six social abilities AI brings to SC.

The social ability of neutrality directly influences vision, particularly by mitigating siloed thinking across departments and promoting a holistic, data-driven view of the SC. This broad perspective supports methodological rigor and enhances flexibility within the SC while minimizing bias, thereby enabling more agile responses to evolving challenges. Additionally, a neutral stance enhances system reliability by fostering independent decision-making, which ensures consistency and objectivity.

The ability of vision requires a fundamental degree of flexibility to accommodate potential future developments. Effective scenario planning depends on the capacity of AI to integrate and respond to new information in real time. Therefore, long-term adaptability requires continuous knowledge acquisition and skill enhancement. Advanced AI facilitates this by enabling the development of strategic alternatives and refining them in response to changing conditions. Through predictive decision-making, AI can preemptively identify potential risks, allowing the system to prepare accordingly and implement proactive measures to counter them. This approach strengthens trust in the system and enhances its overall reliability.

However, the interplay between the social skills of flexibility and reliability has inherent constraints. While rapid responsiveness is an essential skill for AI, it must align with compliance standards and maintain appropriate communicative integrity to safeguard the system's credibility. Further, flexibility is intrinsically linked with adaptability, as continuous system evolution and iterative knowledge exchange are necessary to sustain the SC's responsiveness to environmental fluctuations.

Conversely, adaptability reinforces flexibility because an AI-driven system that is capable of continuous learning and real-time data integration is inherently better equipped to navigate complex and unpredictable scenarios than other systems. The system's high level of intelligence facilitates the efficient acquisition and evaluation of information, as well as effective responses to novel situations.

From a reliability perspective, newly assimilated information and subsequent system adjustments must consistently adhere to established regulatory and operational frameworks. Stability and trust must remain uncompromised even amid continuous change. Ultimately, a reliable AI system is one that meets initial user expectations and is grounded in trust and regulatory compliance. Neutral decision-making is paramount, as a system devoid of internal biases and corporate conflicts enhances its credibility. Reliability is further reinforced through predictive planning, which includes identifying potential vulnerabilities of the system and implementing proactive measures. The symbiotic relationship between flexibility, adaptability, and reliability enables swift and effective responses to changing circumstances while preserving confidence in the system's integrity.

5 | Discussion and Conclusions

Organizations often perceive the integration of autonomous systems into SC operations as a complex challenge. This is

primarily due to the limited research on social implications, with attention typically focused on technical implementation. This study addresses this gap by examining the potential of AI in SCs from a social perspective, with a specific focus on its role in enhancing resilience and capacity for independent operation. Based on an exploratory research design, this study uses semi-structured interviews with 23 subject-matter experts specializing in SC management and AI. This qualitative methodological approach enabled an in-depth exploration of the research gap, allowing for a nuanced understanding of AI's role through comprehensive yet flexible discussions that incorporated individual insights and expertise.

The analysis is grounded in ANT, which provides a robust framework for analyzing the dynamic interactions between technology and its operational environment. ANT facilitates an examination of the interconnected and reciprocal roles of both internal and external components of an SC. Within this framework, AI is conceptualized as an integrated and autonomous actor capable of reshaping organizational networks. This theoretical perspective underscores AI's systemic influence when embedded as a functional actor within corporate structures, reinforcing its potential to enhance SCRes.

5.1 | Theoretical Contributions

The contributions of this study to the academic discourse on the application of AI in SC management are twofold. The first contribution is the identification of six social abilities inherent to AI that emerge when it is integrated into an established network, such as an SC. These abilities were derived from expert insights and mapped against the four phases traditionally associated with SCRes—readiness, response, recovery, and growth. The findings reveal a significant alignment between the identified attributes of AI and these phases. Specifically, the ability referred to as *vision* in our study corresponds to the readiness phase, while *flexibility* and *adaptability* align with the response and growth phases, respectively. Figure 3 illustrates this alignment by comparing the established phases of resilient SCs (Hohenstein et al. 2015) with the six social abilities identified in this study as pivotal to enhancing SCRes.

The first ability, vision, reflects AI's forward-looking capacity. While this does not imply that AI can predict the future with absolute precision, it does enable the identification of the most probable scenarios and the preparation of multiple contingencies in advance. This proactive approach aligns with prior research on foresight in SC management (Dubey et al. 2021; Gruchmann et al. 2024). By anticipating a range of possibilities, AI significantly reduces response times to unforeseen disruptions, thereby enhancing SCRes. Even when AI operates in a supporting capacity rather than as a fully autonomous actor, its predictive capabilities equip SC managers with a spectrum of decision-making options, ultimately bolstering their ability to effectively address unexpected challenges.

The second ability identified in this study, flexibility, closely corresponds to the response phase of SCRes, as frequently emphasized in the literature. This ability underscores the critical need for swift and effective reactions to unforeseen events based on

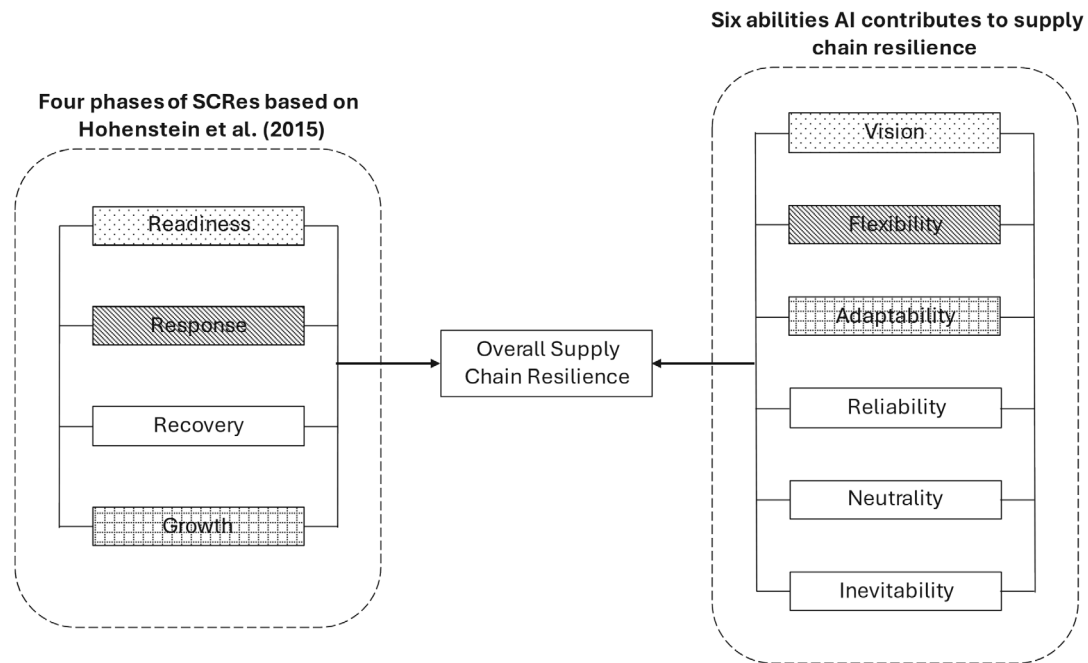


FIGURE 3 | Comparison of the four phases of SCRes, based on Hohenstein et al. (2015), and the social abilities identified in this study.

the most up-to-date information available (Gaudenzi et al. 2023). AI plays a key role in achieving this responsiveness and optimal flexibility, surpassing traditional decision-support systems in terms of both processing power and speed. For instance, during the COVID-19 pandemic, AI was instrumental in coordinating stakeholders, enhancing real-time information processing, and enabling the rapid reconfiguration of distribution channels despite material shortages and logistical delays (Guida et al. 2023; Modgil, Gupta, et al. 2022; Modgil, Singh, et al. 2022). This case underscores the vital role of AI in supporting SCRes by enabling real-time decision-making and effective crisis response.

Third, the adaptability skill underscores AI's ability to engage in continuous learning through ongoing information exchange, aligning with Bhattacharya's (2021) findings. This concept resonates with Megginson's (Megginson 1963) interpretation of Charles Darwin's Origin of Species:

[...] it is not the most intellectual of the species that survives; it is not the strongest that survives; but the species that survives is the one that is able best to adapt and adjust to the changing environment in which it finds itself.

(4)

For AI to effectively adapt to evolving external conditions, it must constantly assimilate new data and remain regularly updated with current information. These continual updates reinforce the foundational structure of AI systems and enable the generation of increasingly tailored and effective solutions. The majority of experts interviewed in this study highlighted the critical importance of this continuous feedback loop, noting that AI's adaptability significantly enhances organizational capabilities by learning from external conditions, reducing system complexity, and strengthening resilience. These findings are

consistent with those of Belhadi et al. (2022), who emphasize the transformative potential of AI adaptability in promoting organizational robustness and agility.

Building on this foundation, this study extends the literature by introducing the additional abilities of inevitability, neutrality, and reliability, offering novel perspectives on the application of AI within SCs. The ability of reliability, in particular, focuses on the interaction between AI and internal corporate systems, as well as its compliance with broader legal frameworks. A major development in this area occurred in July 2024, when the European Union adopted the first transnational AI legislative package (Regulation (EU) 2024/1689 of the European Parliament and of the Council 2024). This legislation introduces a risk-based approach to AI governance and mandates transparency measures, such as the explicit labeling of AI-generated content (Gasser 2023). While the EU has taken the lead in AI regulation, many countries still lack comprehensive legal frameworks (Sofinska 2024). However, globally harmonized legislation is essential to mitigate the risks of AI misuse, as fragmented governance may lead to operational and security challenges (Robles Carrillo 2020). Although the G7 countries have agreed upon a shared code of conduct for AI governance, comprehensive international legislation remains in development (Organisation for Economic Co-operation and Development 2024). In the absence of such regulation, AI systems remain vulnerable to risks such as security breaches, cyberattacks, and unsafe operational behaviors (Jazairy et al. 2024; Pușcă 2020).

The identified skill of reliability also involves the seamless integration of AI into an organization's existing IT infrastructure, a critical factor that influences AI's impact on organizational performance (Themistocleous et al. 2001). While the integration of AI offers significant potential benefits, it also requires careful attention to both technical and economic considerations, including compliance with legal and jurisdictional

frameworks. By adhering to robust legal frameworks, organizations can minimize the risk of disruptions caused by non-compliance, thereby strengthening the resilience of their SCs. This ability underscores the importance of reliable integration and legal safeguards as prerequisites for AI's sustainable and effective contribution to SCRes (Abousaber and Abdalla 2023).

The ability of neutrality reflects the absence of human sensitivities in AI-driven decision-making. Unlike human actors, AI systems operate independently of interpersonal dynamics or departmental biases, maintaining a consistent focus on the overarching goal of achieving a resilient SC. Group-based decisions are often more impartial than those made individually (Keck et al. 2012). In this context, AI-driven decisions can be conceptualized as an individual group decision, given AI's capacity to evaluate information across multiple SC domains from a holistic perspective. Recent research raises concerns about AI not being entirely neutral in decision-making and possibly perpetuating discriminatory outcomes or existing biases; however, such issues generally arise when AI algorithms are trained on biased data (Stinson 2022). This limitation is less relevant in SC applications, as the data used are typically specific, objective, and operationally focused, minimizing the potential for bias.

The ability of inevitability underscores the unavoidable necessity of integrating AI into SC operations. As mentioned by multiple interviewees, successful implementation requires substantial educational efforts. These efforts ensure that managers and decision-makers are informed and equipped to advocate for AI integration, while also preparing employees and end users to understand its capabilities and limitations. The absence of such educational initiatives could hinder the adoption of AI and reduce organizational readiness. According to the experts, organizations that fail to comprehensively incorporate AI into their SCs may risk falling behind competitors, thus reinforcing the imperative of this technological transition.

The second contribution of this study to the literature lies in its conceptualization of AI as an autonomous actor within the SC. Drawing upon ANT as the guiding theoretical framework, this study highlights AI's ability to act and influence network dynamics. Building on the six social abilities of AI identified in this research, it is evident that AI can be understood as an autonomous actor (Calatayud et al. 2019; Xu, Mak, Minaricova, et al. 2024; Xu, Mak, Proselkov, et al. 2024) that integrates social abilities into the surrounding network. This integration underscores AI's ability to operate independently, adapting its functions to specific operational needs within an organization.

Although AI is conceptualized as an independent actor, it simultaneously assumes multiple roles by functioning as an actor, protagonist, and actant within the SC ecosystem. However, in contrast to Latour's (2005) original conception of actors, AI lacks a tangible physical form, a stable identity, or consistent attributes, challenging traditional definitions of agency. This perspective extends beyond traditional understanding and emphasizes the interpersonal dynamics between AI and human counterparts, raising the key question: To what extent will humans adapt to AI as an increasingly familiar presence in their

daily professional environments? As Latour (1992, 254) observes, "It is too full of humans to look like the technology of old, but it is too full of nonhumans to look like the social theory of the past." This statement conveys the view that humans and nonhumans operate as interconnected actors within a network, rejecting a strict distinction between entities such as technology and humans.

The increasing integration of AI as an actor within SCs necessitates targeted efforts in education and technological training (Brockhaus et al. 2023) to prepare individuals for seamless collaboration. Addressing concerns such as job displacement (Cropley et al. 2022; McClure 2018) and the opacity of AI-driven decision-making processes (e.g., black box systems) is essential (Ajunwa 2020). Prior research demonstrates that social attributes are often ascribed to technological systems (Nass et al. 1994; Takeuchi and Naito 1995), a phenomenon equally applicable to AI (Nass et al. 1994). As Norman (1994, 71) states, it is important to understand that "once unleashed, technologies do not disappear," a statement reaffirmed by contemporary research (Jöhnik et al. 2021; Nokelainen et al. 2012). This observation indicates that disruptive technologies persist beyond their initial breakthrough, as they are progressively integrated into society by an increasing number of users. This argument underscores the need for proactive preparation to ensure that AI is perceived as an accessible and integrated element of human-machine interaction rather than a disruptive force.

As Klien et al. (2004) note, collaboration between humans and AI presents challenges, yet many of these obstacles can be mitigated by reducing human mediation and enabling direct communication between AI systems. Operational efficiency within SCs can be significantly improved by minimizing the need for AI to interpret human intentions (Abbass 2019). The findings of this study suggest that AI should assume a greater share of decision-making and operational tasks within SCs, thereby streamlining processes and reducing errors at the human-technology interface. Within the ANT perspective, AI is not only an actor but also a network. By deconstructing AI and analyzing the network of relationships surrounding its implementation, it emerges as a complex, hybrid association that encompasses and integrates natural, technical, and human elements within specific applications. Each implementation of AI requires thorough investigation to fully understand its impact on SC performance.

In addition to acting as an autonomous actor within the broader theoretical framework, AI also operates as part of an evolving, interconnected network shaped by both internal and external influences. The dual conceptualization of AI as both an independent agent and an integrated network illustrates its profound and multifaceted impact on modern SC management.

The second foundational concept of our theory is the notion of the network. Based on the identified ability of reliability—which encompasses attributes such as system trust, compliance with surrounding systems, and etiquette—we propose that AI can be conceptualized not only as an individual actor but also as a network within the SC. Specifically, AI can be conceptualized as an autonomous network comprising social abilities, software, hardware, IT infrastructure, enterprise resource planning systems, and other interconnected elements.

Together, these components form a self-contained microcosm in which various individual actors collaborate toward the overarching goal of creating and sustaining a stable network (Couldry 2008). As demonstrated in Section 4.7 of this paper, all identified social abilities and their interdependencies contribute to maximizing reliability. These contributions foster the formation of a stable network, creating a self-reinforcing cycle that ultimately results in a continuously self-optimizing network.

In the corporate context, this AI network functions as one actor among many within a broader organizational ecosystem. This perspective aligns with the view that human and non-human actors should be treated as equally significant. To ensure the stability of this actor-network, both human and non-human agents should receive equitable development opportunities and financial investments. Further, both must be integrated into the strategic objectives of the organization (Samarghandi et al. 2023).

5.2 | Practical Implications

This study introduces six social abilities AI brings to SCs, which enhance SCRes when extensively implemented. The proposed framework integrates various areas in which organizations must develop capabilities to effectively strengthen SCRes. It provides managers with a structured approach to assess their SC operations and departments, facilitating preparation for upcoming digital transformations. By identifying gaps or underdeveloped capabilities, these organizations can strategically build the competencies necessary for effective AI integration across all relevant areas of the SC.

An ANT perspective is used in this study to emphasize the importance of addressing social factors in tandem with technological advancements when implementing AI in SCs. Given the widespread uncertainty and apprehension surrounding AI, the study highlights the necessity for managers and users to deeply engage with this disruptive technology. It is essential that individuals are provided with the time and resources to fully comprehend and integrate AI into their workflows, rather than merely treating it as an add-on to their existing responsibilities. Such intensive engagement is crucial to foster effective collaboration between AI systems and human workers, thereby optimizing performance within the organization. Further, the study explores the interdependencies among the six social AI abilities to underscore their interconnectedness and the holistic nature of AI's contribution to SCRes.

The findings of the study demonstrate the advantages of AI as an autonomous actor and examine the extent to which it can stabilize SCs. Ultimately, the degree of autonomy granted to AI is determined by the user, who may initially restrict its decision-making authority. As AI demonstrates its effectiveness, it can be entrusted with increasing autonomy, potentially achieving full independence in executing SC processes. The successful implementation of AI within an organization integrates the six identified abilities into the SC, enabling managers to address the black box concept introduced by Callon and Latour (1981) and ultimately enhance the resilience of the organizational SC network.

This framework sets the stage for a new era of SC digitalization in which AI plays a pivotal role in ensuring operational stability and resilience.

5.3 | Future Research Directions

Building on the findings of this study, several avenues for future research can be pursued to further advance the understanding and application of AI in SC management, particularly in the context of SCRes. A crucial area of exploration is the contextual adaptation and scalability of AI integration across varying organizational sizes and sectors. While our research acknowledges the universal applicability of AI, it remains essential to investigate whether variations exist in its effectiveness or the necessary abilities across different scales of enterprises, from sole proprietorships to large multinational corporations. Future research could examine constructs such as digital maturity and resource availability to better tailor AI solutions for small and medium-sized enterprises.

Additionally, longitudinal studies focusing on the temporal evolution of AI's social abilities and their impact on SCRes could yield valuable insights. Understanding how these capabilities develop and mature over time, and whether all abilities need to be concurrently activated or can be staggered, may refine implementation strategies across different stages of SC growth. Considering the dynamic nature of AI, exploring scenarios where its predictive, flexible, and adaptive skills are nurtured incrementally could optimize resilience efforts.

Further exploration of AI's role within specific SC sectors may offer nuanced contributions. Case studies embedded within individual segments, such as procurement, distribution, or logistics, could elucidate sector-specific benefits and challenges. Such detailed analyses could enhance generalizability and lead to specialized strategies optimized for particular operational contexts.

Another promising direction lies in integrating ANT with other theoretical frameworks to enrich the understanding of AI's role as both an actor and a network. Incorporating theories that address sociotechnical interactions or organizational behavior could provide a more comprehensive lens for evaluating AI's integration into SC ecosystems. This interdisciplinary approach may clarify AI's network interactions and amplify its strategic impact.

Finally, quantitative assessments of the interdependencies among the identified social abilities of AI could establish a robust framework for understanding their interactions. Mathematical models or simulations may offer objective insights into the synergistic effects of these abilities on SCRes, potentially leading to more precise and predictive strategies for AI implementation.

5.4 | Limitations of the Study

This study's limitations largely pertain to its scope and methodological approach, which constrain an exhaustive analysis of AI's role and potential within SC ecosystems. First, our inquiry

does not delve into the differential impact of AI across diverse organizational scales. Although AI's universal potential is recognized, its practical implementation may not be uniformly advantageous for all enterprises, particularly when accounting for disparities in resource availability and digital maturity. Future empirical work should segment enterprises by size to explore AI's differential benefits and constraints.

Second, the research does not address the temporal dynamics of AI's social abilities comprehensively. While these abilities are pivotal to SCRes, the study lacks a temporal lens to observe their evolution or the sequential activation required for optimal outcomes. This gap necessitates longitudinal research to chronicle the development trajectory of AI capabilities and their sustained impact on resilience.

Third, the study adopts ANT without concurrent theoretical frameworks that might offer complementary insights into AI's actor-network roles and interactions. Despite ANT's initial application as a theoretical backdrop, its limitations, such as vague actor definitions, call for integrative approaches with other theories to fortify interpretations and analyses of AI's role as both an actor and a network within SC contexts.

Finally, the subjective representation of the interdependencies among AI's social abilities introduces another limitation. The qualitative assessments are grounded in expert interviews and author perspectives, which may lack mathematical precision. Incorporating quantitative methods to explore these relationships systematically could provide objectivity and a deeper understanding, offering more structured strategies for implementing AI to enhance SCRes.

5.5 | Concluding Remarks

The increasing integration of AI into SC management presents both opportunities and challenges, necessitating a deeper understanding of its role within established networks. This study addresses a research gap by identifying six social abilities inherent to AI and analyzing AI's agency within the SC through the lens of ANT. These contributions provide a nuanced perspective of AI's impact on SCRes and its function as an autonomous actor in dynamic SCs. From a theoretical standpoint, the findings of this study contribute to the ongoing discourse on digital transformation in SC management by reframing AI not merely as a technological tool but as an active participant shaping SCs. By aligning the identified AI abilities with the phases of resilient SCs—readiness, response, recovery, and growth—this study offers a novel framework that contextualizes AI's role within established resilience paradigms.

The conceptualization of AI as an actor, rather than a passive enabler, advances theoretical understandings of human-machine collaboration, highlighting the necessity of considering AI's decision-making capabilities, adaptability, and systemic interactions when integrating these tools into SCs. The application of the ANT framework to AI in SCs extends existing research on sociotechnical transitions by recognizing AI as both an individual actor and a network entity. This dual conceptualization

emphasizes AI's transformative potential to reshape SC structures and operational processes. By acknowledging AI's social abilities—inevitability, neutrality, flexibility, vision, adaptability, and reliability—this study underscores the importance of governance mechanisms, ethical considerations, and regulatory frameworks to ensure AI's effective and sustainable integration into SCs. Finally, this research offers direction for future inquiries into the evolving relationship between AI and SC management, advocating for a holistic perspective that integrates technological capabilities with organizational strategy and human-AI interaction. As AI continues to permeate SCs, developing a deeper understanding of its agency and networked influence will be essential for designing resilient, adaptive, and ethically sound SCs.

Acknowledgments

Open Access funding enabled and organized by Projekt DEAL.

Conflicts of Interest

The authors declare no conflicts of interest.

References

- Aarland, M. 2024. "Cybersecurity in Digital Supply Chains in the Procurement Process: Introducing the Digital Supply Chain Management Framework." *Information and Computer Security* 33: 5–24. <https://doi.org/10.1108/ICS-10-2023-0198>.
- Abbass, H. A. 2019. "Social Integration of Artificial Intelligence: Functions, Automation Allocation Logic and Human-Autonomy Trust." *Cognitive Computation* 11, no. 2: 159–171. <https://doi.org/10.1007/s12559-018-9619-0>.
- Abousaber, I., and H. Abdalla. 2023. "Review of Using Technologies of Artificial Intelligence in Companies." *International Journal of Communication Networks and Information Security* 15, no. 1: 217–228. <https://doi.org/10.17762/ijcnis.v15i1.5743>.
- Adams, W. C. 2015. "Conducting Semi-Structured Interviews." In *Handbook of Practical Program Evaluation*, 492–505. Wiley. <https://doi.org/10.1002/9781119171386.ch19>.
- Ajunwa, I. 2020. "The "Black Box" at Work." *Big Data & Society* 7, no. 2. <https://doi.org/10.1177/2053951720938093>.
- Akter, S., K. Michael, M. R. Uddin, G. McCarthy, and M. Rahman. 2022. "Transforming Business Using Digital Innovations: The Application of AI, Blockchain, Cloud and Data Analytics." *Annals of Operations Research* 308, no. 1–2: 7–39. <https://doi.org/10.1007/s10479-020-03620-w>.
- Ambulkar, S., J. Blackhurst, and S. Grawe. 2015. "Firm's Resilience to Supply Chain Disruptions: Scale Development and Empirical Examination." *Journal of Operations Management* 33, no. 1: 111–122. <https://doi.org/10.1016/j.jom.2014.11.002>.
- Attinasi, M. G., L. Boeckelmann, and B. Meunier. 2023. "The Economic Costs of Supply Chain Decoupling." *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4532103>.
- Atwani, M., M. Hlyal, and J. Elalami. 2022. "A Review of Artificial Intelligence Applications in Supply Chain." *ITM Web of Conferences* 46: 03001. <https://doi.org/10.1051/itmconf/20224603001>.
- Baldea, M., A. T. Georgiou, B. Gopaluni, et al. 2025. "From Automated to Autonomous Process Operations." *Computers & Chemical Engineering* 196: 109064. <https://doi.org/10.1016/j.compchemeng.2025.109064>.

- Barredo Arrieta, A., N. Díaz-Rodríguez, J. Del Ser, et al. 2020. "Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges Toward Responsible AI." *Information Fusion* 58: 82–115. <https://doi.org/10.1016/j.inffus.2019.12.012>.
- Baryannis, G., S. Validi, S. Dani, and G. Antoniou. 2019. "Supply Chain Risk Management and Artificial Intelligence: State of the Art and Future Research Directions." *International Journal of Production Research* 57, no. 7: 2179–2202. <https://doi.org/10.1080/00207543.2018.1530476>.
- Bechtsis, D., N. Tsolakis, E. Iakovou, and D. Vlachos. 2022. "Data-Driven Secure, Resilient and Sustainable Supply Chains: Gaps, Opportunities, and a New Generalised Data Sharing and Data Monetisation Framework." *International Journal of Production Research* 60, no. 14: 4397–4417. <https://doi.org/10.1080/00207543.2021.1957506>.
- Belhadi, A., S. Kamble, S. Fosso Wamba, and M. M. Queiroz. 2022. "Building Supply-Chain Resilience: An Artificial Intelligence-Based Technique and Decision-Making Framework." *International Journal of Production Research* 60, no. 14: 4487–4507. <https://doi.org/10.1080/00207543.2021.1950935>.
- Benbya, H., T. H. Davenport, and S. Pachidi. 2020. "Artificial Intelligence in Organizations: Current State and Future Opportunities." *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3741983>.
- Bengtsson, F., and P. J. Ågerfalk. 2011. "Information Technology as a Change Actant in Sustainability Innovation: Insights From Uppsala." *Journal of Strategic Information Systems* 20, no. 1: 96–112. <https://doi.org/10.1016/j.jsis.2010.09.007>.
- Berthet, E. T., G. M. Hickey, and L. Klerkx. 2018. "Opening Design and Innovation Processes in Agriculture: Insights From Design and Management Sciences and Future Directions." *Agricultural Systems* 165: 111–115. <https://doi.org/10.1016/j.agry.2018.06.004>.
- Bhattacharya, D. 2021. "Competing in the Age of AI: Strategy and Leadership When Algorithms and Networks Run the World." *Strategic Analysis* 45, no. 3: 264–266. <https://doi.org/10.1080/09700161.2021.1918951>.
- Birkstedt, T., M. Minkkinen, A. Tandon, and M. Mäntymäki. 2023. "AI Governance: Themes, Knowledge Gaps and Future Agendas." *Internet Research* 33, no. 7: 133–167. <https://doi.org/10.1108/INTR-01-2022-0042>.
- Blackhurst, J., K. S. Dunn, and C. W. Craighead. 2011. "An Empirically Derived Framework of Global Supply Resiliency." *Journal of Business Logistics* 32, no. 4: 374–391. <https://doi.org/10.1111/j.0000-0000.2011.01032.x>.
- Bode, C., S. M. Wagner, K. J. Petersen, and L. M. Ellram. 2011. "Understanding Responses to Supply Chain Disruptions: Insights From Information Processing and Resource Dependence Perspectives." *Academy of Management Journal* 54, no. 4: 833–856. <https://doi.org/10.5465/amj.2011.64870145>.
- Boyko, R., D. Shumyhai, and M. Gladka. 2017. *Concept, Definition and Use of an Agent in the Multi-Agent Information Management Systems at the Objects of Various Nature*, 59–63. https://doi.org/10.1007/978-3-319-48923-0_8.
- Brandon-Jones, E., B. Squire, C. W. Autry, and K. J. Petersen. 2014. "A Contingent Resource-Based Perspective of Supply Chain Resilience and Robustness." *Journal of Supply Chain Management* 50, no. 3: 55–73. <https://doi.org/10.1111/jscm.12050>.
- Brintrup, A. 2020. "Artificial Intelligence in the Supply Chain." In *The Oxford Handbook of Supply Chain Management*, 209–236. Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780190066727.013.24>.
- Brockhaus, S., R. van Hoek, and S. DeNunzio. 2023. "Future-Proofing Supply Chain Education." *Transportation Journal* 62, no. 4: 355–368. <https://doi.org/10.5325/transportationj.62.4.0355>.
- Bui Trong, H., and U. Bui Thi Kim. 2020. "Application of Information and Technology in Supply Chain Management: Case Study of Artificial Intelligence—A Mini Review." *European Journal of Engineering Research and Science* 5, no. 12: 19–23. <https://doi.org/10.24018/ejers.2020.5.12.2254>.
- Calatayud, A., J. Mangan, and M. Christopher. 2019. "The Self-Thinking Supply Chain." *Supply Chain Management: An International Journal* 24, no. 1: 22–38. <https://doi.org/10.1108/SCM-03-2018-0136>.
- Callon, M. 1980. *Struggles and Negotiations to Define What Is Problematic and What Is Not*, 197–219. https://doi.org/10.1007/978-94-009-9109-5_8.
- Callon, M. 1984. "Some Elements of a Sociology of Translation: Domestication of the Scallops and the Fishermen of St Brieuc Bay." *Sociological Review* 32, no. 1_suppl: 196–233. <https://doi.org/10.1111/j.1467-954X.1984.tb00113.x>.
- Callon, M. 1990. "Techno-Economic Networks and Irreversibility." *Sociological Review* 38, no. 1_suppl: 132–161. <https://doi.org/10.1111/j.1467-954X.1990.tb03351.x>.
- Callon, M., and B. Latour. 1981. "Unscrewing the Big Leviathan; or How Actors Macrostructure Reality, and How Sociologists Help Them To Do So?" *Advances in Social Theory and Methodology*: 277–303.
- Callon, M., and B. Latour. 1992. "Don't Throw the Baby out With the Bath School! A Reply to Collins and Yearley." *Science as Practice and Culture*: 343–368.
- Cao, L., V. Gorodetsky, and P. A. Mitkas. 2009. "Agent Mining: The Synergy of Agents and Data Mining." *IEEE Intelligent Systems* 24, no. 3: 64–72. <https://doi.org/10.1109/MIS.2009.45>.
- Ch. Meyer, J. 2008. "Agent Technology." In *Wiley Encyclopedia of Computer Science and Engineering*, 1–8. Wiley. <https://doi.org/10.1002/9780470050118.ecse007>.
- Channell, D., and R. Volti. 1991. "Society and Technological Change." *Technology and Culture* 32, no. 4: 1150. <https://doi.org/10.2307/3106191>.
- Choi, T., S. W. Wallace, and Y. Wang. 2018. "Big Data Analytics in Operations Management." *Production and Operations Management* 27, no. 10: 1868–1883. <https://doi.org/10.1111/poms.12838>.
- Chowdhury, M. M. H., and M. Quaddus. 2017. "Supply Chain Resilience: Conceptualization and Scale Development Using Dynamic Capability Theory." *International Journal of Production Economics* 188: 185–204. <https://doi.org/10.1016/j.ijpe.2017.03.020>.
- Corbin, J. M., and A. Strauss. 1990. "Grounded Theory Research: Procedures, Canons, and Evaluative Criteria." *Qualitative Sociology* 13, no. 1: 3–21. <https://doi.org/10.1007/BF00988593>.
- Couldry, N. 2008. "Actor Network Theory and Media: Do They Connect and on What Terms?" <https://api.semanticscholar.org/CorpusID:28809184>.
- Cresswell, K. M., A. Worth, and A. Sheikh. 2010. "Actor-Network Theory and Its Role in Understanding the Implementation of Information Technology Developments in Healthcare." *BMC Medical Informatics and Decision Making* 10, no. 1: 67. <https://doi.org/10.1186/1472-6947-10-67>.
- Cropley, D. H., K. E. Medeiros, and A. Damadzic. 2022. *The Intersection of Human and Artificial Creativity*, 19–34. https://doi.org/10.1007/978-3-031-14549-0_2.
- Dash, R., M. McMurtrey, C. Rebman, and U. K. Kar. 2019. "Application of Artificial Intelligence in Automation of Supply Chain Management." *Journal of Strategic Innovation and Sustainability* 14, no. 3. <https://doi.org/10.33423/jsis.v14i3.2105>.
- Deiva Ganesh, A., and P. Kalpana. 2022. "Future of Artificial Intelligence and Its Influence on Supply Chain Risk Management – A Systematic Review." *Computers & Industrial Engineering* 169: 108206. <https://doi.org/10.1016/j.cie.2022.108206>.
- Dennehy, D., J. Oredo, K. Spanaki, S. Despoudi, and M. Fitzgibbon. 2021. "Supply Chain Resilience in Mindful Humanitarian Aid Organizations: The Role of Big Data Analytics." *International Journal of Operations &*

- Production Management* 41, no. 9: 1417–1441. <https://doi.org/10.1108/IJOPM-12-2020-0871>.
- Denzin, N. K. 2017. *The Research Act*. Routledge. <https://doi.org/10.4324/9781315134543>.
- Dey, P. K., S. Chowdhury, A. Abadie, E. Vann Yaroson, and S. Sarkar. 2024. “Artificial Intelligence-Driven Supply Chain Resilience in Vietnamese Manufacturing Small- and Medium-Sized Enterprises.” *International Journal of Production Research* 62, no. 15: 5417–5456. <https://doi.org/10.1080/00207543.2023.2179859>.
- Dietzmann, C., and Y. Duan. 2022. “Artificial Intelligence for Managerial Information Processing and Decision-Making in the Era of Information Overload.” <https://doi.org/10.24251/HICSS.2022.720>.
- Dubey, R., D. J. Bryde, C. Blome, D. Roubaud, and M. Giannakis. 2021. “Facilitating Artificial Intelligence Powered Supply Chain Analytics Through Alliance Management During the Pandemic Crises in the B2B Context.” *Industrial Marketing Management* 96: 135–146. <https://doi.org/10.1016/j.indmarman.2021.05.003>.
- Eisenhardt, K. M., and M. E. Graebner. 2007. “Theory Building From Cases: Opportunities and Challenges.” *Academy of Management Journal* 50, no. 1: 25–32. <https://doi.org/10.5465/amj.2007.24160888>.
- European Parliament & Council of the European Union. 2024. “Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligenceIntelligence.” Official Journal of the European Union, L 202, 1–144. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32024R1689>.
- Fahimnia, B., and A. Jabbarzadeh. 2016. “Marrying Supply Chain Sustainability and Resilience: A Match Made in Heaven.” *Transportation Research Part E: Logistics and Transportation Review* 91: 306–324. <https://doi.org/10.1016/j.tre.2016.02.007>.
- Flick, U. 2018. *Doing Triangulation and Mixed Methods*. SAGE Publications Ltd. <https://doi.org/10.4135/9781529716634>.
- Franzoni, V. 2023. *From Black Box to Glass Box: Advancing Transparency in Artificial Intelligence Systems for Ethical and Trustworthy AI*, 118–130. https://doi.org/10.1007/978-3-031-71114-1_9.
- Gallivan, M. J. 2001. “Organizational Adoption and Assimilation of Complex Technological Innovations.” *ACM SIGMIS Database: The DATABASE for Advances in Information Systems* 32, no. 3: 51–85. <https://doi.org/10.1145/506724.506729>.
- Gams, M., I. Y.-H. Gu, A. Härmä, A. Muñoz, and V. Tam. 2019. “Artificial intelligence and ambient intelligence.” *Journal of Ambient Intelligence and Smart Environments* 11, no. 1: 71–86. <https://doi.org/10.3233/AIS-180508>.
- Gasser, U. 2023. “An EU Landmark for AI Governance.” *Science* 380, no. 6651: 1203. <https://doi.org/10.1126/science.adj1627>.
- Gaudenzi, B., R. Pellegrino, and I. Confente. 2023. “Achieving Supply Chain Resilience in an Era of Disruptions: A Configuration Approach of Capacities and Strategies.” *Supply Chain Management: An International Journal* 28, no. 7: 97–111. <https://doi.org/10.1108/SCM-09-2022-0383>.
- Gieryn, T. F., W. E. Bijker, and J. Law. 1994. “Shaping Technology/ Building Society: Studies in Sociotechnical Change.” *Technology and Culture* 35, no. 2: 438. <https://doi.org/10.2307/3106331>.
- Gioia, D. A., K. G. Corley, and A. L. Hamilton. 2013. “Seeking Qualitative Rigor in Inductive Research.” *Organizational Research Methods* 16, no. 1: 15–31. <https://doi.org/10.1177/1094428112452151>.
- Glaser, B., and A. Strauss. 1970. “Theoretical Sampling.” In *Sociological Methods. A Sourcebook*, 105–114. Aldine Publishing Company.
- Greenhalgh, T., and R. Stones. 2010. “Theorising Big IT Programmes in Healthcare: Strong Structuration Theory Meets Actor-Network Theory.” *Social Science & Medicine* 70, no. 9: 1285–1294. <https://doi.org/10.1016/j.socscimed.2009.12.034>.
- Gruchmann, T., G. M. Stadtfeld, M. Thürer, and D. Ivanov. 2024. “Supply Chain Resilience as a System Quality: Survey-Based Evidence From Multiple Industries.” *International Journal of Physical Distribution & Logistics Management* 54, no. 1: 92–117. <https://doi.org/10.1108/IJPDLM-06-2023-0203>.
- Guida, M., F. Caniato, A. Moretto, and S. Ronchi. 2023. “The Role of Artificial Intelligence in the Procurement Process: State of the Art and Research Agenda.” *Journal of Purchasing and Supply Management* 29, no. 2: 100823. <https://doi.org/10.1016/j.pursup.2023.100823>.
- Gupta, S., S. Modgil, R. Meissonier, and Y. K. Dwivedi. 2024. “Artificial Intelligence and Information System Resilience to Cope With Supply Chain Disruption.” *IEEE Transactions on Engineering Management* 71: 10496–10506. <https://doi.org/10.1109/TEM.2021.3116770>.
- Gupta, V., D. Ivanov, and T.-M. Choi. 2021. “Competitive Pricing of Substitute Products Under Supply Disruption.” *Omega* 101: 102279. <https://doi.org/10.1016/j.omega.2020.102279>.
- Haenlein, M., and A. Kaplan. 2019. “A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence.” *California Management Review* 61, no. 4: 5–14. <https://doi.org/10.1177/0008125619864925>.
- Hald, K. S., and M. Spring. 2023. “Actor–Network Theory: A Novel Approach to Supply Chain Management Theory Development.” *Journal of Supply Chain Management* 59, no. 2: 87–105. <https://doi.org/10.1111/jscm.12296>.
- Hallikas, J., M. Immonen, and S. Brax. 2021. “Digitalizing Procurement: The Impact of Data Analytics on Supply Chain Performance.” *Supply Chain Management: An International Journal* 26, no. 5: 629–646. <https://doi.org/10.1108/SCM-05-2020-0201>.
- Hangl, J., V. J. Behrens, and S. Krause. 2022. “Barriers, Drivers, and Social Considerations for AI Adoption in Supply Chain Management: A Tertiary Study.” *Logistics* 6, no. 3: 63. <https://doi.org/10.3390/logistics6030063>.
- Harry, B., K. M. Sturges, and J. K. Klingner. 2005. “Mapping the Process: An Exemplar of Process and Challenge in Grounded Theory Analysis.” *Educational Researcher* 34, no. 2: 3–13. <https://doi.org/10.3102/0013189X034002003>.
- Hasija, A., and T. L. Esper. 2022. “In Artificial Intelligence (AI) we Trust: A Qualitative Investigation of AI Technology Acceptance.” *Journal of Business Logistics* 43, no. 3: 388–412. <https://doi.org/10.1111/jbl.12301>.
- Hlady-Rispal, M., and E. Jouison-Laffitte. 2014. “Qualitative Research Methods and Epistemological Frameworks: A Review of Publication Trends in Entrepreneurship.” *Journal of Small Business Management* 52, no. 4: 594–614. <https://doi.org/10.1111/jsbm.12123>.
- Hohenstein, N.-O., E. Feisel, E. Hartmann, and L. Giunipero. 2015. “Research on the Phenomenon of Supply Chain Resilience.” *International Journal of Physical Distribution & Logistics Management* 45, no. 1/2: 90–117. <https://doi.org/10.1108/IJPDLM-05-2013-0128>.
- Horvitz, E. 2017. “AI, People, and Society.” *Science* 357, no. 6346: 7. <https://doi.org/10.1126/science.aao2466>.
- Ivanov, D. 2021a. “Lean Resilience: AURA (Active Usage of Resilience Assets) Framework for Post-COVID-19 Supply Chain Management.” *International Journal of Logistics Management* 33, no. 4: 1196–1217. <https://doi.org/10.1108/IJLM-11-2020-0448>.
- Ivanov, D. 2021b. “Supply Chain Viability and the COVID-19 Pandemic: A Conceptual and Formal Generalisation of Four Major Adaptation Strategies.” *International Journal of Production Research* 59, no. 12: 3535–3552. <https://doi.org/10.1080/00207543.2021.1890852>.
- Ivanov, D., A. Pavlov, A. Dolgui, D. Pavlov, and B. Sokolov. 2016. “Disruption-Driven Supply Chain (Re)-planning and Performance Impact Assessment With Consideration of Pro-Active and Recovery

- Policies." *Transportation Research Part E: Logistics and Transportation Review* 90: 7–24. <https://doi.org/10.1016/j.tre.2015.12.007>.
- Jazairy, A., M. Brho, I. Manuj, and T. J. Goldsby. 2024. "Cyber Risk Management Strategies and Integration: Toward Supply Chain Cyber Resilience and Robustness." *International Journal of Physical Distribution & Logistics Management* 54, no. 11: 1–29. <https://doi.org/10.1108/IJPDLM-12-2023-0445>.
- Jöhnik, J., M. Weißert, and K. Wyrski. 2021. "Ready or Not, AI Comes—An Interview Study of Organizational AI Readiness Factors." *Business & Information Systems Engineering* 63, no. 1: 5–20. <https://doi.org/10.1007/s12599-020-00676-7>.
- Jüttner, U., and S. Maklan. 2011. "Supply Chain Resilience in the Global Financial Crisis: An Empirical Study." *Supply Chain Management: An International Journal* 16, no. 4: 246–259. <https://doi.org/10.1108/13598541111139062>.
- Kallio, H., A. Pietilä, M. Johnson, and M. Kangasniemi. 2016. "Systematic methodological review: developing a framework for a qualitative semi-structured interview guide." *Journal of Advanced Nursing* 72, no. 12: 2954–2965. <https://doi.org/10.1111/jan.13031>.
- Kaplan, A., and M. Haenlein. 2019. "Siri, Siri, in My Hand: Who's the Fairest in the Land? On the Interpretations, Illustrations, and Implications of Artificial Intelligence." *Business Horizons* 62, no. 1: 15–25. <https://doi.org/10.1016/j.bushor.2018.08.004>.
- Kar, A. K., and A. K. Kushwaha. 2023. "Facilitators and Barriers of Artificial Intelligence Adoption in Business—Insights From Opinions Using Big Data Analytics." *Information Systems Frontiers* 25, no. 4: 1351–1374. <https://doi.org/10.1007/s10796-021-10219-4>.
- Kar, S., A. K. Kar, and M. P. Gupta. 2021. "Modeling Drivers and Barriers of Artificial Intelligence Adoption: Insights From a Strategic Management Perspective." *Intelligent Systems in Accounting, Finance and Management* 28, no. 4: 217–238. <https://doi.org/10.1002/isaf.1503>.
- Kassa, A., D. Kitaw, U. Stache, B. Beshah, and G. Degefu. 2023. "Artificial Intelligence Techniques for Enhancing Supply Chain Resilience: A Systematic Literature Review, Holistic Framework, and Future Research." *Computers & Industrial Engineering* 186: 109714. <https://doi.org/10.1016/j.cie.2023.109714>.
- Keck, S., E. Diecidue, and D. V. Budescu. 2012. "Group Decisions Under Ambiguity: Convergence to Neutrality." *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2040655>.
- Khakurel, J., B. Penzenstadler, J. Porras, A. Knutas, and W. Zhang. 2018. "The Rise of Artificial Intelligence Under the Lens of Sustainability." *Technologies* 6, no. 4: 100. <https://doi.org/10.3390/technologies6040100>.
- Klien, G., D. D. Woods, J. M. Bradshaw, R. R. Hoffman, and P. J. Feltovich. 2004. "Ten Challenges for Making Automation a 'Team Player' in Joint Human-Agent Activity." *IEEE Intelligent Systems* 19, no. 6: 91–95. <https://doi.org/10.1109/MIS.2004.74>.
- Klumpp, M., and H. Zijm. 2019. "Logistics Innovation and Social Sustainability: How to Prevent an Artificial Divide in Human–Computer Interaction." *Journal of Business Logistics* 40, no. 3: 265–278. <https://doi.org/10.1111/jbl.12198>.
- Koponen, J., S. Julkunen, A. Laajalahti, M. Turunen, and B. Spitzberg. 2023. "Work Characteristics Needed by Middle Managers When Leading AI-Integrated Service Teams." *Journal of Service Research* 28: 168–185. <https://doi.org/10.1177/10946705231220462>.
- Kumar, D., R. K. Singh, R. Mishra, and T. U. Daim. 2023. "Roadmap for Integrating Blockchain With Internet of Things (IoT) for Sustainable and Secured Operations in Logistics and Supply Chains: Decision Making Framework With Case Illustration." *Technological Forecasting and Social Change* 196: 122837. <https://doi.org/10.1016/j.techfore.2023.122837>.
- Latour, B. 1992. "10 'Where Are the Missing Masses? The Sociology of a Few Mundane Artifacts'." In *Shaping Technology/Building Society: Studies in Sociotechnical Change*, 225–258. MIT Press.
- Latour, B. 1999. *Pandora's Hope: Essays on the Reality of Science Studies*. Harvard University Press.
- Latour, B. 2005. *Reassembling the Social*. Oxford University Press. <https://doi.org/10.1093/oso/9780199256044.001.0001>.
- Law, J. 2008. "Actor Network Theory and Material Semiotics." In *The New Blackwell Companion to Social Theory*, 141–158. Wiley. <https://doi.org/10.1002/9781444304992.ch7>.
- Law, J., and J. Hassard. 1999. *Actor Network Theory and After*. Wiley-Blackwell.
- Leake, D. B. 2001. "Artificial Intelligence." <https://api.semanticscholar.org/CorpusID:18409035>.
- Lee, H., G. Harindranath, S. Oh, and D.-J. Kim. 2015. "Provision of Mobile Banking Services From an Actor–Network Perspective: Implications for Convergence and Standardization." *Technological Forecasting and Social Change* 90: 551–561. <https://doi.org/10.1016/j.techfore.2014.02.007>.
- Legg, S., and M. Hutter. 2007. "Universal Intelligence: A Definition of Machine Intelligence." *Minds and Machines* 17, no. 4: 391–444. <https://doi.org/10.1007/s11023-007-9079-x>.
- Luo, J. S., D. M. Hilty, L. L. Worley, and J. Yager. 2006. "Considerations in Change Management Related to Technology." *Academic Psychiatry* 30, no. 6: 465–469. <https://doi.org/10.1176/appi.ap.30.6.465>.
- Madushanki, A. R., M. N. Halgamuge, W. S. Wirasagoda, and A. Syed. 2019. "Adoption of the Internet of Things (IoT) in Agriculture and Smart Farming Towards Urban Greening: A Review." *International Journal of Advanced Computer Science and Applications* 10, no. 4. <https://doi.org/10.14569/IJACSA.2019.0100402>.
- Maitlis, S., and S. Sonenshein. 2010. "Sensemaking in Crisis and Change: Inspiration and Insights From Weick (1988)." *Journal of Management Studies* 47, no. 3: 551–580. <https://doi.org/10.1111/j.1467-6486.2010.00908.x>.
- Martin, K., and B. Parmar. 2022. "What Firms Must Know Before Adopting AI: The Ethics of AI Transparency." *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4207128>.
- Mateos-Garcia, J. C. 2018. "The Complex Economics of Artificial Intelligence." *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3294552>.
- McCarthy, J., M. L. Minsky, N. Rochester, and C. E. Shannon. 1955. *A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence*. Dartmouth College.
- McClure, P. K. 2018. "'You're Fired,' Says the Robot." *Social Science Computer Review* 36, no. 2: 139–156. <https://doi.org/10.1177/0894439317698637>.
- Meggison, L. C. 1963. "Lessons From Europe for American Business." *Southwestern Social Science Quarterly* 44, no. 1: 3–13. <http://www.jstor.org/stable/42866937>.
- Melnyk, S., D. J. Closs, S. Griffis, C. Zobel, and J. Macdonald. 2014. "Understanding Supply Chain Resilience." *Supply Chain Management Review* 18: 34–41.
- Min, S., Z. G. Zacharia, and C. D. Smith. 2019. "Defining Supply Chain Management: In the Past, Present, and Future." *Journal of Business Logistics* 40, no. 1: 44–55. <https://doi.org/10.1111/jbl.12201>.
- Minsky, M. L. 1968. *Semantic Information Processing*. MIT Press.
- Modgil, S., S. Gupta, R. Stekelorum, and I. Laguir. 2022. "AI Technologies and Their Impact on Supply Chain Resilience During COVID-19." *International Journal of Physical Distribution & Logistics*

- Management 52, no. 2: 130–149. <https://doi.org/10.1108/IJPDLM-12-2020-0434>.
- Modgil, S., R. K. Singh, and C. Hannibal. 2022. “Artificial Intelligence for Supply Chain Resilience: Learning From Covid-19.” *International Journal of Logistics Management* 33, no. 4: 1246–1268. <https://doi.org/10.1108/IJLM-02-2021-0094>.
- Mohsen, B. M. 2023. “Impact of Artificial Intelligence on Supply Chain Management Performance.” *Journal of Service Science and Management* 16, no. 1: 44–58. <https://doi.org/10.4236/jssm.2023.161004>.
- Moosavi, J., A. M. Fathollahi-Fard, and M. A. Dulebenets. 2022. “Supply Chain Disruption During the COVID-19 Pandemic: Recognizing Potential Disruption Management Strategies.” *International Journal of Disaster Risk Reduction* 75: 102983. <https://doi.org/10.1016/j.ijdrr.2022.102983>.
- Münch, C., E. Marx, L. Benz, E. Hartmann, and M. Matzner. 2022. “Capabilities of Digital Servitization: Evidence From the Socio-Technical Systems Theory.” *Technological Forecasting and Social Change* 176: 121361. <https://doi.org/10.1016/j.techfore.2021.121361>.
- Musick, G., T. A. O'Neill, B. G. Schelble, N. J. McNeese, and J. B. Henke. 2021. “What Happens When Humans Believe Their Teammate Is an AI? An Investigation Into Humans Teaming With Autonomy.” *Computers in Human Behavior* 122: 106852. <https://doi.org/10.1016/j.chb.2021.106852>.
- Nag, R., K. G. Corley, and D. A. Gioia. 2007. “The Intersection of Organizational Identity, Knowledge, and Practice: Attempting Strategic Change via Knowledge Grafting.” *Academy of Management Journal* 50, no. 4: 821–847. <https://doi.org/10.5465/amj.2007.26279173>.
- Nass, C., J. Steuer, and E. R. Tauber. 1994. “Computers Are Social Actors.” In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems Celebrating Interdependence—CHI '94*, 72–78. <https://doi.org/10.1145/191666.191703>.
- Naz, F., A. Kumar, A. Majumdar, and R. Agrawal. 2022. “Is Artificial Intelligence an Enabler of Supply Chain Resiliency Post COVID-19? An Exploratory State-Of-The-Art Review for Future Research.” *Operations Management Research* 15, no. 1–2: 378–398. <https://doi.org/10.1007/s12063-021-00208-w>.
- Nilsson, N. 2009. *The Quest for Artificial Intelligence*. Cambridge University Press.
- Niranjan, K., K. S. Narayana, and M. V. A. L. N. Rao. 2021. “Role of Artificial Intelligence in Logistics and Supply Chain.” In *2021 International Conference on Computer Communication and Informatics (ICCCI)*, 1–3. <https://doi.org/10.1109/ICCCI50826.2021.9402625>.
- Nitsche, B., J. Brands, H. Treiblmaier, and J. Gebhardt. 2023. “The Impact of Multiagent Systems on Autonomous Production and Supply Chain Networks: Use Cases, Barriers and Contributions to Logistics Network Resilience.” *Supply Chain Management: An International Journal* 28, no. 5: 894–908. <https://doi.org/10.1108/SCM-07-2022-0282>.
- Nokelainen, T. S., O. Dedehayir, and J. Järvinen. 2012. “Why Displaced Technologies Won't Go Away: The Case of the LP Record.” *Academy of Management Proceedings* 2012, no. 1: 15476. <https://doi.org/10.5465/AMBPP.2012.15476abstract>.
- Norman, D. A. 1994. “How Might People Interact With Agents.” *Communications of the ACM* 37, no. 7: 68–71. <https://doi.org/10.1145/176789.176796>.
- Organisation for Economic Co-operation and Development. 2024. “Hiroshima AI Process (HAIP) International Code of Conduct for Organizations Developing Advanced AI Systems.” <https://Oecd.Ai/En/G7>.
- Pal, A., S. Gopi, and K. M. Lee. 2023. “Fintech Agents: Technologies and Theories.” *Electronics* 12, no. 15: 3301. <https://doi.org/10.3390/electronics12153301>.
- Pauli, T., E. Marx, E. Fieft, C. Marheine, and M. Matzner. 2025. “Inhibitors and Enablers of Leverage in Digital Industrial Platform Ecosystems.” *Business & Information Systems Engineering*. <https://doi.org/10.1007/s12599-024-00896-1>.
- Pauwels, P., and P. Matthyssens. 2004. “The Architecture of Multiple Case Study Research in International Business.” In *Handbook of Qualitative Research Methods for International Business*. Edward Elgar Publishing. <https://doi.org/10.4337/9781781954331.00020>.
- Pavlov, A., D. Ivanov, D. Pavlov, and A. Slinko. 2019. “Optimization of Network Redundancy and Contingency Planning in Sustainable and Resilient Supply Chain Resource Management Under Conditions of Structural Dynamics.” *Annals of Operations Research* 349: 495–524. <https://doi.org/10.1007/s10479-019-03182-6>.
- Pettit, T. J., K. L. Croxton, and J. Fiksel. 2019. “The Evolution of Resilience in Supply Chain Management: A Retrospective on Ensuring Supply Chain Resilience.” *Journal of Business Logistics* 40, no. 1: 56–65. <https://doi.org/10.1111/jbl.12202>.
- Pettit, T. J., J. Fiksel, and K. L. Croxton. 2010. “Ensuring Supply Chain Resilience: Development of A Conceptual Framework.” *Journal of Business Logistics* 31, no. 1: 1–21. <https://doi.org/10.1002/j.2158-1592.2010.tb00125.x>.
- Pournader, M., H. Ghaderi, A. Hassanzadegan, and B. Fahimnia. 2021. “Artificial Intelligence Applications in Supply Chain Management.” *International Journal of Production Economics* 241: 108250. <https://doi.org/10.1016/j.ijpe.2021.108250>.
- Pratt, M. G. 2008. “Fitting Oval Pegs Into Round Holes.” *Organizational Research Methods* 11, no. 3: 481–509. <https://doi.org/10.1177/1094428107303349>.
- Pujawan, I. N., and A. U. Bah. 2022. “Supply Chains Under COVID-19 Disruptions: Literature Review and Research Agenda.” *Supply Chain Forum: An International Journal* 23, no. 1: 81–95. <https://doi.org/10.1080/16258312.2021.1932568>.
- Puşcă, C. 2020. “Legal Aspects on the Implementation of Artificial Intelligence.” *EAI Endorsed Transactions on Creative Technologies* 7, no. 24: 164174. <https://doi.org/10.4108/eai.13-7-2018.164174>.
- Rakowski, R., and P. Kowaliková. 2024. “The Political and Social Contradictions of the Human and Online Environment in the Context of Artificial Intelligence Applications.” *Humanities and Social Sciences Communications* 11, no. 1: 289. <https://doi.org/10.1057/s41599-024-02725-y>.
- Riad, M., M. Naimi, and C. Okar. 2024. “Enhancing Supply Chain Resilience Through Artificial Intelligence: Developing a Comprehensive Conceptual Framework for AI Implementation and Supply Chain Optimization.” *Logistics* 8, no. 4: 111. <https://doi.org/10.3390/logistics8040111>.
- Riahi, Y., T. Saikouk, A. Gunasekaran, and I. Badraoui. 2021. “Artificial Intelligence Applications in Supply Chain: A Descriptive Bibliometric Analysis and Future Research Directions.” *Expert Systems With Applications* 173: 114702. <https://doi.org/10.1016/j.eswa.2021.114702>.
- Rice, J. B. J., and F. Caniato. 2003. “Building a Secure and Resilient Supply Network.” *Supply Chain Management Review* 7, no. 5: 22–30.
- Richey, R. G., T. R. Morgan, K. Lindsey-Hall, and F. G. Adams. 2016. “A Global Exploration of Big Data in the Supply Chain.” *International Journal of Physical Distribution & Logistics Management* 46, no. 8: 710–739. <https://doi.org/10.1108/IJPDLM-05-2016-0134>.
- Richey, R. G., A. S. Roath, F. G. Adams, and A. Wieland. 2022. “A Responsiveness View of Logistics and Supply Chain Management.” *Journal of Business Logistics* 43, no. 1: 62–91. <https://doi.org/10.1111/jbl.12290>.
- Robles Carrillo, M. 2020. “Artificial Intelligence: From Ethics to Law.” *Telecommunications Policy* 44, no. 6: 101937. <https://doi.org/10.1016/j.telpol.2020.101937>.

- Rodríguez-Espíndola, O., S. Chowdhury, A. Beltagui, and P. Albores. 2020. "The Potential of Emergent Disruptive Technologies for Humanitarian Supply Chains: The Integration of Blockchain, Artificial Intelligence and 3D Printing." *International Journal of Production Research* 58, no. 15: 4610–4630. <https://doi.org/10.1080/00207543.2020.1761565>.
- Russo, D. 2024. "Navigating the Complexity of Generative AI Adoption in Software Engineering." *ACM Transactions on Software Engineering and Methodology* 33, no. 5: 1–50. <https://doi.org/10.1145/3652154>.
- Safari, A., V. Balicevac Al Ismail, M. Parast, I. Gölgeci, and S. Pokharel. 2024. "Supply Chain Risk and Resilience in Startups, SMEs, and Large Enterprises: A Systematic Review and Directions for Research." *International Journal of Logistics Management* 35, no. 2: 680–709. <https://doi.org/10.1108/IJLM-10-2022-0422>.
- Saldana, J. 2015. *The Coding Manual for Qualitative Researchers*. SAGE Publications. <https://books.google.de/books?id=ZhxiCgAAQBAJ>.
- Samarghandi, H., D. Askarany, and B. Dehkordi. 2023. "A Hybrid Method to Predict Human Action Actors in Accounting Information System." *Journal of Risk and Financial Management* 16, no. 1: 37. <https://doi.org/10.3390/jrfm16010037>.
- Samoili, S., M. L. Cobo, E. Gómez, G. De Prato, F. Martínez-Plumed, and B. Delipetrev. 2020. "AI Watch. Defining Artificial Intelligence. Towards an Operational Definition and Taxonomy of Artificial Intelligence." <https://api.semanticscholar.org/CorpusID:216021594>.
- Sanders, N. R., T. Boone, R. Ganeshan, and J. D. Wood. 2019. "Sustainable Supply Chains in the Age of AI and Digitization: Research Challenges and Opportunities." *Journal of Business Logistics* 40, no. 3: 229–240. <https://doi.org/10.1111/jbl.12224>.
- Schlögl, S., C. Postulka, R. Bernsteiner, and C. Ploder. 2019. *Artificial Intelligence Tool Penetration in Business: Adoption, Challenges and Fears*, 259–270. https://doi.org/10.1007/978-3-030-21451-7_22.
- Scholten, K., and S. Schilder. 2015. "The Role of Collaboration in Supply Chain Resilience." *Supply Chain Management: An International Journal* 20, no. 4: 471–484. <https://doi.org/10.1108/SCM-11-2014-0386>.
- Sharma, M., S. Luthra, S. Joshi, and A. Kumar. 2022. "Implementing Challenges of Artificial Intelligence: Evidence From Public Manufacturing Sector of an Emerging Economy." *Government Information Quarterly* 39, no. 4: 101624. <https://doi.org/10.1016/j.giq.2021.101624>.
- Sharma, R., A. Shishodia, A. Gunasekaran, H. Min, and Z. H. Munim. 2022. "The Role of Artificial Intelligence in Supply Chain Management: Mapping the Territory." *International Journal of Production Research* 60, no. 24: 7527–7550. <https://doi.org/10.1080/00207543.2022.2029611>.
- Sheffi, Y. 2007. *The Resilient Enterprise*. MIT Press.
- Shim, Y., and D.-H. Shin. 2016. "Analyzing China's Fintech Industry from the Perspective of Actor–Network Theory." *Telecommunications Policy* 40, no. 2–3: 168–181. <https://doi.org/10.1016/j.telpol.2015.11.005>.
- Singh, R. K., S. Modgil, and A. Shore. 2024. "Building Artificial Intelligence Enabled Resilient Supply Chain: A Multi-Method Approach." *Journal of Enterprise Information Management* 37, no. 2: 414–436. <https://doi.org/10.1108/JEIM-09-2022-0326>.
- Söderström, O., T. Paasche, and F. Klausner. 2014. "Smart Cities as Corporate Storytelling." *City* 18, no. 3: 307–320. <https://doi.org/10.1080/13604813.2014.906716>.
- Sofinska, I. 2024. *Legal Framework on Trustworthy Artificial Intelligence and Blockchain Technology Application*, 104–107. https://doi.org/10.1007/978-3-031-56776-6_10.
- Stinson, C. 2022. "Algorithms Are Not Neutral." *AI and Ethics* 2, no. 4: 763–770. <https://doi.org/10.1007/s43681-022-00136-w>.
- Stone, J., and S. Rahimifard. 2018. "Resilience in Agri-Food Supply Chains: A Critical Analysis of the Literature and Synthesis of a Novel Framework." *Supply Chain Management: An International Journal* 23, no. 3: 207–238. <https://doi.org/10.1108/SCM-06-2017-0201>.
- Swanson, D., and Y. Suzuki. 2020. "COVID-19 Carves New Facets of Supply Chain Disruption." *Transportation Journal* 59, no. 4: 325–334. <https://doi.org/10.5325/transportationj.59.4.0325>.
- Takeuchi, A., and T. Naito. 1995. "Situating Facial Displays." In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems—CHI '95*, 450–455. <https://doi.org/10.1145/223904.223965>.
- Themistocleous, M., Z. Irani, and R. M. O'Keefe. 2001. "ERP and Application Integration." *Business Process Management Journal* 7, no. 3: 195–204. <https://doi.org/10.1108/14637150110392656>.
- Thürer, M., I. Tomašević, M. Stevenson, et al. 2020. "A Systematic Review of China's Belt and Road Initiative: Implications for Global Supply Chain Management." *International Journal of Production Research* 58, no. 8: 2436–2453. <https://doi.org/10.1080/00207543.2019.1605225>.
- Tracy, S. J. 2010. "Qualitative Quality: Eight "Big-Tent" Criteria for Excellent Qualitative Research." *Qualitative Inquiry* 16, no. 10: 837–851. <https://doi.org/10.1177/1077800410383121>.
- Tu, M. 2018. "An Exploratory Study of Internet of Things (IoT) Adoption Intention in Logistics and Supply Chain Management." *International Journal of Logistics Management* 29, no. 1: 131–151. <https://doi.org/10.1108/IJLM-11-2016-0274>.
- Umar, M., and M. M. J. Wilson. 2024. "Inherent and Adaptive Resilience of Logistics Operations in Food Supply Chains." *Journal of Business Logistics* 45, no. 1. <https://doi.org/10.1111/jbl.12362>.
- Van Maanen, J. 1998. *Qualitative Studies of Organizations (Issue Bd. 1)*. SAGE Publications. <https://books.google.de/books?id=rQ3rQLH1Ba4C>.
- von Soest, C. 2023. "Why Do we Speak to Experts? Reviving the Strength of the Expert Interview Method." *Perspectives on Politics* 21, no. 1: 277–287. <https://doi.org/10.1017/S1537592722001116>.
- Walsham, G., and S. Sahay. 1999. "GIS for District-Level Administration in India: Problems and Opportunities." *MIS Quarterly* 23, no. 1: 39. <https://doi.org/10.2307/249409>.
- Wang, M., A. Hill, Y. Liu, K. Hwang, and M. K. Lim. 2025. "Supply Chain Digitalization and Agility: How Does Firm Innovation Matter in Companies?" *Journal of Business Logistics* 46, no. 1: e70007. <https://doi.org/10.1111/jbl.70007>.
- Wang, P. 2019. "On Defining Artificial Intelligence." *Journal of Artificial General Intelligence* 10, no. 2: 1–37. <https://doi.org/10.2478/jagi-2019-0002>.
- Wieland, A. 2021. "Dancing the Supply Chain: Toward Transformative Supply Chain Management." *Journal of Supply Chain Management* 57, no. 1: 58–73. <https://doi.org/10.1111/jscm.12248>.
- Wieland, A., and C. F. Durach. 2021. "Two Perspectives on Supply Chain Resilience." *Journal of Business Logistics* 42, no. 3: 315–322. <https://doi.org/10.1111/jbl.12271>.
- Wooldridge, M. 2002. *Intelligent Agents: The Key Concepts*, 3–43. https://doi.org/10.1007/3-540-45982-0_1.
- Wooldridge, M., and N. R. Jennings. 1995. "Intelligent Agents: Theory and Practice." *Knowledge Engineering Review* 10, no. 2: 115–152. <https://doi.org/10.1017/S0269888900008122>.
- Xu, L., S. Mak, and A. Brintrup. 2021. "Will Bots Take Over the Supply Chain? Revisiting Agent-Based Supply Chain Automation." *International Journal of Production Economics* 241: 108279. <https://doi.org/10.1016/j.ijpe.2021.108279>.
- Xu, L., S. Mak, M. Minaricova, and A. Brintrup. 2024. "On Implementing Autonomous Supply Chains: A Multi-Agent System Approach." *Computers in Industry* 161: 104120. <https://doi.org/10.1016/j.compind.2024.104120>.

Xu, L., S. Mak, Y. Proselkov, and A. Brintrup. 2024. "Towards Autonomous Supply Chains: Definition, Characteristics, Conceptual Framework, and Autonomy Levels." *Journal of Industrial Information Integration* 42: 100698. <https://doi.org/10.1016/j.jii.2024.100698>.

Yan, F., L. Chen, F. Jia, and Y. Liu. 2023. "Building Supply Chain Resilience Through Collaborative Innovation: An Information Processing Theory Perspective." *Journal of Digital Economy* 2: 233–243. <https://doi.org/10.1016/j.jdec.2024.01.004>.

Yin, R. K. 2009. *Case Study Research: Design and Methods*. Vol. 5. SagePublications, Inc.

Yoon, J., S. Talluri, and C. Rosales. 2020. "Procurement Decisions and Information Sharing Under Multi-Tier Disruption Risk in a Supply Chain." *International Journal of Production Research* 58, no. 5: 1362–1383. <https://doi.org/10.1080/00207543.2019.1634296>.

Yurui, L., Z. Xuanchang, C. Zhi, L. Zhengjia, L. Zhi, and L. Yansui. 2021. "Towards the Progress of Ecological Restoration and Economic Development in China's Loess Plateau and Strategy for More Sustainable Development." *Science of the Total Environment* 756: 143676. <https://doi.org/10.1016/j.scitotenv.2020.143676>.

Zamani, E. D., C. Smyth, S. Gupta, and D. Dennehy. 2023. "Artificial Intelligence and Big Data Analytics for Supply Chain Resilience: A Systematic Literature Review." *Annals of Operations Research* 327, no. 2: 605–632. <https://doi.org/10.1007/s10479-022-04983-y>.

Zhao, G., M. Vazquez-Noguerol, S. Liu, and J. C. Prado-Prado. 2024. "Agri-Food Supply Chain Resilience Strategies for Preparing, Responding, Recovering, and Adapting in Relation to Unexpected Crisis: A Cross-Country Comparative Analysis From the COVID-19 Pandemic." *Journal of Business Logistics* 45, no. 1. <https://doi.org/10.1111/jbl.12361>.

Appendix 1

Coding Scheme

