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Artificial intelligence techniques for enhancing supply chain resilience: A systematic literature review, holistic framework, and future research

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ABSTRACT

Today's supply chains (SC) have become vulnerable to unexpected and ever-intensifying disruptions from myriad sources. Consequently, the concept of supply chain resilience (SCRes) has become crucial to complement the conventional risk management paradigm, which has failed to cope with unexpected SC disruptions resulting in severe consequences affecting SC performances and making business continuity questionable. Advancements in cutting-edge technologies like artificial intelligence (AI) and their potential to enhance SCRes by improving critical antecedents across different phases have attracted the attention of scholars and practitioners. The research from academia and the practical interest of the industry have yielded significant publications at the nexus of AI and SCRes during the last two decades. However, the applications and examinations have been primarily conducted independently, and the extant literature is dispersed into research streams despite the complex nature of SCRes. To bridge this gap, this study undertakes a systematic literature review involving 106 peer-reviewed articles. Through curation, synthesis, and consolidation of up-to-date literature, the study presents a comprehensive overview of developments spanning from 2010 to 2022. Bayesian networks are the most topical ones among the 13 AI techniques evaluated. Concerning the critical antecedents, visibility is the first ranking to be realized by the techniques. The study revealed that AI techniques support only the first 3 phases of SCRes (readiness, response, and recovery), and readiness is the most popular one, while no evidence has been found for the growth phase. The study proposed an AI-SCRes framework to inform research and practice to holistically approach SCRes. It also provided implications for practice, policy, and theory as well as gaps for impactful future research.

1. Introduction

Supply chains (SCs) are the backbone of the national economy of a county as they consistently provide markets, businesses, and society with goods and services (e.g., food, medical supplies, raw materials, spare parts, communication, and mobility). Recently, SCs have been growing in length and complexity (Basole & Bellamy, 2014; Blackhurst et al., 2011; Pettit et al., 2013) to gain competitiveness in local and global markets, thereby reaping the efficiencies from operating at lower costs. The pressure to reduce SC costs led to offshore most of the manufacturing and R&D-related activities (Katsaliaki et al., 2021). However, complexities in the extended networks (Barroso et al., 2015; Snyder et al., 2016), interdependencies, and interconnectedness among the globally dispersed heterogeneous and autonomous entities (Basole & Bellamy, 2014) exposed SCs to operate in an uncertain, dynamic, competitive, vulnerable, risky, ambiguous, and volatile business environment (Lechler et al., 2019). SC disruptions from myriad sources, including technological changes, pandemic outbreaks, catastrophic events (e.g., natural disasters), socio-political instabilities, political interventions, terrorism, energy crises, economic recessions, changing customers' preferences, and so forth (Chowdhury & Quaddus, 2017; Christopher & Peck, 2004; Er Kara et al., 2020; Golgeci & Ponomarov, 2013; Lawrence et al., 2020; Lechler et al., 2019; Mubarik & Bontis, 2021; Pettit et al., 2019; Rice & Caniato, 2003; Tordecilla et al., 2021) are representing risks to SCs (Golgeci & Ponomarov, 2013). The adoption of modern management philosophies to enhance effectiveness and reduce operating costs (Barroso et al., 2015), such as the lean practices, leveled and just-in-time production (Jüttner et al., 2003), and accurate

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scheduling of transportation systems (Katsaliaki et al., 2021) also created brittleness in SCs with no slack available to fall back on when disruptions take effect (Barroso et al., 2015; Blackhurst et al., 2011; Rajagopal et al., 2017; Snyder et al., 2016).

The inherent complexities of the evolving SCs and the external forces affecting them have introduced many changes in the equation governing SCs (Aliahmadi et al., 2022). Many unexpected and unprecedented disruptive events notoriously affected today's SCs severely (Ganesh & Kalpana, 2022). Among others, the Brexit (Hendry et al., 2019; Lechler et al., 2019), US-Chines trade war, and the Covid-19 pandemic (Belhadi et al., 2021b; Ganesh & Kalpana, 2022; Govindan et al., 2020; Naz et al., 2021; Pournader & Kach, 2020; Queiroz et al., 2020; Rahman et al., 2022) are the most recent, popular, and critical ones (Ivanov, 2021; Mubarik & Bontis, 2021; Spieske & Birkel, 2021; Tordecilla et al., 2021). The events have revealed the vulnerability and the lack of preparedness in SCs for unexpected disruptions and the inefficiency of the conventional SC risk management paradigm (Pettit et al., 2019).

The severe consequences resulting from SC disruptions can include decreases in company revenue (Hosseini et al., 2016), lowered customers services (Rajagopal et al., 2017), delays in production ramp-ups (Belhadi et al., 2021b; Ponnambalam et al., 2014), and deliveries (Basole & Bellamy, 2014), loss of sales (Y. Liu et al., 2020), lowered product quality (Bhamra et al., 2011; Jüttner et al., 2003; Lorenc et al., 2021) increased SC and shortage costs (Rahman et al., 2022), loss of production facilities and work forces shortages (Govindan et al., 2020; Tummala & Schoenherr, 2011) in life saving-commodities such as blood (Lawrence et al., 2020; Shokouhifar & Ranjbarimesan, 2022), loss of brand reputation (Chae, 2015; Fan & Stevenson, 2018), and even loss of the entire business (Blackhurst et al., 2011; Heckmann et al., 2015; Jüttner & Maklan, 2011; Ojha et al., 2018; Rajagopal et al., 2017; Snyder et al., 2016). The disruptive impacts frequently yield ripple effects across the entire supply chain (Ivanov, 2020; Ivanov et al., 2019; Pavlov et al., 2019; Queiroz et al., 2020).

Given the consequences, embracing the culture of resilience (Pettit et al., 2019) and complementing the conventional risk management approach with resilience are imperative. Supply chain resilience (SCRes) is the ability to proactively plan and design an SC network to anticipate unexpected disruptions and to adaptively respond by maintaining control over structure and function of a post-event robust state operation, if possible, better than the one before the disruption, thus gaining competitive advantage in the long run by bouncing back faster than the rivals (Abeysekara et al., 2019; Altay et al., 2018; Belhadi et al., 2021c; Dubey et al., 2019; Gölgeci & Kuivalainen, 2020; Ivanov, 2021; Jüttner & Maklan, 2011; Kaviani et al., 2020; Kwak et al., 2018; Spieske & Birkel, 2021; Zavala-Alcívar et al., 2020). Instead of addressing disruptive risks in a piecemeal fashion, with resiliency, organizations intend to address disruptions with a system approach (Pettit et al., 2019). The concept of resilience greatly appeals to the organization. However, its effective adoption needs the development of various capabilities aligned with the SC partners (A. Ali et al., 2017). Among others is an IT approach that promotes business continuity (Naz et al., 2021), a culture of readiness in contingency actions, long-term partnerships, and government policy that supports flexibility (Katsaliaki et al., 2021).

Current research outcomes in the field of SCRes have shown a promising result that cutting-edge technologies like artificial intelligence (AI) hold to develop, maintain, and enhance SCRes (Dolgui & Ivanov, 2020; Ivanov et al., 2019; Katsaliaki et al., 2021; Koot et al., 2021; Modgil et al., 2022; Naz et al., 2021; Ralston & Blackhurst, 2020; Spieske & Birkel, 2021; Zamani et al., 2022) and support the conventional SC risk management practices (Aboutorab et al., 2021; I. Ali & Govindan, 2021; Baryannis et al., 2019b; Ganesh & Kalpana, 2022; Shah et al., 2021). AI techniques can interpret external data correctly, learn from such data, and use those learnings to achieve specific goals through flexible adaptation (Dhamija & Bag, 2020; Grover et al., 2020; Haenlein & Kaplan, 2019; Sharma et al., 2020). Given these capabilities, AI techniques are best at clarifying uncertainties (Zamani et al., 2022), and they can be used in identifying, assessing, and controlling risks in SCs (Baryannis et al., 2019b). They can also be utilized for building systemic resilience in SCs as they can support the readiness, response, and recovery phases of SCRes which had not been possible with the classical information processing systems that are very simplistic (Pettit et al., 2019; Ralston & Blackhurst, 2020; Spieske & Birkel, 2021) and techniques to deal with the disruptions that are intensifying in today's globally growing and complex SCs.

In response to calls by scholars to carry out more research studies at the nexus of enabling technologies like AI and SCRes (Dolgui & Ivanov, 2020; Ivanov et al., 2019; Ivanov & Dolgui, 2021; Katsaliaki et al., 2021; Koot et al., 2021; Spieske & Birkel, 2021), significant research progress has been made in recent times. Many empirical works exploring the applications of AI in SCRes have been reported, and the significant difference between the firms adopting AI and others not adopting AI has been revealed empirically (Belhadi et al., 2021c; Gölgeci & Ponomarov, 2015). The research from academia and the practical interest of the industry have yielded significant publications at the nexus of AI and SCRes during the last two decades.

However, the concept of SCRes is complex (Spieske & Birkel, 2021) and multi-disciplinary (Iftikhar et al., 2021, 2022), extending beyond the scope of conventional risk management paradigm (Fiksel, 2015). It is manifested by multiple variables (Arsovski et al., 2017) that require an aggregative approach for comprehensive understanding. Moreover, applications and examinations have been conducted independently, resulting in the dispersion of existing literature across various research streams. This dispersal persists despite the complex nature of SCRes, highlighting the gap in reviewing the potential of AI techniques to build and enhance SCRes within SC networks. Consequently, a systematic literature review becomes imperative to consolidate the fragmented knowledge base, propose a comprehensive framework for guiding research and practical implementation, and identify current trends and opportunities that can shape impactful future research.

In this regard, recent prior works by Naz et al. (2021), Zamani et al. (2022), and Iftikhar et al. (2022) offer some insightful literature reviews at the nexus of AI and SCRes. Iftikhar et al. (2022) conducted a bibliometric analysis at the nexus of innovative technologies, including AI, data analytics, and SCRes. Their analysis uncovered critical research cluster, the evolution of research, knowledge trajectories, and methodological advancements in the area. Zamani et al. (2022) conducted a systematic literature review at the nexus of AI, big data analytics (BDA), and SCRes. Their study evaluated the current state of AI and BDA within SCRes literature. Despite demonstrating the relevance of AI in SCRes, both reviews works primarily discuss AI and SCRes concepts at a somewhat abstract level. However, they do not explicitly delve into how AI techniques can substantially enhance SCRes.

The only study that directly examines research outputs at the nexus of AI techniques and SCRes was conducted by Naz et al. (2021). They examined the potential research contribution in the field of AI ad SCRes with a specific purpose to let project management perform well post the Covid-19 pandemic era. The review delved into various research themes within SCRes and highlighted the general benefits of AI techniques. However, while their review underscores the potential of AI techniques in SCRes, it falls short in elucidating how these techniques contribute specifically to the diverse facets of SCRes.

The conceptual development from the state-of-the-art reviews indicates that the antecedents are the building elements that contribute to the readiness, response, recovery, and growth phases of SCRes (Hohenstein et al., 2015). When addressing SCRes using AI, it is crucial to carefully consider and evaluate the specific techniques and their inherent capabilities. Therefore, review at the nexus of AI and SCRes has to be with regard to the specific techniques and their capabilities contributing to the critical antecedents and the phases of SCRes. Furthermore, the scattered knowledge based have to be integrated into a comprehensive framework to inform research and practice in a holistic manner. However, To the best of the authors' knowledge, there has been no review work with the deliberation of the abovementioned aspects.

Therefore, to fill in the stated gaps, the study's objectives are to:

- Exhaustively curate and synthesize fragmented knowledge base to draw insight into the evolution of research at the nexus of AI and SCRes,
- Identify and evaluate studies with regard to the applied AI techniques and their capabilities in realizing SCRes,
- Examine the applications of AI techniques in realizing specific antecedents and phases of SCRes and addressing specific SCRes tasks,
- Develop a conceptual framework based on synthesized positive relationships between AI techniques and SCRes that inform a holistic practice of AI in SCRes, and
- Draw a clear picture of the missing aspects in using AI techniques in SCRes and the promising avenues for more future impactful research at the nexus of AI and SCRes.

The remainder of the paper is structured as follows. Section 2 presents background on AI taxonomy and SCRes. In section 3, the systematic literature review methodology is outlined and applied. Questions are formulated, and relevant articles are collected and analyzed to answer the questions. An AI-SCRes framework is developed and presented in section 4 based on the synthesized relationships between AI techniques, SCRes antecedents, and phases to answer research questions further and inform research and practice. The implications of the study in terms of practice, policy, and theory and directions for promising avenues for more future impactful research are presented in section 5. Finally, section 6 discusses the conclusion concerning the research questions and the results obtained and acknowledges the limitation of this study.

2. Background of the study

2.1. Artificial intelligence techniques

Artificial intelligence (AI) is concerned with the automation of intelligent behavior (Luger, 2009) and is defined as "a system's ability to interpret external data correctly, to learn from such data (Baryannis et al., 2019a; Spieske & Birkel, 2021), and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Dhamija & Bag, 2020; Grover et al., 2020; Haenlein & Kaplan, 2019; Sharma et al., 2020). AI algorithms are inspired by how human cognitive systems and natural organisms operate to process information through learning, adaptation, reproduction, and survival (Belhadi et al., 2021a; Min, 2010; Toorajipour et al., 2021). Following the works of Bundy (1997) and Toorajipour et al.(2021) regarding "AI techniques," we refer to algorithms, architectures, data or knowledge formalism, and methodologies that can be described in a clear, precise manner. Based on the frequent applications of the techniques in the field of SCRes, they are categorized into five classes: machine learning, fuzzy logic, multi-agent intelligent systems, rough set theory, and genetic algorism.

Machine learning (ML) is a subfield of AI (Makkar & Devi, 2020; Sharma et al., 2020), which is a technical process by which a system is trained to perform assigned tasks with no human intervention (Cavalcante et al., 2019; Min, 2010) to keep improving on its own and to learn from the pattern of available data (Egidi & Manzini, 2015; P. Kim, 2017; Ni et al., 2020). ML algorithms learn from data without relying on a predetermined equation as a model. ML is proposed to tackle the failure of the pioneer expert systems (Luger, 2009) to remember subsequent solutions. In ML, prediction models are built on electronic historical data to predict and find hidden patterns to make accurate (Mohri et al., 2018) future decisions where humans could not (Giri et al., 2019; Ni et al., 2020). The algorithms are data-driven methods combining fundamental statistics and optimization concepts (Mohri et al., 2018). Appendix A provides brief descriptions of the prominent ML algorithms, fuzzy logic, multi-agent intelligent systems, rough set theory, and genetic algorithms.

2.2. Supply chain resilience

Resilience is a multi-disciplinary and multi-dimensional concept that is researched in different areas of knowledge, such as social science, psychology, economics, engineering, etc. (Altay et al., 2018; Asamoah et al., 2020; Chowdhury & Quaddus, 2017; Dubey et al., 2021; Elleuch et al., 2016; Gölgeci & Kuivalainen, 2020; Hosseini & Ivanov, 2020; Mishra et al., 2019; Patel et al., 2022; Pettit et al., 2013; Ponomarov & Holcomb, 2009; Tukamuhabwa et al., 2015) and has its origin in Latin, where(resilio) had the meaning of springing back; recoiling; rebounding (Ponis & Koronis, 2012). The concept of supply chain resilience (SCRes) has emerged as a reaction to increased disruptions in supply chains (Ivanov, 2021) and inadequacies of the classical risk management paradigm, which is an event-oriented approach for well-known and predictable disruptive events (Agarwal et al., 2021; Fiksel, 2015; Jüttner & Maklan, 2011; Mandal, 2020; Hohenstein et al., 2015; Pettit et al., 2013; Zavala et al., 2019). Fiksel (2015) argues that in the face of complexity and turbulence, when disruptions are often unknowable and unforeseen, risk assessment, one of the tasks of the classical risk management paradigm, becomes intractable, and its practices are no longer adequate. Adaptation may be needed to remain competitive in the face of disruptions. Fiksel (2015) further stresses that not all risks are identified or anticipated and may be hard to quantify.

Despite its examinations in many scientific studies, there is no universally accepted definition of SCRes (A. Ali et al., 2017; Dubey et al., 2019; Han et al., 2020; Zavala et al., 2019). Ali et al. (2017) analyzed the concept of SCRes in 103 journal articles and discovered that the definitions differ in the distinct capabilities to be contained in the phases when dealing with disruptions. We base our definition for the review on the works of Ali et al. (2017), Hohenstein et al. (2015), and Spieske & Birkel (2021), who introduced four district phases: readiness, response, recovery, and growth and Zavala-Alcívar et al. (2020), Dubey et al. (2019), Abeysekara et al. (2019), Kaviani et al. (2020), Altay et al. (2018), Kwak et al.(2018), Gölgeci & Kuivalainen (2020), Jüttner & Maklan (2011), and Scholten et al. (2019), who defined SCRes as "the ability to proactively plan and design the SC network for anticipating unexpected disruptions, respond adaptively to disruptions while maintaining control over structure and function transcending to a post-event robust state operation, if possible, more favorable than one prior to the disruption, thus gaining competitive advantage (growth)".

Readiness (1) describes the proactive buildup of all the measures and capabilities in the pre-disruption state necessary to eliminate possible disruptions and absorb the negative impact of SC disruptions (A. Ali et al., 2017; Iftikhar et al., 2022; Kamalahmadi & Parast, 2016). **Response** (2) refers to the capabilities to build and countermeasures to be carried out directly after a disruption is experienced to respond adaptively. Velocity (speed) is the foremost importance in avoiding negative consequences for SCs. **Recovery** (3) includes the capabilities and actions that focus on restoring the SC's performance levels. Finally, **Growth** (4) refers to capabilities and measures target achieving superior SC performance after the disruption. Here, learning from the subsequent disruptions experiences to gain competitive advantage is critical. The phases are summarized in chronological order in Fig. 1.

3. Systematic review of AI-SCRes literature

The purpose of the research is to explore the applications of AI techniques in SCRes by gaining deep and comprehensive insights into previous research at the nexus of AI and SCRes. To attain the objectives of the research and overcome the recognized weakness in the traditional narrative review method (Tranfield et al., 2003), we adopted an evidence-based (Rousseau et al., 2008; Snyder, 2019) systematic literature review method (SLRM). The SLRM is an explicit, transparent, and

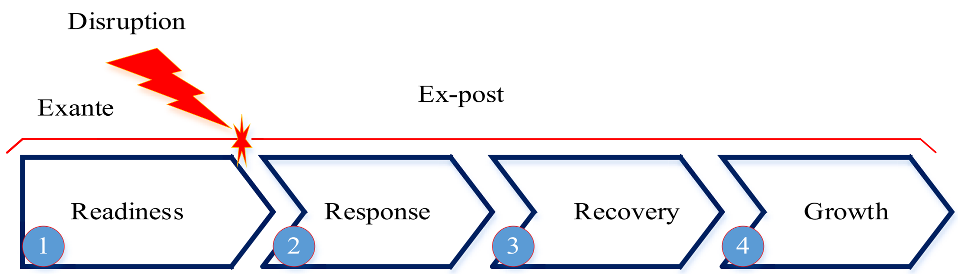

Fig. 1. SCRes phases. Source: adapted from (Hohenstein et al., 2015).

reproducible approach to identify, evaluate, and synthesize the existing body of completed and recorded research work produced by researchers, scholars, and practitioners effectively and unbiasedly (Denyer & Tranfield, 2009; Fink, 2014; Rousseau et al., 2008).

Our SLRM is guided by a set of five-step processes which is proposed by Denyer & Tranfield (2009), as shown in Fig. 2. This procedure was implemented by Ali et al. (2017), Hohenstein et al. (2015), Lima et al. (2018), and Humdan et al. (2020) to review research works in SCRes and by Younis et al. (2021), Spieske & Birkel (2021), Fan & Stevenson (2018), Toorajipour et al. (2021), Imran & Gölgeci (2019) and Han et al. (2020) to review research works focusing on the applications of AI and related topics in supply chain management.

We contribute to the research phenomenon at the nexus of AI and SCRes by identifying, analyzing, synthesizing, interpreting, and reporting the fragmented literature(into research streams) and developing a comprehensive framework that displays the relationships and hierarchical order of how AI techniques enhance SCRes.

3.1. Question formulation

A proper SLR is based on clearly defined, informative, well-formulated, and answerable research questions that guide the study (Bryman, 2007; Denyer & Tranfield, 2009; Fink, 2014; Rousseau et al., 2008). To achieve the objectives of the research, our structured review targets to answer eight crucial research questions:

RQ1: How research at the nexus of AI and SCRes has evolved?

RQ2: What AI techniques have been utilized for research and practical applications in SCRes?

RQ3: Which capabilities of AI are being utilized in addressing SCRes specific problems?

RQ4: Which antecedents of SCRes are realized using AI techniques?

RQ5: Which phases of SCRes do the enhanced antecedents support?

RQ6: What are the critical specific tasks of SCRes mostly addressed by applying the techniques?

RQ7: How can AI techniques be adopted to enhance SCRes?

RQ8: What are the opportunities for more future impactful research at the nexus of AI and SCRes?

3.2. Locating studies

The purpose of searching and collecting journal articles is to create a comprehensive list of core contributions that minimize bias with regard to the review questions (Denyer & Tranfield, 2009). Consistent with other previous systematic reviews in supply chain risk and resilience management (Imran & Gölgeci, 2019; A. Ali et al., 2017; Fan & Stevenson, 2018; Ganesh & Kalpana, 2022; Han et al., 2020; Iftikhar et al., 2022; Kochan & Nowicki, 2018; Lima et al., 2018; Naz et al., 2021; Hohenstein et al., 2015; Rahman et al., 2022; Shah et al., 2021; Spieske & Birkel, 2021) four essential criteria; namely time horizon, database selection, journal selection, and, keyword definition were deployed to locate relevant studies to guarantee the quality of the systematic literature review.

Time horizon: We did a pilot search on Scopus and Google Scholar to reveal the significant production of scientific articles in the field. Based on the pilot search, 2010 was preferred as a starting point for the time horizon and the period from 2010 to 2022 (as of August). Because the majority of the scientific articles and a large number of new trends and applications contributing to the topic at the nexus of AI and SCRes have emerged during this period, we limited the analysis to the scientific articles that were published between 2010 and 2022.

Database selection: Elsevier's Scopus and Google Scholar databases were used to search scientific articles contributing to the research questions. The Scopus electronic database covers a superior number of journals (Chadegani et al., 2013; Iftikhar et al., 2022; Imran & Gölgeci, 2019; Mongeon & Paul-Hus, 2016; Naz et al., 2021; Sharma et al., 2020) to major publishers such as Elsevier, Taylor and Francis, IEEE, Emerald, and Springer (Sharma et al., 2020). The Scopus database is the largest searchable abstract and citation source of searching literature that is continuously expanded and updated (Chadegani et al., 2013). The Scopus database only contains peer-reviewed articles (Mongeon & Paul-Hus, 2016). Since its coverage is more extensive than other databases for automated searching of peer-reviewed articles (Imran & Gölgeci, 2019; Baryannis et al., 2019b; Iftikhar et al., 2022), and highly overlaps with other databases like Web of Science (Rolf et al., 2022), Scopus was selected to automatically retrieve the peer-reviewed scientific articles. Google Scholar, as a complementary database (Fan & Stevenson, 2018; Ni et al., 2020), was utilized to manually collect peer-reviewed articles that meet the study location and inclusion criteria that could not be found in the automated searching (if any) and to collect peer-reviewed articles discovered from cross-referencing all the citations and bibliographies during reading in the full documents.

Journal selection: To ensure the quality of our systematic literature review, we focused on scientific articles published in peer-reviewed academic journals. The peer-review process is a quality indicator that enables the assessment of studies' conceptual and methodological rigor leading to a better technical product. Hence, peer-reviewed academic

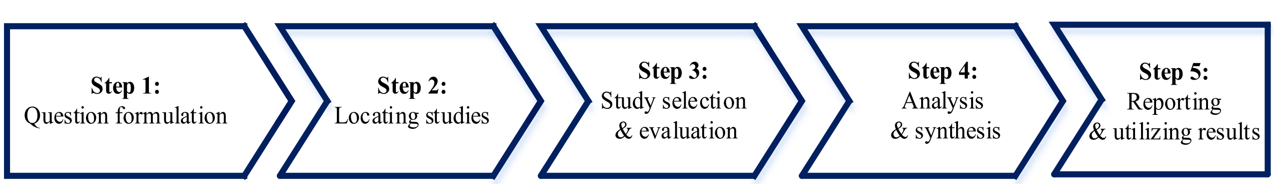

Fig. 2. SLR method: Source adopted from (Denyer & Tranfield, 2009).

journals are considered to be of higher quality than non-peer-reviewed journals.

Definitions of keywords: To identify and locate relevant studies in the online databases, we identified 33 keywords from basic literature in AI and SCRes. The identification process was carried out by taking a preliminary survey with combination and iteration processes on the databases to get keywords that enable finding relevant articles contributing to our research questions. The processes targeted in finding articles in the fields of SCRes and AI and at the nexus of the two fields. In doing so, three categories of keywords were generated to specify conceptual boundaries in the stated areas. Category 1 relates to supply chain management (2 keywords), category 2 relates to resilience management (5 keywords), and category 3 relates to artificial intelligence (26 keywords). In category1, we considered that the terms "supply chain" and "supply network" could make the broad field of supply chain management. In category 2, the terms; "resilience," "disruption," "vulnerability, y" "agility," and "robustness" were considered to make the field of resilience management based on the basic literature and recent systematic review works (A. Ali et al., 2017; Golan et al., 2020; Han et al., 2020; Imran & Gölgeci, 2019; Lima et al., 2018; Rahman et al., 2022; Younis et al., 2021).

In category 3, following recent systematic literature works, AI was represented by the terms; "multi agent systems," "agent-based systems,""expert systems," "fuzzy logic," "genetic algorithm," "rough set theory, " "knowledge representation," "reasoning," "automated reasoning," "deep learning," "machine learning," " artificial intelligence," "artificial neural network," "Bayesian network," "support vector machine," "logistic regression," "linear regression," "recurrent neural network," "convolutional neural network," "Bayes classifier", "k means", "ensemble learning", "instance based learning," "decision trees," "random forest," "backpropagation," and "Q learning" (Belhadi et al., 2021a; Breitenbach et al., 2021; Ganesh & Kalpana, 2022; Grover et al., 2020; Hanga & Kovalchuk, 2019; Naz et al., 2021; Riahi et al., 2021; Schroeder & Lodemann, 2021; Sharma et al., 2020; Riahi et al., 2021; Toorajipour et al., 2021; Younis et al., 2021). In both searches, the one automated in Scopus and manual search in Google Scholar, the combinations of the keywords from the three categories were applied to peer-peer reviewed articles' titles, abstracts, and keywords. The summary of the keywords is presented in Table 1.

3.3. Selection and evaluation of studies

We used the PRISMA (Preferred Reporting Items for Systematic and Meta-Analyses) methodology to select and evaluate the peer-reviewed articles that have potential contributions to the systematic review objectives and research questions. Our automated search in Scopus by combining the three categories of keywords and applying the study location criteria resulted in a preliminary sample of 824 articles. After discarding duplicates, 799 peer-reviewed articles remained in the sample. After applying all the screening criteria, 425 peer-reviewed articles remained in the sample. These 425 articles were written in English, published between 2010 and 2022 (as of August), and published under the peer-review process. The abstracts and conclusions of the 425 peer-reviewed articles were read to see if the articles have the potential to contribute to the research questions. Here, the focus was to select only peer-reviewed articles that address or revolve around the intersection of at least one AI technique and one SCRes antecedent more specifically. 123 articles were discarded, and 302 peer-reviewed articles remained in the sample. These 302 articles were read in their entirety, and only 87 articles were included in the systematic review. Peer-reviewed articles referenced in the 87 articles that meet the study location and eligibility criteria were manually collected using the Google Scholar database. A manual search was also implemented in Google Scholar to look for articles that could have been missed during the automated search session in the Scopus database. A total of 19 peer-reviewed articles that comply with the study location and inclusion criteria were included in the sample, making the total number of articles 106. These 106 peer-reviewed articles were used in the analysis process, and we refer to them as "the sample" in the rest of the paper. Table 2 presents the summary of the inclusion criteria and the rationale behind them, and Fig. 3 presents the selection and evaluation process (PRISMA).

3.4. Analysis and synthesis

Synthesis and analysis of the sample were conducted to obtain and develop new insights and knowledge (Denyer & Tranfield, 2009; Snyder, 2019) concerning the research topic at the nexus of SCRes and AI that would not have been apparent through reading individual articles and then to propose future research directions based on the gaps identified from the detailed review. Appendix B was developed to classify and summarize the articles based on the background knowledge presented in

Table 2
Summary of the inclusion criteria.

Inclusion criteria	Rationale
Peer-reviewed journal articles	Peer-review journals publish only quality articles in the fields than the non-peer-reviewed ones (A. Ali et al., 2017; Hohenstein et al., 2015).
Only peer-reviewed articles published between 2010 & 2022	Our preliminary survey indicated that significant production of articles at the nexus of AI & SCRes started in 2010
Articles addressing at least 1 SCRes antecedent & 1 AI technique	The study targets applications of AI in SCRes.
Only empirical research (excluding conceptual research and literature reviews)	To base on a verifiable evidence for the applications of AI in SCRes.
Based on the keywords defined	Defined based on the subject matters and recent review works in SCRes & AI & their intersection (A. Ali et al., 2017; Belhadi et al., 2021a; Breitenbach et al., 2021; Golan et al., 2020; Grover et al., 2020; Han et al., 2020; Hanga & Kovalchuk, 2019; Lima et al., 2018; Naz et al., 2021; Rahman et al., 2022; Riahi et al., 2021; Schroeder & Lodemann, 2021; Sharma et al., 2020; Toorajipour et al., 2021; Younis et al., 2021).
Articles published in the English language	The English language dominates in the research field of supply chain management (A. Ali et al., 2017) and AI.

Table 1
Summary of keywords.

Category I	Operator	Category II	Operator	Category III
"supply chain" OR "supply network"	AND	"resilience", OR "disruption" OR "vulnerability" OR "agility" OR "robustness"	AND	"multi agent systems" OR "agent based systems" OR"expert systems" OR "fuzzy logic" OR "genetic algorithm" OR "rough set theory "OR "knowledge representation" OR "reasoning" OR "automated reasoning" OR "deep learning", OR "machine learning" OR " artificial intelligence" OR "artificial neural network" OR "Bayesian network" OR "support vector machines" OR "logistic regression" OR "linear regression" OR "recurrent neural network" OR "convolutional neural network" OR "Bayes classifier", "k means" OR "ensemble learning", "instance based learning", OR "decision trees", OR "random forest" OR "backpropagation" OR "Q learning"

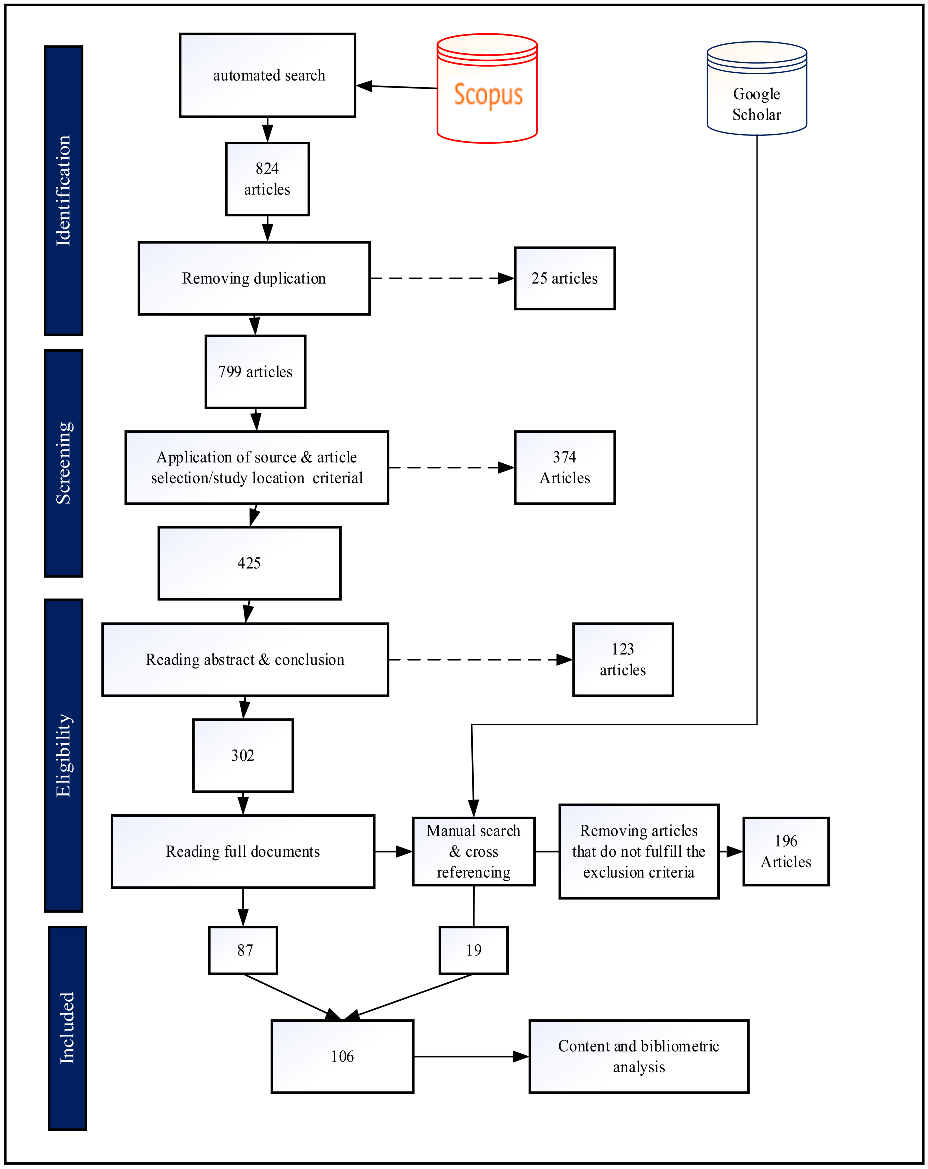

Fig. 3. PRISMA based study selection and evaluation process.

section 2 and the contributions of the 106 articles analyzed. The classification is based on AI techniques adopted, inherent AI capabilities utilized, SCRes antecedents realized, SCRes phases supported, and SCRes specific tasks achieved with the techniques.

3.4.1. *Bibliometric analysis*

Biblioshiny, an interactive web interface of the R package for bibliometrics, which is an efficient tool for quantitative research in bibliometrics (Aria & Cuccurullo, 2017; Riahi et al., 2021; Xie et al., 2020) was employed to carry out descriptive bibliometric analysis to indicate trends, annual article production, the most relevant articles sources, and contributing authors in the production of scientific articles at the nexus of AI and SCRes (Ganesh & Kalpana, 2022; Naz et al., 2021; Shah et al., 2021). SC disruptions emanating from major natural disasters, economic recessions, political and social instabilities, and the increase in the complexity of globally growing SC networks made the trend from the annual article production graph as presented in Fig. 4.

Early exploration into AI techniques' application for SCRes and risk assessment commenced around 2010. As the techniques matured, attention shifted towards demonstrating proof of concepts and fostering industrial adoptions. Case studies effectively highlighted the tangible benefits of AI brought to improving SCRes. This evolution led to AI's utilization for data analytics and predictive modeling, aiding in anticipating and managing disruptions effectively. Research intensified as awareness grew about the vulnerability of SCs, leading to greater exploration of AI techniques roles in addressing disruptions. consequently the use of AI and related technologies in SC risk management and resilience increased in response to SC disruptions. Consistent with the recent systematic review works, our survey indicates that in the years 2019 and 2020, the applications of AI techniques made the maximum contribution which was due to the Covid-19 global pandemic that revealed the vulnerability and the lack of resilience in SCs across the globe (Ganesh & Kalpana, 2022; Golan et al., 2020; Iftikhar et al., 2022; Naz et al., 2021; Shah et al., 2021; Spieske & Birkel, 2021; Younis et al., 2021). This indicated that in response to the pandemic, the use of AI techniques to develop business continuity capabilities and make automated and intelligent decisions have increased. Brexit and the US-Chinese trade war also have contributed to the research interest in SCRes.

The shortlisted 106 peer-reviewed articles were published in 73 multidisciplinary academic journals. The result indicates the topic's multidisciplinary nature. Regarding the relevancy of sources, The

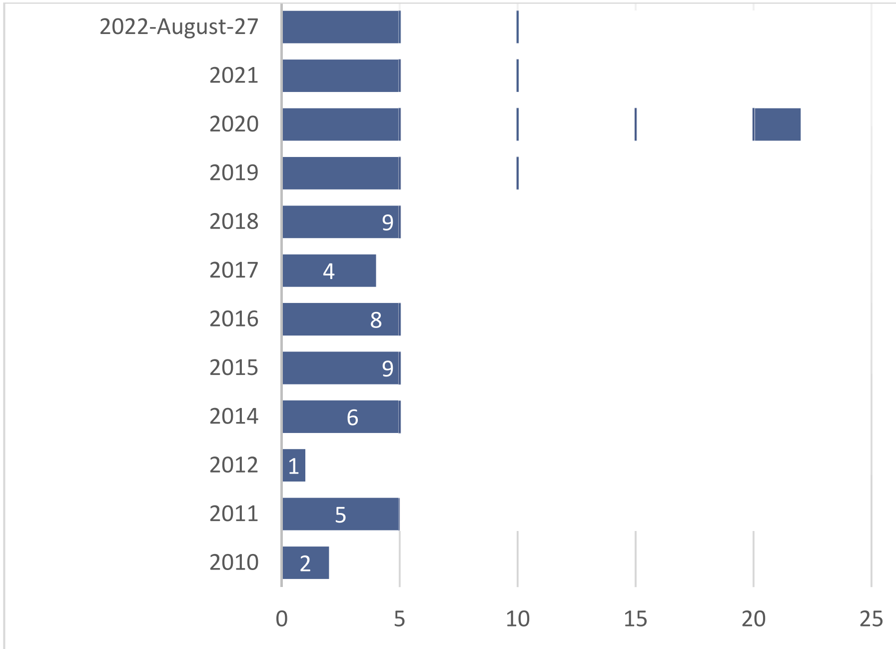

Fig. 4. Annual scientific production of studies (as of 27 August 2022)(n = 106).

International Journal of Production Research contributed 12 articles (11%), the International Journal of Production Economics 7 articles (7%), Computers and Industrial Engineering 5 articles (5%), Mathematical Problems in Engineering 3 articles (3%), and Reliability Engineering and Safety Systems 3 articles (3%) as presented in Fig. 5.

Concerning the contribution of articles by authorship, Table 3 presents the top ten influential authors with the highest contribution among the shortlisted 106 peer-reviewed articles. Hosseini Seyedmohsen is the leading author in the field with five publications, and the authors Brintrup A, Jaradat R, and Liu Z follow with four articles contributions each in the research field at the nexus of AI and SCRes. Using text-mining techniques, the frequency of the keywords in the authors' document keywords is presented in Fig. 6, in a word cloud format, with the size of the words representing the frequency of use in the sample. Our analysis indicated that supply chain, resilience, risk management, and machine learning are the most recurring keywords. The academic and practice focus on addressing SC disruptions with the concepts of resilience and risks management, and the emerging AI tools(e.g., machine learning) to support analyses in the stated concepts have contributed to the frequency of occurrences of the keywords in the extant literature. The network of keywords also have been developed with the help of VOSviewer software and presented in Fig. 7. The figure indicates how the keywords are co-occurring or coupling in the extant literature. The network strength (the thickness of the arcs connecting the keyword nodes) among the coupled keywords reveals the focus given by authors that concurrently address the concepts of supply chain management, SCRes, SC disruptions, and AI techniques. Overall, the network bonds reveal the research attention given to investigating and enhancing

Table 3
Important authors publishing articles.

Authors	Articles
Hosseini S	5
Brintrup A	4
Jaradat R	4
Liu Z	4
Li J	3
Mcfarlane D	3
Woodall P	3
Yang Z	3
Blos Mf	2
Chu C	2

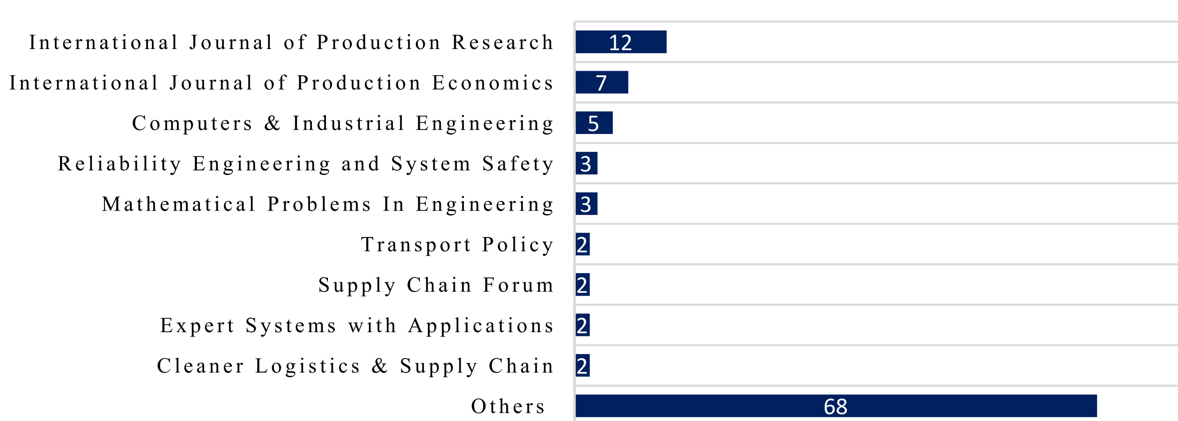

Fig. 5. Journal-wise publications(n = 106).

Fig. 6. Word cloud indicating important key words.

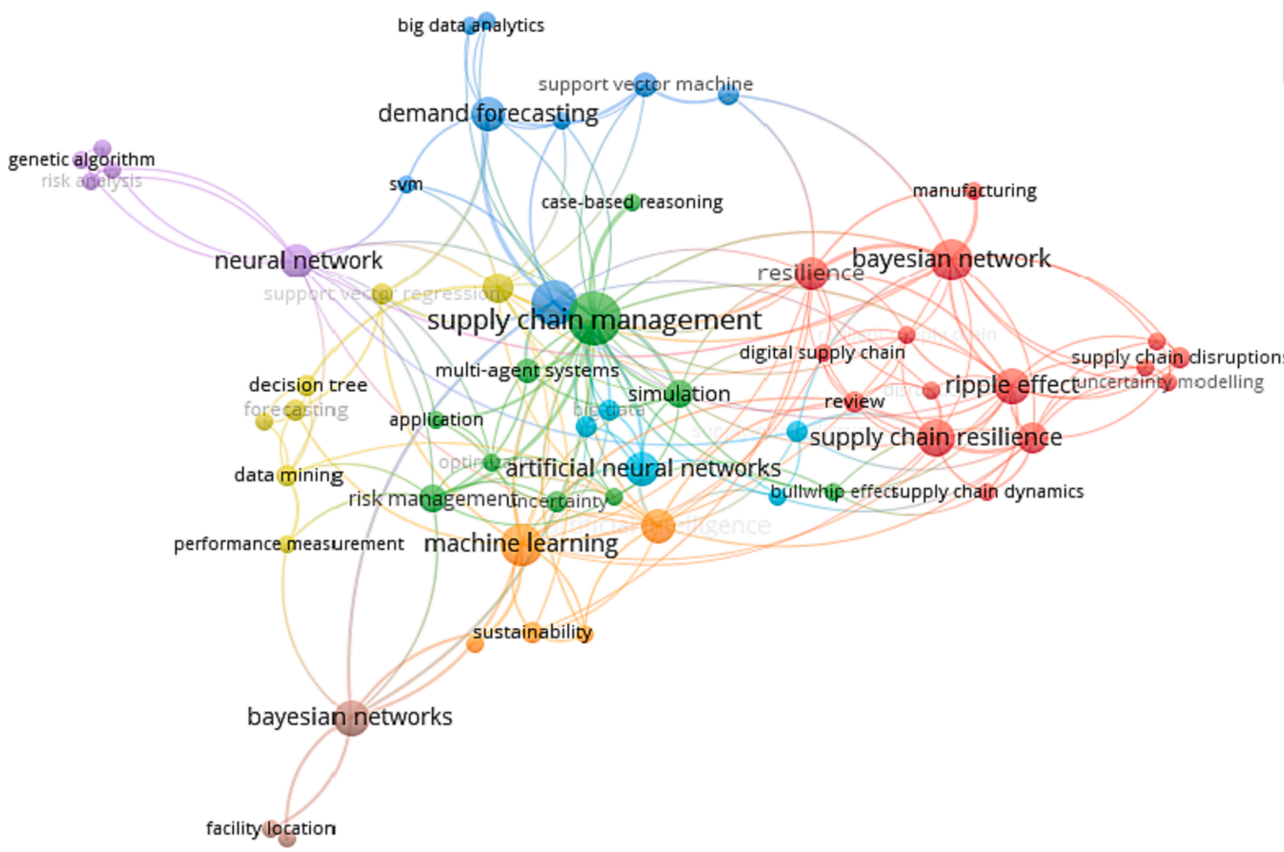

Fig. 7. Visualization of the bibliometric network of keywords (n = 58).

resilience and risk management practices with the help of AI techniques in the literature of the field of supply chain management.

3.4.2. Application of AI techniques in SCRes

Content analysis was carried out to evaluate the sample based on classifications on the AI techniques applied, the capability of AI utilized, the SCRes antecedents realized, the SCRes phases supported, and the specific tasks of SCRes achieved. A brief description of AI techniques evaluated in our sample has been presented in Appendix A.

3.4.2.1. AI techniques. Evaluating the sample to answer the research questions was conducted first by classifying the studies based on the characteristics of the AI techniques the papers adopted or revolved around. Following the works of Bundy (1997) and Toorajipour et al. (2021) regarding “AI techniques,” we refer to algorithms, architectures, data or knowledge formalism, and methodologies that can be described in a clear, precise manner. Our analysis and evaluation are based on the recent works of Ramirez-Peña et al. (2020) and Spieske & Birkel (2021) that assume one AI technology can contribute to more than one antecedent of SCRes. The distribution of our sample based on the adopted AI techniques is presented in Fig. 8.

Bayesian networks, in the form of Bayes classifiers, dynamic, and static BNs, are the most frequently used techniques of AI among the publications in our sample (25%; 25 out of 106 papers). BNs are utilized to realize all antecedents of SCRes studies in our sample. The maximum number of publications (16 out of 25 papers) adopting BNs contributed to the SCRes antecedent of visibility. Specific SCRes tasks were addressed when realizing the different antecedents. Because BNs are well recognized as the rigorous methodology to quantify risk, model uncertainty, and make decisions in the presence of structural dynamics (Fenton & Neil, 2019; Hosseini & Ivanov, 2020; Qazi & Akhtar, 2020), they are appropriate tools for modeling and measuring supply chain risks and resilience, as well as controlling the ripple effect from disruption propagations in multi-echelon supply chains (Hosseini & Ivanov, 2020).

In this survey, the contributions of BNs for supply chain resilience included resilient supplier selections, modeling and analyzing the ripple effect of disruption propagations, modeling and assessing systems and supply chain resilience, quantifying and predicting supply chain risks and disruptions, modeling and measuring supply chains' and suppliers' vulnerabilities to disruptions, predicting and classification of critical supply chain variables, supply chain performance evaluation under uncertainties, modeling and analysis of the interdependencies among supply chain players, and predicting uncertain demands.

Multi-agent intelligent systems (MAIS) are the second most popular AI technique in the sample, making 16% (17 out of 106 papers) of the contribution. MAIS are utilized to realize all the antecedents of SCRes studied in the sample. The maximum number of papers implementing MAIS was used to realize collaboration (14 out of 16 papers) and visibility (15 out of 16 papers) of SCRes antecedents. This is due to the capabilities of the MAIS to represent SC players for efficient information sharing and collaboration before, during, and after the event of SC risks associated with disruptions. The potential to both make decisions independently and support SC players to make intelligent decisions have contributed significantly to the popularity and topicality of MAIS in SCRes over the years.

Since SCRes and supply chain risk management address problems that engage different players interacting with each other, each with different and possibly conflicting needs (Baryannis et al., 2019a; Giannakis & Louis, 2011), supply chain resilience management lends itself to multi-agent formalization in which players in the SC can be modeled as intelligent agents (Baryannis et al., 2019a). In SCs, Intelligent agents can represent players like suppliers, customers, manufacturers, retailers, etc., and adjust their behavior to anticipate, respond adaptively, and recover from predicted and unpredicted disruptions when modeling supply chains with multi-agent intelligent systems (Baryannis et al., 2019a). Through their learning capability, MAIS can efficiently demonstrate the proactive and autonomous behavior of the participating agents in mitigating and rectifying SC disruptions in real-time (Bansal et al., 2005; Giannakis & Louis, 2011; Kwon et al., 2007; L. Lu & Wang, 2008). Multi-agent systems have been used as simulation tools for inventory management to reduce costs and improve fill rate, to resolve collaboration issues among supply chain entities that arise due to uncertain supply and demand, and to reduce costs and the bullwhip effect in a multi-stage supply chain (Baryannis et al., 2019a). The applications of MAIS in supply chain resilience are diverse, and the summary is presented in Appendix B.

Artificial neural networks (ANNs) and genetic algorithms (GA) also contributed a significant number of papers in the sample (12%; 13 out of 106 papers and 9%; 10 out of 106 papers respectively). ANNs are adopted in realizing all the antecedents of SCRes. The maximum contributions by ANN are seen in visibility (12 out of 13 papers) and awareness (8 out of 13 papers) antecedents of SCRes. ANN is a powerful ML algorithm to identify non-linear input/output relationships in supply chain resilience management. ANN can be used to assess supply chain risk (Baryannis et al., 2019a) and warn supply chain managers against potential competitors. The application of neural networks in supply chains has varied and towards different variables (Guillermo-Muñoz

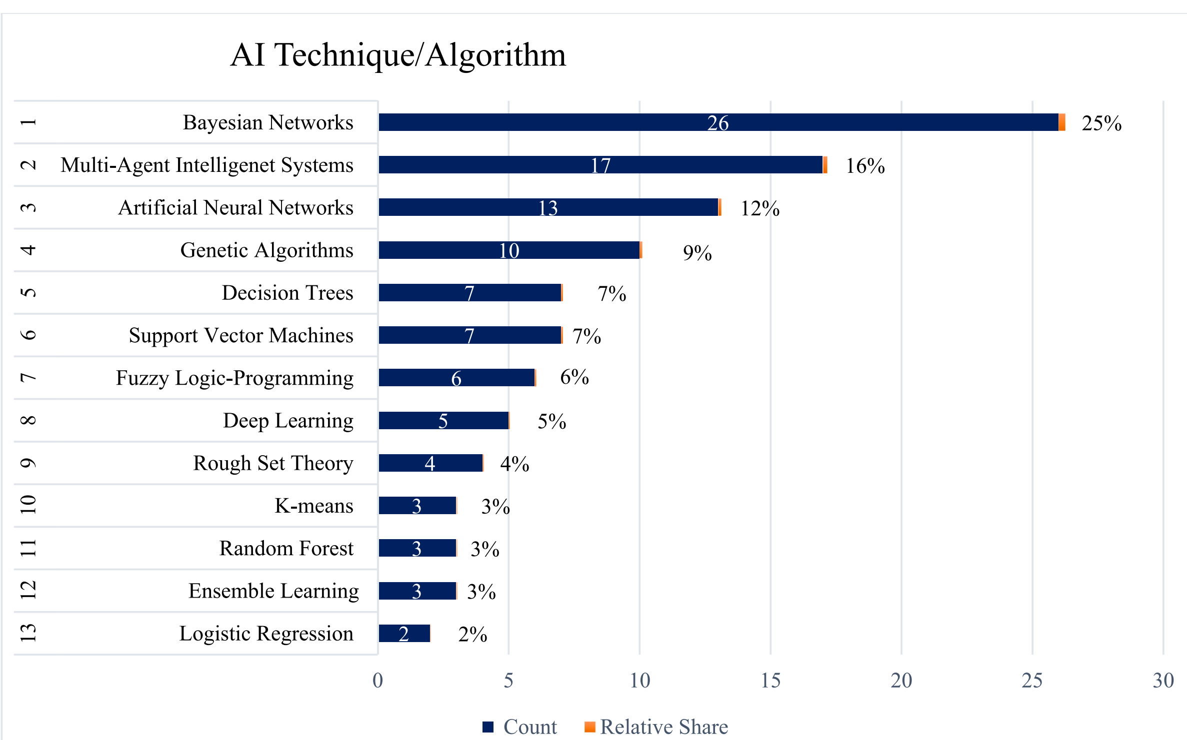

Fig. 8. Distribution of articles based on the adopted AI technique (n = 106).

et al., 2020). According to our analysis, the applications of ANN in supply chain resilience are found to be predicting and detecting anomalies in supply chains (Fanoodi et al., 2019; Kochak & Sharma, 2015; Lorenc et al., 2021; Ma & Peng, 2014; Protogerou et al., 2021) supporting the supply chain network optimization process under disruption considerations (Sharifnia et al., 2021), resilient supplier selection (El-Hiri et al., 2019), and predicting and enhancing the level of SCRes antecedents like integration (Guillermo-Muñoz et al., 2020) and visibility (Silva et al., 2017).

GA is adopted to deal with most of the antecedents of SCRes studies in the sample. Most papers (9 out of 10) adopting GAs dealt with the SCRes antecedent of SC configuration. Due to their intelligent capability, based on natural evolution, to deal with complex problems, they were utilized to solve SC network optimization problems under the risks of uncertain disruptions. The applications and contributions of GAs in supply chain resilience include: selecting resilient suppliers and order allocation under disruption risks (Esmaeili-Najafabadi et al., 2021), examining the impact agility and flexibility have on supply chain responsiveness during disruptions (Shekarian et al., 2020), and designing and optimizing resilient supply chain networks under operational and disruptions risks (Y. Liu et al., 2020; P. Peng et al., 2011; Tong et al., 2020; Vali-siar et al., 2022; X. Wang et al., 2022; Yan & Ji, 2020; Yavari et al., 2020). Papers addressing the antecedents of SCRes in the sample applied popular machine learning algorithms such as decision trees (DT) and support vector machines (SVM). Both DT and SVM contributed to seven papers each, accounting for 7% of the total sample. On the other hand, logistic regression (LR) had the lowest contribution (Fig. 8).

3.4.2.2. AI capabilities utilized. AI techniques have various potential capabilities that can be utilized to realize SCRes. The second classification to evaluate the sample was based on the utilized AI capabilities when adopting the techniques to realize SCRes antecedents. Prediction, automated reasoning, clustering, decision-making, decision support, and optimization are identified as the frequently utilized AI capabilities in the sample. Fig. 9 presents the distribution of the sample with regard to the AI capabilities utilized. Prediction, mostly based on regression and classification learnings, is the most popular capability of AI utilized in the sample. 56 (53% of 106) articles in the sample have utilized prediction in realizing the antecedents of SCRes through tackling SCRes problems. Decision support is the next topical (16%; 17 out of 106 papers) capability of AI utilized in all of the AI techniques adopted in the sample. The remaining contributions are made by automated reasoning, decision-making, and clustering (7%, 6%, and 4%, respectively). The need to predict future disruptions and the need to clarify uncertainties made "prediction" to be the most topical capability of AI in SCRes. The need to make quick and intelligent decisions before and during disruptions made the decision-support capability of AI the second most adopted in SCRes. The growing need to design and operate efficiently resilient SCs contributed to the frequent use of the optimization capability of AI.

3.4.2.3. Scres antecedents realized. Similar to the claim by Spieske & Birkel (2021) and Iftikhar et al. (2022), we assume that AI techniques do not enhance or influence SCRes directly; instead, specific antecedents are needed as mediating variables. From our review of the extant literature, there is no consistency in the use of terminologies for SCRes antecedents. The array of terms from our investigation includes; attributes (Al-Talib et al., 2020), capabilities (Barroso et al., 2011; Han et al., 2020; Behzadi et al., 2020), principles (Kamalahmadi & Parast, 2016), elements (A. Ali et al., 2017; Belhadi et al., 2021c; Christopher & Peck, 2004; Karl et al., 2018; Hohenstein et al., 2015; Zavala-Alcívar et al., 2020), antecedents (Hosseini et al., 2019; Iftikhar et al., 2022; Imran & Gölgeci, 2019; Patel et al., 2022; Spieske & Birkel, 2021) conceptual drivers (Imran & Gölgeci, 2019), pillars (Hosseini et al., 2019), competencies (Andreas & Wallenburg, 2012), enhancers (Blackhurst et al., 2011), performance indicator (Singh et al., 2019), and enablers (Pereira et al., 2014).

The antecedents are proposed from conceptual review works and the outgrowths of SCRes definitions, and few of them have been empirically validated in industrial settings. In this review, we focus on those key antecedents that are empirically validated, frequently addressed in our sample when applying AI techniques for SCRes, and based on previous frameworks (Christopher & Peck, 2004; Jüttner & Maklan, 2011; Spieske & Birkel, 2021). The conceptual framework, representing the level of analysis for agility, flexibility, awareness, visibility, SC configuration, collaboration, velocity, supply chain (re-) engineering, and resilient sourcing as key antecedents of building and enhancing SCRes, has been presented in Fig. 10. The antecedents are the mediating variables between supply chain resilience and AI techniques. An agile supply chain has the ability to respond rapidly to unpredictable changes in demand and supply or any changed conditions (Christopher & Peck, 2004; G. Li et al., 2006; Ponomarov & Holcomb, 2009). Agility is considered a combined antecedent that captures visibility, velocity (A. Ali et al., 2017; Hohenstein et al., 2015; Rajesh, 2016; Spieske & Birkel, 2021), and flexibility (Juan et al., 2021; Jüttner & Maklan, 2011).

Agility can be seen as an essential construct for building resilient supply chains (Abeysekara et al., 2019; Carvalho et al., 2012; Jüttner & Maklan, 2011; Wieland et al., 2013) and Sturm et al. (2021) deployed agility as a construct of SC resilience in their empirical investigations. With their empirical investigation, Zhuo et al. (2021) revealed agility's positive influence on SCRes. SC (re-) engineering is a combined

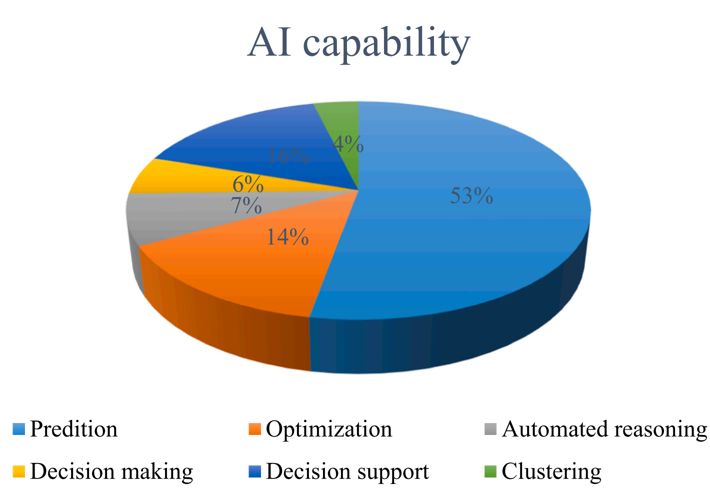

Fig. 9. Distribution of the articles based on utilized AI capabilities (n = 106).

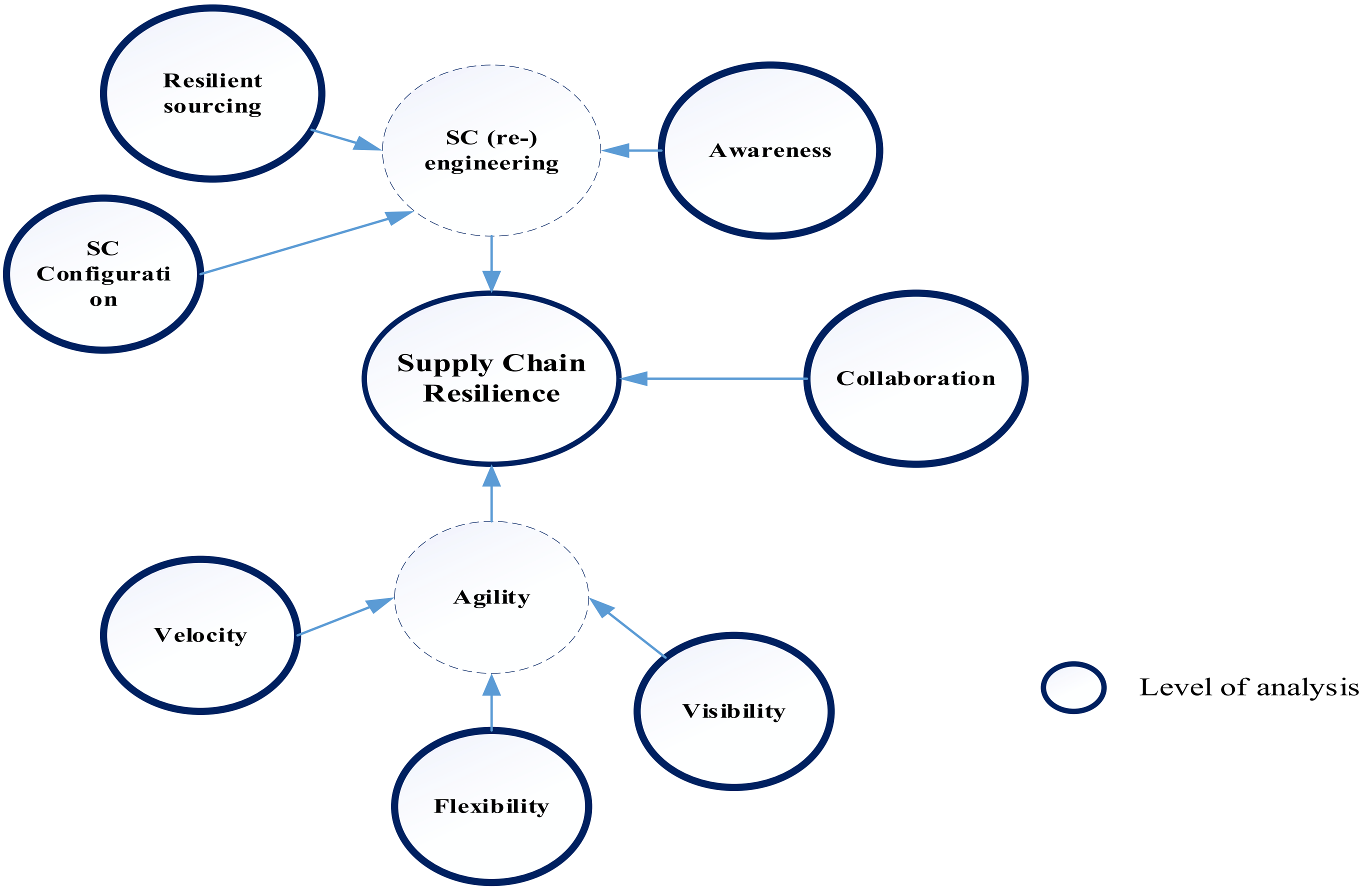

Fig. 10. SCRes antecedents.

antecedent that captures resilient sourcing, SC network design issues under uncertainties, and awareness about the entire SC structure (Spieske & Birkel, 2021). Before evaluating the sample in terms of the antecedents, this subsection briefly discusses the antecedents addressed in the sample.

Visibility: SC visibility or transparency (Wichmann et al., 2020), which refers to the capability of "being perceived by the eye or mind" (Jüttner & Maklan, 2011, p. 248), is the SC's ability to access information on the identities, locations, and status of entities transiting among manufacturers, suppliers, and customers, captured in timely messages about events, along the planned dates for the events (Basole & Bellamy, 2014; Christopher & Peck, 2004; Goh et al., 2009; Jüttner & Maklan, 2011; Pettit et al., 2013; Soni et al., 2014; Spieske & Birkel, 2021; Wieland et al., 2013). The important constructs for SC visibility are sensing, learning, coordinating, and integrating (Wei & Wang, 2010). Visibility ensures confidence in managing a risk event situation in supply chain networks (Christopher & Peck, 2004; Jüttner & Maklan, 2011; Singh et al., 2019; Wichmann et al., 2020). Invisibility in SC networks severely hampers SC actors' capability to respond to any disruptions (Jüttner & Maklan, 2011; Mubarik et al., 2021). As complex SC networks are characterized by limited visibility, potential disruptive risks are hidden, and the cascading effects might not be noticed (Fiksel, 2015). As SC visibility reduces the probability and impact of SC disruption, it leads to SC resilience (Dubey et al., 2019). The works by (Mubarik et al., 2021) and (Wieland et al., 2013) empirically validated the positive impact of visibility on SCRes.

Flexibility: SC flexibility is defined by Jüttner & Maklan (2011) as "being able to bend easily without breaking" and is regarded as an inherent part of resilience by Peck (2005). Flexibility is the ease with which an SC can change its range number (possible options) and range heterogeneity(the degree of difference between options) to cope with market changes or events while performing well (Jüttner & Maklan, 2011; Skipper & Hanna, 2009; Stevenson & Spring, 2007). Flexibility entails creating capabilities within the SC organizations to respond (Ila et al., 2008; Rice & Caniato, 2003). Flexibility in SCs may include flexibility in workforce skill, production, organization, market, responsiveness, product, logistics, operational system, work game plans, and sourcing(with permit switching from suppliers) (Fantazy et al., 2009; Ivanov, 2021; Hohenstein et al., 2015; Rice & Caniato, 2003; Singh et al., 2019) and ensures the changes caused by the disruptive events can be absorbed through effective response (Skipper & Hanna, 2009). Therefore, it is the ability to encounter, resolve, and, when appropriate, exploit unexpected emergencies (Jüttner & Maklan, 2011).

Velocity: Velocity in SCs is the ability to adapt to unexpected changes in demand and supply (Christopher & Peck, 2004; Jüttner & Maklan, 2011; Singh et al., 2019) in the smallest amount of time (A. Ali et al., 2017; Pettit et al., 2013). Velocity focuses on the organization's pace of flexible adaptations (Stevenson & Spring, 2007), with lead time as a key indicator of SC velocity (Jüttner & Maklan, 2011). This includes organizations' flexibility to respond quickly to disruptions in manufacturing, transportation, sourcing, or labor (Hohenstein et al., 2015; Ivanov et al., 2019; Spieske & Birkel, 2021). In order to benefit from "the first mover advantage" that disruptive events entail during disruptions, velocity is a critical antecedent of SCRes that can shift the SC to a better performance than the pre-disruption phase. Firms that adapt quickly may identify upside opportunities and capture competitive advantages before their competitors (Fiksel, 2015; Ribeiro & Barbosa-Povoa, 2018). Since velocity helps discover disruptive events in a timely manner (before they occur if possible), helps to quickly respond when they occur, aids in recovering fast, and helps to grow in disruption times by gaining competitive advantages (Patel et al., 2022), it can be considered a SCRes antecedent that contributes to the four phases.

SC configuration: SC configuration is concerned with the design or redesign of an optimal robust SC network that is capable of copying with network disruptions (A. Ali et al., 2017; Andreas & Wallenburg, 2012; Y. Kim et al., 2015) and controlling the bullwhip and ripple effects emanating from operational and disruptions risks respectively(Hosseini et al., 2019). In addition to cost and customer services, SC configuration, a critical antecedent of SCRes, considers resiliency as one of the objective functions of SC network optimization (Christopher & Peck, 2004). The supply chains' growing global, less vertically integrated, lean-oriented, and the rapid advances in technology and customers' expectations have made SC networks vulnerable to disruptions of unplanned and unpredicted events (Baryannis et al., 2019b; Christopher & Peck, 2004; Jain et al., 2017; Shekarian et al., 2020; Singh et al., 2019; Svensson, 2000). Hence, redundancies or "safety nets" (Andreas & Wallenburg, 2012) have to be embedded in the SC networks to stabilize the network during supply, production, and transportation disruptions times (Ivanov et al., 2017). Among the prominent strategies to build redundancies in robust SC networks to enhance resilience are multiple sourcing, increased inventory, backup production capacity (A. Ali et al., 2017; Ivanov et al., 2017), supplier segregation, multiple transportation channels, backup suppliers, and raw materials substitutions (Hosseini et al., 2019; Hosseini & Barker, 2016).

Since most of the strategies for building redundancies come at a cost, SC configuration utilizes principles to make the trade-off between "efficiency and redundancy" to optimize the SC network (Christopher & Peck, 2004; Spieske & Birkel, 2021; Zsidisin & Wagner, 2010). Network topological principles or metrics like network density and complexity, node and link criticality, node and link heterogeneity, connectivity, efficiency, centrality, diversity, robustness, modularity, and betweenness are used to design resilient SCs capable of absorbing and resisting node and link level disruptions (Adobor, 2020; A. Ali et al., 2017; Arora & Ventresca, 2018; Chauhan et al., 2021; Dixit et al., 2020; Kazemian et al., 2021; Y. Kim et al., 2015; Mari et al., 2015; Meng et al., 2018; Mikhail et al., 2019; Perera et al., 2017; Spieske & Birkel, 2021).

Resilient sourcing: Sourcing decisions play a crucial role in SCRes and can address strategies like single sourcing, multiple sourcing (Esmaeili-Najafabadi et al., 2021), global sourcing, and local sourcing (Christopher & Peck, 2004; Lawrence et al., 2020). Supplier selection, one of the sourcing decisions, is a multi-criteria decision-making problem (Cavalcante et al., 2019; Hosseini & Khaled, 2019; G. Li, 2007), and the primary criteria are cost, quality, lead time, service level, and flexibility (Hosseini & Barker, 2016). However, suppliers are the most common source of external disruption risks in modern supply chains. According to the report by (Hosseini et al., 2019), more than half of SC disruptions emerge from the first-tier suppliers and affect the entire SC through propagation(the ripple effect). Supplier disruptions can impose huge losses on the entire SC as they cut all the flows (Hosseini & Khaled, 2019). Therefore, the supplier selection process must also consider the suppliers' ability to mitigate risk or resilience (Nepal & Yadav, 2015; Rajesh & Ravi, 2015). Resilient supplier development and evaluation had helped firms obtain better performance when similar disruptions affected similar suppliers (Cavalcante et al., 2019). As a result, resilient sourcing has become one of the critical antecedents of SCRes.

Collaboration: SC collaboration can be defined as the alignment of SC players' forces and sharing resources for mitigating disruption risks (Abeysekara et al., 2019; Christopher & Peck, 2004; Jüttner & Maklan, 2011; Patel et al., 2022; Ponomarov & Holcomb, 2009; Spieske & Birkel, 2021). The collaborative partnership helps to anticipate disruptions and manage risks efficiently (Singh et al., 2019). Collaboration in SCs is interpreted by Parast et al. (2019) as the "glue that holds firms in crisis together." It is apparent that since SC vulnerability and resilience are network-wide concepts, the management of disruptions risks has to be network-wide too (Christopher & Peck, 2004). Incentive alignment and decision synchronization are critical as they are essential to successfully responding to disruptions in SCs (Shekarian & Mellat Parast, 2021).

Awareness: Situation awareness involves an understanding of SC vulnerabilities and making appropriate arrangements for such occasions, and the ability to discern a possible disruption can be sensed and interpreted (Datta et al., 2007; Han et al., 2020; Singh et al., 2019) through early caution systems and congruity arrangement (A. Ali et al., 2017; Pettit et al., 2010). These practices require coordination, information sharing, and pre-existing knowledge (A. Ali et al., 2017; Jain et al., 2017; Vargo & Seville, 2011). With high levels of situation awareness, SCs can detect structural shifts in the market, political and social change, demographic trends, and technological advances. Situation awareness enhances the sensitivity of SCs to poetical threats to the SC network. Overall, SC understanding is necessary to identify the critical path and potential bottlenecks in SCs (Christopher & Peck, 2004). This can be facilitated by modeling and mapping tools (A. Ali et al., 2017; Gardner & Cooper, 2003). Modeling and mapping techniques are crucial to enable vulnerability analyses and scenario simulations before actually facing SC disruptions (Ahmadpour et al., 2017; Biao et al., 2014; Blos et al., 2018; Giannakis & Louis, 2011; Ivanov, 2017; Nair & Vidal, 2011; Spieske & Birkel, 2021).

The sample was evaluated in terms of the antecedents of SCRes that we claimed would mediate the relationship between SCRes and AI. Our analysis and evaluation are based on the recent works of (Ramirez-Peña et al., 2020) and (Spieske & Birkel, 2021) that assume one AI technique can contribute to more than one antecedent of SCRes. In most articles, more than one antecedent of SCRes was realized, which resulted in 272 references from 106 studies in the sample. Following the works by Spieske & Birkel (2021) & Hohenstein et al. (2015), the relative shares of the SCRes antecedents from the total contribution were calculated. Fig. 11 displays the results of the analysis.

The finding from the evaluation of the sample in terms of the antecedents of SCRes revealed that visibility had received greater attention from researchers and practitioners. Visibility is leading as 35% (94 out of 272 references) of the research effort was devoted to it in our sample. The obtained result is in line with our expectations. The need to boast end-to-end SC visibility for developing and enhancing SCRes that can mitigate disruptive risks has grown, and advancements in AI techniques contributed a lot to achieving visibility. Scholars' research calls as a future avenue also contributed to the publication growth that addresses visibility with AI techniques. The result is also consistent with the one obtained by Spieske & Birkel (2021), whose objective was to analyze the application of industry 4.0 (I4.0), in which AI is a subfield, in SCRes. Their finding shows that visibility has received 34% of the research effort in their systematic literature review sample. Relatively closer results were obtained by Ali et al. (2017) and Hohenstein et al. (2015), who investigated the research development of SCRes. MAIS, BNs, and ANNs have contributed the most to realizing visibility (Appendix B).

Awareness is the second most addressed antecedent by references (23%, 62 out of 272). BNs and ANNs have contributed the most in realizing the SCRes antecedent of awareness. The ambition of

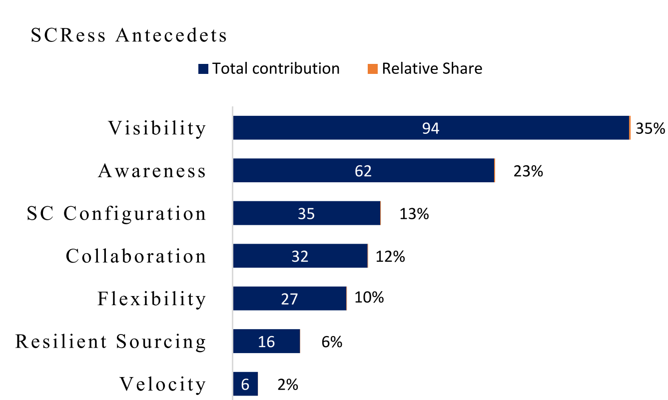

Fig. 11. Distribution of contributions with regard to realized SCRes antecedents (n = 272).

practitioners and scholars to develop an understanding of SC vulnerabilities and make appropriate arrangements (Datta et al., 2007; Han et al., 2020; Singh et al., 2019) before disruptions take effect and the promise of AI techniques to detect anomalies in SCs are among the driving forces that resulted in significant publications. This finding is slightly consistent with the results obtained by Spieske & Birkel (2021) and Ali et al. (2017).

SC configuration was addressed by 13% of the references. This was apparent by the attention given by scholars and practitioners to design and reconfigure efficiently resilient SC networks capable of resisting and coping with disruptions. GA and MAIS have contributed the most in realizing the antecedent SC configuration. AI techniques' proven potential to support in generating optimal solutions for complex network optimization problems also contributed to the significant production of publications. However, this contradicts the results obtained by Ali et al. (2017). In their finding, SC configuration is the most popular antecedent of SCRes. Collaboration has received limited attention despite its benefit to holding organizations during disruption times and the proven AI capability like MAIS to foster collaborative and intelligent decision-making in SCs before and during disruptions. The result is consistent with the one obtained by Spieske & Birkel (2021) and Ali et al. (2017).

Velocity is the least addressed antecedent among the references in the sample, accounting for only 2%. However, we anticipated that the need for fast anomaly detection, quick response to disruptions, and the capability of AI to support these requirements and facilitate intelligent decision-making would result in significant research publications on velocity. One possible reason for the limited focus on velocity could be considering it as an aspect of agility within research streams. This finding aligns with the results obtained by Ali et al. (2017), but it contradicts the findings of Spieske & Birkel (2021), who identified velocity as the second most popular antecedent of SCRes realized through I4.0 enabling technologies. This discrepancy may be due to I4.0 technologies other than supporting velocity. An unexpected result was also obtained for resilient sourcing (6%). It is the second least addressed antecedent in the sample. This could be attributed to its integration as an element of other antecedents like "SC configuration" in research streams like procurement and SCM. BNs have contributed the most in realizing the antecedent resilient sourcing. AI techniques' contribution to realizing the antecedents and phases of SCRes are summarized and presented in Appendix B.

3.4.2.4. Supported SCRes phases. The sample was evaluated in terms of the SCRes phases the studies refer to or revolve around. In some studies, more than one phase was discussed, which resulted in 131 SCRes references from 106 publications. We followed the same logic as in section 3.4.2.3 to determine the most popular and topical SCRes phases in the sample. We determined the relative importance of the phases based on the total references and references addressing the phases from the sample. The results are depicted in Fig. 12. Most papers (93% of 131 references) concentrated on the readiness and response phases. Readiness is the most topical (65%; 85 out of 131 references) SCRes phase. Response is the next most popular phase of SCRes as 28% of the SCRes phase references in the sample targeted addressing the response phase. The recovery phase has received 7% (9 of the 131 references) attention in our sample. Our evaluation revealed that no focus has been given to the growth phase of SCRes. The results obtained for readiness, response, recovery, and growth are consistent with the recent findings obtained by Spieske & Birkel (2021), who reported research studies at the intersection of I4.0 technologies (for which AI is a subfield) and SCRes focus on readiness, response, recovery, and growth with shares of 48%,42%, 10%, and 0% respectively. However, our finding on the readiness phase deviates from the results obtained by Ali et al. (2017) and Hohenstein et al.(2015), who investigated the research trends in SCRes and reported that most studies on SCRes focused on the recovery phase and failed to address the readiness phase. Baryannis et al. (2019b), who investigated research studies that apply AI technologies for SCRM, also reported that most studies focused on the response phase of SCRM.

For the rationale behind our findings, especially on the readiness phase, we draw insights on four issues. The first is the need to be prepared for the unexpected/unknown of SCs to be more resilient. By definition, resiliency is anticipating and preparing for the unexpected, especially for disruptive risks of low probability and high consequence. The second is the ease of use and effectiveness of AI technologies for anticipating in the readiness phase (Spieske & Birkel, 2021). The third is the tendency of researchers to focus on the readiness phase as recommended by prior researchers in the field of SCRes (A. Ali et al., 2017; Hohenstein et al., 2015). The fourth is a paradigm shift by SC practitioners that used to present reluctance to the proactive SCM activities and assume the risks of disruptions are uncertain and time-consuming (Grötsch et al., 2013) to a more resilient focused perception. The recent disruptive events like the Tornadoes, Brexit, the US-Chinese war, the COVID-19 pandemic, and cutting-edge (disruptive) AI technologies in SCRes have triggered the research interests focusing on the readiness phase of SCRes. No reference from our sample addresses the growth phase of SCRes. This is also similar to the results obtained by Spieske & Birkel (2021). Zamani et al. (2022) also reported AI's unexplored capability to contribute to the growth (adaptation) phase of SCRes. Previous systematic literature reviews on SCRes also indicate that few studies focus on the growth phase (A. Ali et al., 2017; Hohenstein et al., 2015). It is evident that the long-term perspective of SCRes on SCs has been missed (Spieske & Birkel, 2021). However, the lessons learned from disruptions and making faster responses than the competitors can help firms gain a competitive advantage (Abeysekara et al., 2019; Jüttner & Maklan, 2011; Patel et al., 2022) after the disruptions are gone.

3.4.2.5. Specific SCRes tasks and industry types. Evaluation of the sample was conducted concerning the AI techniques' contribution to

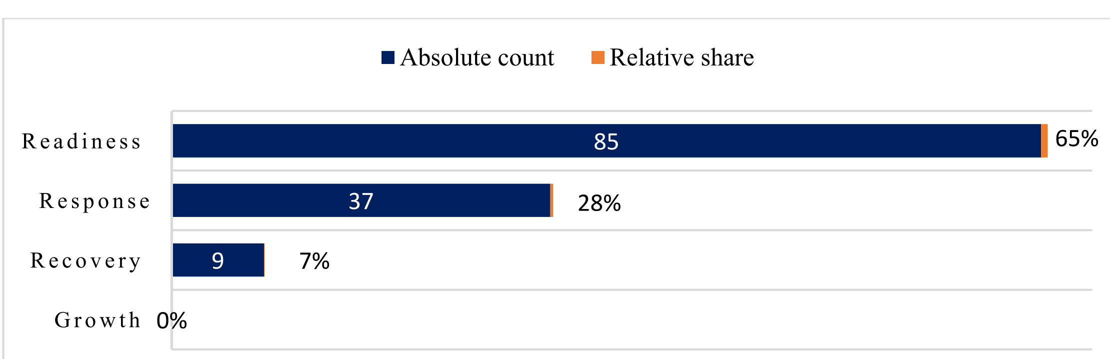

Fig. 12. Contribution of references for SCRes phase (n = 131).

achieving specific tasks of SCRes. The tasks were summarized in Appendix B for simplicity and information truncation. The SCRes phases and antecedents are addressed by directly or indirectly achieving specific SCRes tasks. Providing insights into risk and disruptions is the topper among the specific tasks investigated at an aggregate level (43% of the 106 articles). This indicates that practitioners' and academicians' motivation and struggle to identify disruptions before happening using AI techniques have contributed to the significant production of articles in the field. The AI techniques helping to make effective decisions under uncertainties is the second most topical task of SCRes in the sample (14 % of the 106 articles). This result was triggered by the fact that intelligent and quick decision-making under uncertainties fosters SCRes in the four phases. Fig. 13 presents the contribution of the tasks as evaluated in the sample.

The last evaluation of the sample was conducted concerning the industries that the authors investigated. Among these industries, the manufacturing sector, which includes automotive, electronics, equipment, metals, and more emerged as the prominent researched (comprising 59 % of the 106 articles). Following, transportation and logistics accounted for the second highest share of the research attention at the intersection of AI and SCRes (11% of the 106 articles). In contrast, pharmaceuticals, textile and garment, service, and SMEs are the least addressed types of industry in the sample. It is evident that the manufacturing and transportation sectors have received the most significant shares in of the research attention, owing to their prominent positions within the SC management field. However, as Fig. 14 illustrates, there exists a distinct imbalance in the distribution of research focus.

4. AI-SCRes framework

In this section, detailed sample analysis was carried out to synthesize relationships among the components (AI techniques, antecedents, and phases of SCRes) on which the systematic literature review was implemented. Overall, our findings from analyzing the sample indicate that AI techniques have various potential applications to enhance antecedents of SCRes in three phases. Based on the different connections detected among the components, relationships are established, discussed, and displayed in the framework developed. An AI-antecedent-phase (AAP) application framework was introduced based on the findings of the systematic review and previous conceptual frameworks developed to inform research and practice in SCRes. As we previously claimed that critical antecedents mediate the relationships between AI-based techniques and SCRes, we centered our discussions on the antecedents of SCRes.

Awareness: Among the seven critical antecedents of SCRes analyzed in the sample, awareness is the one that all AI techniques help to enhance. AI techniques enable to map SC networks to visualize and analyze the networks. Mapping techniques can improve understanding of dependencies that lead to SC complexity (Han et al., 2020; Singh et al., 2019; Spieske & Birkel, 2021) and potential bottlenecks (pitch points and critical paths) (Christopher & Peck, 2004; Er Kara et al., 2020). For instance, Wichmann et al. (2020) applied deep learning and natural language processing to automatically generate rudimentary SC maps and verify the existing SC maps to extract buyer–supplier relationships.

With an enhanced understanding of SCs, triggering factors can be detected earlier (Fiksel, 2015); risks can be quantified, and consequences on key SC key performance indicators can be evaluated with the help of intelligent techniques (Er Kara et al., 2020; Spieske & Birkel, 2021). In this regard, Lorenc et al. (2021) used ANN to detect disruption related to temperature anomalies in the cold chain. Lorence et al. (2020) also utilized ANN to predict the highest probability of rail cargo theft for areas. The expert-elicited and ML-based Bayesian networks can leverage SC network awareness. For instance, Lawrence et al. (2020) leveraged expert elicited-BN to model and analyze supplier vulnerability to severe weather risk. Lockamy & McCormack (2012) also used BN to develop supplier risk profiles to determine the risk exposure of a company's revenue stream. Liu et al. (2021) used dynamic BN for disruption risk assessment under the supply chain ripple effect. Hosseini et al. (2020) also utilized dynamic BN to quantify the ripple effect of supplier disruption on manufacturers in terms of total utility and service level. Molina Serrano et al. (2018) leveraged ML-based BN to classify and predict port variables for leveraging the understanding of the Spanish port system. Overall, all the AI techniques in the sample have contributed to enhancing the antecedent awareness. As depicted in Fig. 15, awareness supports all the first three phases of SCRes.

Visibility: The inherent capabilities of AI to support predictive and reactive decision-making can enhance end-to-end visibility and transparency (Spieske & Birkel, 2021; F. Zhang et al., 2020). Such transparency in supply and demand can reduce vulnerability in SCs (Silva et al., 2017). All the techniques evaluated in the sample contributed to building and enhancing visibility. In this context, Silva et al. (2017) used ANNs to improve SC visibility. Ma & Peng (2014) leveraged coupled

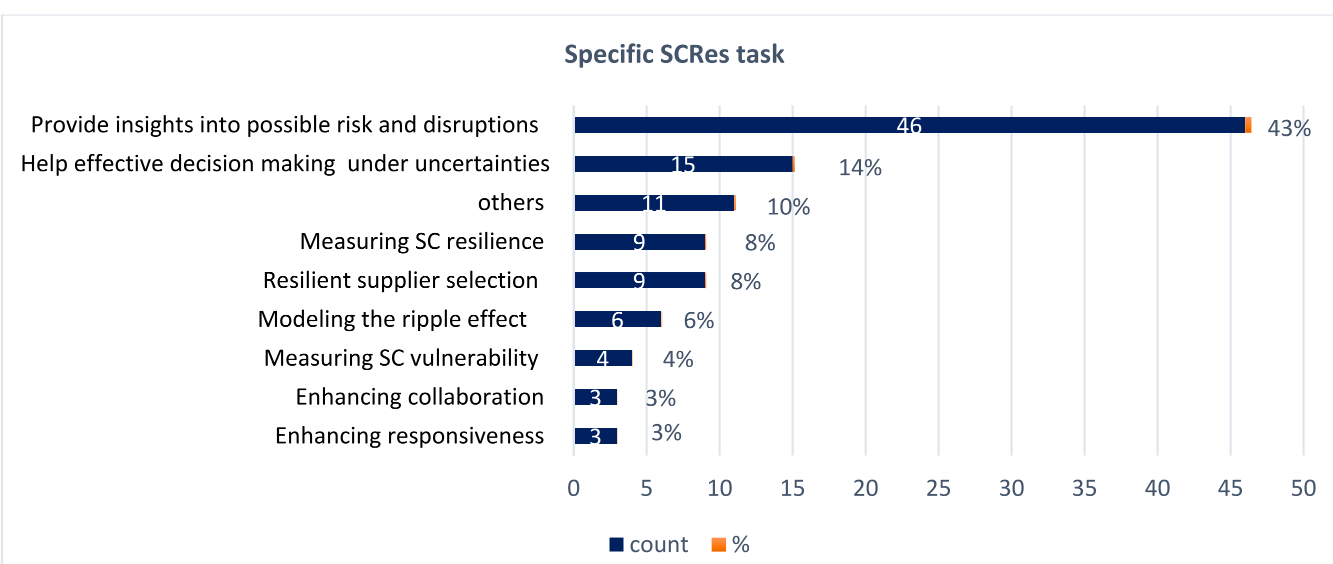

Fig. 13. Contribution of referees with regard to specific SCRes task achieved.

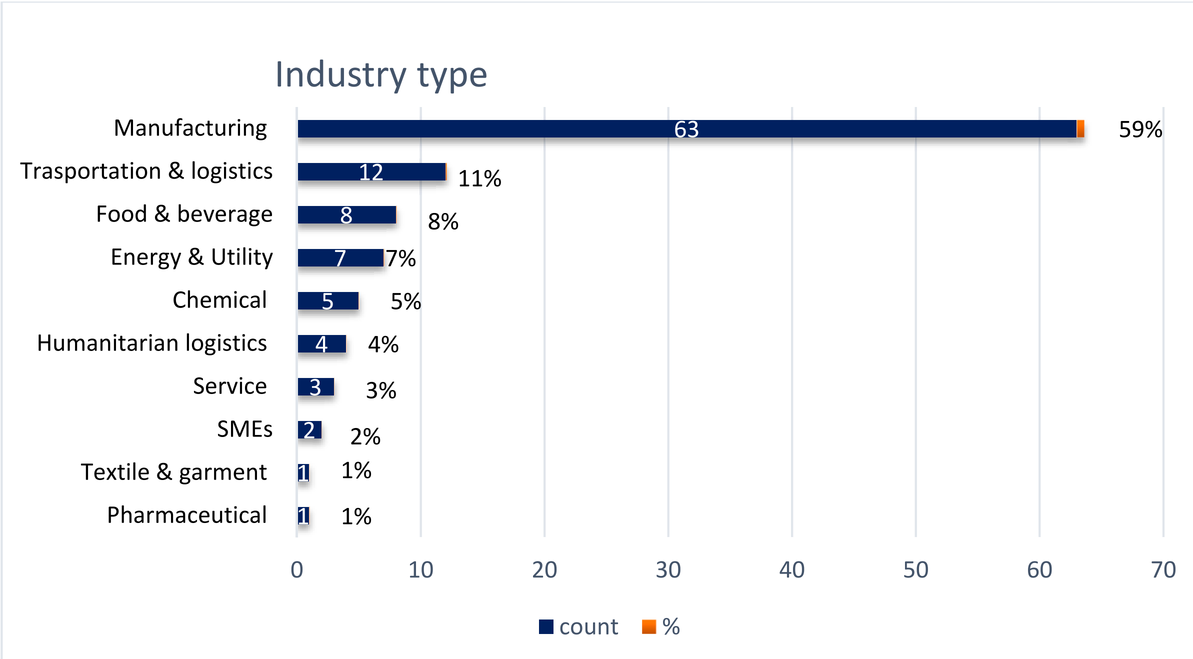

Fig. 14. Contribution of referees with regard to industry type addressed (n = 131).

ANN and grey model to predict labor turnover tendency. Daoping et al. (2015) also implemented ANN to study the knowledge sharing efficiency of a knowledge service network of an agile SC. Giannakis (2016) developed a multi-agent-based SC management system that incorporates big data analytics that exerts autonomous control actions to explore the effects of the systems on SC agility, for which visibility is an element to it. Hossain (2020) leveraged BNs to model and assess interdependencies between critical infrastructures in inland water ports and the surrounding SC network. W. Wang (2021) used DT to train and evaluate a risk prediction model. Our survey shows that BNs and ANNs have contributed the most to enhancing the antecedent visibility. As depicted in Fig. 15, visibility supports the first three phases of SCRes.

Collaboration: AI techniques can allow condensing and communicating relevant findings and SC disruptions to all players (Chae, 2015) and making collaborative decisions on issues related to risk and disruption management (Ahmadpour et al., 2017; Blos et al., 2018; Iftikhar et al., 2022; khayyam & Herrou, 2018; Kwon et al., 2011) and resiliency (Iftikhar et al., 2022). In this regard, Kwon et al. (2011) leveraged an agent-based web service approach for supply chain collaboration to enhance flexibility. Blos et al. (2018) developed a collaborative and autonomous disruption management framework for an SC with dispersed firms. MAIS were also used by Ahmadpour et al. (2017) to estimate SC risk collaboratively. Guillermo (2020) used ANN to predict the level of integration in SCs with variables including collaboration. Overall, eight AI techniques support collaboration and, MAIS have contributed the lion's share. Our analysis revealed that collaboration boasts the first three phases of SCRes.

SC configuration: AI techniques with optimization and machine learning capabilities can help SC network configuration by taking into consideration resiliency to cope with disruptions (Belhadi et al., 2021a; Hosseini et al., 2019; Iftikhar et al., 2022; Ivanov & Dolgui, 2021; Modgil et al., 2022; Naz et al., 2021). The techniques support making a tradeoff between flexibility (Spieske & Birkel, 2021) and efficiency (Zamani et al., 2022) when introducing resiliency in SC's structure and network (Modgil et al., 2022). Techniques with optimization capability enable testing alternative SC network setups and possible redundancies (Hosseini et al., 2019; Spieske & Birkel, 2021). From our analysis of the sample, eight techniques proved to boast the SC configuration antecedent of SCRes. GA and MAIS are the prominent techniques contributing to SC configuration. For instance, X. Wang et al. (2022) leveraged an extended GA algorithm to optimize SC network design under disruption risk. Nair & Vidal (2011) examined SC network topology and robustness against disruptions from random failure and targeted attacks. Overall, SC configuration enhances the first three phases of SCRes.

Velocity: Better understanding and transparency built with AI in SCs enable to quickly detect disruptions and make adaptive recovery faster (Modgil et al., 2021, 2022; Zamani et al., 2022). Our analysis revealed that few references addressed or revolved around velocity. BNs, ANN, and MAIS are the techniques utilized by references to address velocity. For instance, Louis (2016) developed multi agent-based supply chain management system to explore supply chain agility with speed, responsiveness, and flexibility dimensions. Protogerou (2021) leveraged multi-agent intelligent systems based on ANN to detect anomalies earlier in the internet of things (IoT) ecosystem. The detail of AI references contributing to specific SCRes tasks under the antecedents, including velocity, has been presented in Appendix B. Velocity is the only antecedent supporting only the first two phases of SCRes.

Resilient sourcing: AI techniques have proven to support decisions related to resilient sourcing. They are leveraged to superior and resilient supplier selection (Cavalcante et al., 2019; Zamani et al., 2022). Our analysis revealed that eleven techniques have proved to support resilient sourcing decisions. BNs are the prominent techniques utilized for resilient supplier selection. In this regard, Hosseini & Barker (2016) leveraged BN to quantify the appropriateness of suppliers across primary, green, and resilience criteria. Nepal & Yadav (2015) also used BN as a framework for sourcing risk analysis during supplier selection. El-Hiri et al. (2019) Presented a generic supplier selection model based on ANN to help manufacturers choose the most efficient suppliers and monitor their performance. As can be seen from Fig. 15, resilient sourcing supports the first three phases of SCRes.

Flexibility: Our analysis revealed that AI techniques help to support decision-making when introducing flexibility and agility in SCs and examining SC's flexibility level to disruptions. Nine techniques have proven to support building and evaluating flexibility. MAIS are the most utilized among the techniques. For example, Blos et al. (2015) developed an agent-based SC system to mitigate disruptions with strategies including a flexible supply base and transportation. Bastug & Yercan

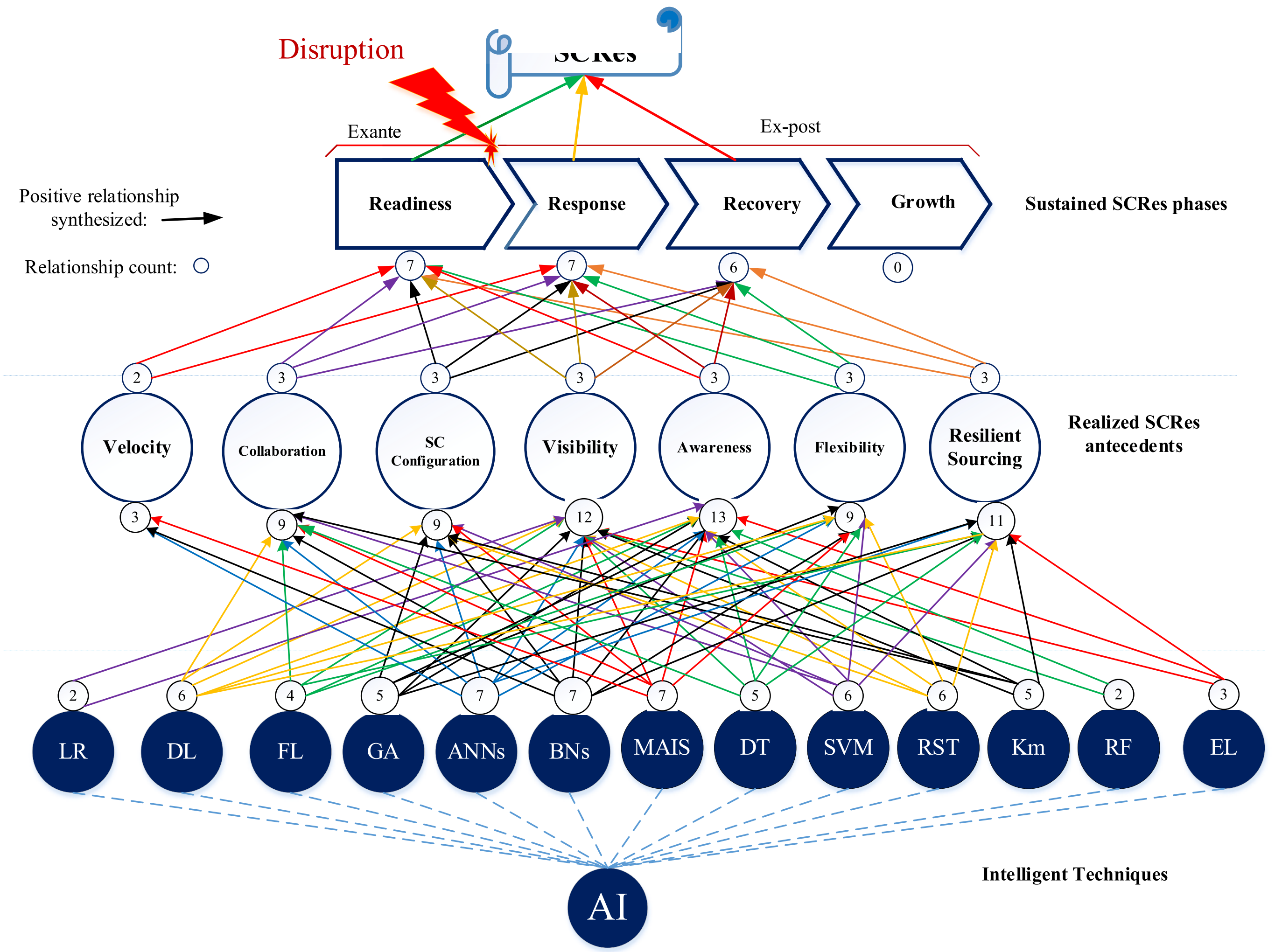

Fig. 15. AI-antecedent-phase (AAP) application framework. Notes. LR: logistic regression, BNs: Bayesian networks, MAIS: multi-agent intelligent systems, DL: deep learning, FL: fuzzy logic, GA: genetic algorithm, ANNs: artificial neural networks, DT: decision tree, SVM: support vector machine, RST: rough set theory, Km: k means algorithm, RF: random forest, EL: ensemble learning.

(2021) leveraged sentiment analysis with SVM methodology to assess Covid-19 related tweets and re-tweets by logistic organizations with regard to competitive priorities that lead to sustainable competitive advantage. Competitive priorities were evaluated across several dimensions, including flexibility and responsiveness. Shekarian et al. (2020) examined the effect of flexibility and agility on improving SC responsiveness to disruptions. They utilized optimization techniques, including GA, to help decision-makers to anticipate how much improvement in flexibility and agility would lead to an improvement in responsiveness. Likewise, Hae Lee et al. (2010) leveraged ANN to measure SC flexibility with the dimensions of time, quantity, and cash flow. The relationships synthesized from the analysis have revealed that flexibility supports the first three phases of SCRes.

Overall, the findings indicate that AI techniques have tremendous potential for supporting antecedents of SCRes in the first three phases. A comprehensive framework was developed to represent the scattered and fragmented knowledge base from the research streams to help address the complexity in SCRes systematically. The framework provides adequate knowledge that cannot be gained from reading individual research reports.

The AI-SCRes framework displays the synthesized relationships and hierarchical order, with antecedents mediating the positive relationships between SCRes and AI techniques. Arrows indicate the positive relationships obtained from the analysis. Numbers labeled in circles show the number of relationships detected with the variables before and after the variable of interest (AI technique, antecedents and phases of SCRes). The framework systematically answers the research question of how AI techniques enhance SCRes. Through this comprehensive framework, we intend to guide practitioners to successfully adopt AI techniques for building and enhancing SCRes and researchers to use it as a conceptual framework for further researching empirical works in SCRes.

5. Implications of the study and future research directions

5.1. Practical implications

Today's SCs operate in a globally growing, complex, and dynamic business environment full of uncertainties and disruptions of different likelihoods and consequences affecting SC performances. Recent catastrophic disruptive events, with low probability and high consequences, like the Covid-19, have revealed the vulnerabilities and the lack of resilience in SCs across the globe and the ineffectiveness of the classical risk management paradigm. Therefore, SCM executives and practitioners are expected to complement the conventional risk management approach with resiliency, a system approach to addressing uncertainties and coping with unexpected disruptions. Findings from our SLR and the framework developed based on the findings have crucial implications for practitioners in SCM. Our findings offer unique opportunities for SC practitioners to employ AI techniques that are proven scientifically by researchers to contribute to mitigating SC disruptions risks. Executives in SCM and related areas can reap the benefits of AI techniques to strengthen the resiliency needed to anticipate and respond adaptively to uncertain and unpredicted SC disruptions emanating from the complex and dynamic business environment.

BNs are the prominent and most topical techniques of AI utilized to enhance the seven (evaluated in the sample) antecedents of SCRes that we consider the building blocks of resiliency in SCs. Practitioners can deploy BNs, for example, to select resilient suppliers, measure the resilience of SCs, model and evaluate vulnerabilities in SCs, investigate the interdependencies among resilience capabilities, and vulnerabilities in SCs. MAIS are the second most important technique of AI proven by researchers to contribute to SCRes. Practitioners can leverage MAIS, for instance, to support decision-making and even let intelligent agents make decisions on behalf of the SC actors during disruption when accurate but quick decisions are needed under complex and challenging conditions. Our findings and proposed framework shed light on awareness among SC practitioners about the AI techniques, antecedents, and relevant phases to consider in building resiliency in SC. Practitioners can leverage the proposed framework to select appropriate AI techniques when addressing or enhancing critical SCRes antecedents supporting resiliency in the four phases. Practitioners also can refer to Appendix B when they want to address specific SCRes tasks. We recommend practitioners benefit from the first mover advantage for gaining competitive advantage from resiliency presented during disruptions, as disruptions are not only inevitable but also beneficial (Fiksel, 2015). Finally, we recommend that practitioners foster the culture of data collection to reap the benefits ML algorithms provide for learning patterns and irregularities in SC operations.

5.2. Policy implications and interventions

Because SCs are the backbone of global economies, the vulnerabilities and the negative consequences of SCs resulting from disruptions can hinder national economic development and affect human lives. Therefore, policymakers are expected to contribute to reducing vulnerabilities and enhancing resiliency in SCs. Our analysis revealed critical antecedents to build and enhance resiliency in SCs and the benefits AI techniques have in reducing vulnerabilities and fostering resiliency in the first three phases of SCRes. AI techniques have the potential to clarify uncertainties from information gaps in this complex and dynamic business environment.

Regarding the critical antecedents of SCRes, policymakers should consider public digital and other related infrastructure to be utilized by SCs to strengthen the collaboration among the SC members and to enhance transparency and end-to-end SC visibility. In order to facilitate resilient sourcing, policymakers can come up with alternative national sourcing strategies and even can relax stringent national sourcing strategies that hinder the degree of flexibility during disruptions times. Regarding AI and related digital technologies, policymakers can subsidize investment in developing new and innovative AI techniques and algorithms that can benefit resiliency in supply chains. This can provide SC practitioners with affordable, innovative digital technologies. Policymakers are also expected to cultivate and enforce the culture of data collection that enable SCs to clarify future uncertainties by implementing ML algorithms.

5.3. Theoretical implications and directions for future

The value of our SLR lies in its ability to synthesize and consolidate fragmented research at the nexus of AI and SCRes and help to provide a basis for further advancement of the topic. Therefore, based on the findings from our sample analysis and the increasing number of research calls by researchers in recent literature, we outlined potential research opportunities in the rest of this section.

5.3.1. Least addressed antecedents and phases of SCRes

Our analysis regarding the SCRes phases indicates that no research has been done that explores AI techniques in realizing the growth phase of SCRes and that a minority (7%) of the references addressed or revolved around the recovery phase of SCRes. Therefore, we encourage future researchers in both SCRes and at the nexus of AI and SCRes to focus more specifically on the recovery and growth phases of SCRes. This can keep the attention of SC practitioners in the direction of long-term SCRes benefits and the possibilities to attain competitive advantages after disruptions are gone. Concerning the critical antecedents of SCRes, the findings revealed that less attention has been given to velocity (2%) and resilient sourcing (6%) antecedents of SCRes by references in the sample. Speedy detection of anomalies, developing recovery plans faster, and responding to disruptions quickly are crucial elements of SCRes and help to reap the advantages of first movers in a given business during disruptions in addition to being resilient. Therefore, there is a need to focus on the velocity antecedent of SCRes in the recent future. Sourcing resiliently also plays a magnificent role when supplying material and inputs during supplier disruptions. Hence, future researchers in SCRes and at the nexus of AI and SCRes have to focus on the resilient sourcing antecedent of SCRes.

5.3.2. Underrepresented and unexplored AI techniques

Our analysis indicates that most AI techniques are underrepresented in SCRes, as depicted in Fig. 8. We encourage researchers to utilize the full potential of AI with theoretical and practical future research works. Ensemble learning (EL) algorithms are developed from a collection of ML algorithms to utilize the unique capabilities of individual algorithms, and they have the potential to address SCRes problems and enhance SCRes antecedents. However, a minority of the references in our sample (3%) deployed EL algorithms to realize the antecedents of SCRes. Hence, we recommend that future researchers unleash the potential hybrid ML algorithms in realizing SCRes. There are varieties of AI and ML algorithms. We have presented only those AI techniques explored in our sample. Therefore, future research at the nexus of AI and SCRes is expected to explore the remaining techniques. For instance, expert systems can be utilized to enhance the effectiveness of risk management activities and as a base for knowledge representation and inferencing when making an intelligent decision with regard to managing disruptions and building resiliency in SCs. Expert systems also can be hybridized with multi-agent intelligent systems to automate the decisions making of agents representing SC players at times of disruptions.

5.3.3. Further theoretical and empirical investigations

Findings from analysis of the sample confirm that AI techniques have the potential to support SCRes through its antecedents. However, AI's influencing impact on enhancing SCRes has to be empirically examined to see the significant difference between the firms adopting and non-adopting AI. Therefore, we recommend that researchers in SCM empirically examine the impact AI adoption has in enhancing SCRes and other SC key performance indicators.

Because SCRes is an emerging topic until now, there have yet to be universally validated and accepted metrics or indexes to quantify SCRes. Hence, we encourage future researchers to investigate the critical antecedents' interdependencies as constructs to measure SCRes and validate our proposed framework. Our framework can be a good foundation for modeling and measuring resiliency SCs in the four phases. Our analysis of the sample concerning the types of industries the authors researched indicate a distinct imbalance in the distribution of research focus (Fig. 14). Therefore, future research at the nexus of AI and SCRes should address the sectors that have received the least attention. For instance, the food and beverage industry is critical for global food security, with its value chain extending into the agricultural sector, which is highly vulnerable to disruptions due to its sensitivity and complexity.

Hence, there is a need for more research to investigate the food and beverage SCs, applying AI to enhance their resilience. Furthermore, the topical nature of resilience and the complexity of the modern global business environment have spurred numerous research effort in SCRes. We anticipate that *meta*-analytical systematic literature reviewers will significantly contribute to advancing the field of SCRes and shedding light on areas necessitating further exploration.

6. Conclusion and limitations of the study

6.1. Conclusion

The primary objective of this study was to capture the current state of research and practice and potential applications of AI techniques for developing and enhancing SCRes. A systematic literature review was adopted to curate and review relevant articles published at the nexus of AI and SCRes between 2010 and 2022. We shortlisted 106 peer-reviewed journal articles based on logical selection criteria. This SLR is one among the research works conducted in response to the calls by practitioners and researchers in the domain of SCM to carry out research for developing and enhancing SCRes to complement the conventional risk management approach that was ineffective in dealing with the unexpected SC disruptions emanating from the globally growing and complex business environment and to capture the potential cutting-edge technologies like AI have for enhancing SCRes. To date, the uniqueness of our review lies in its distinct taxonomies deployed to categorize research findings on the topic and the framework proposed to inform both research and practice at the nexus of AI and SCRes. The shortlisted articles were categorized under the AI techniques deployed in addressing SCRes, the utilized inherent capabilities of the technique, the antecedents that serve as building blocks of SCRes, and the phases (based on the state-of-the-art definition of SCRes) that AI techniques reported to enhance.

The analysis and synthesis carried out on the sample provided answers to the research questions. Regarding RQ1, research at the nexus of AI and SCRes is still evolving. Some unexpected disruptions like Brexit, the US-Chines trade war, and the Covid-19 pandemic were believed to be the forces making the peaks in the trend of publications over the years. This result is consistent with other related works and it is expected that the number of publications addressing SCRes and cutting-edge technologies enabling it will grow gradually. International Journal of Production Research is the dominant source publishing most of the articles and Hosseini is the key author in the article production. RQ2 was answered by isolating thirteen frequently used AI techniques for supporting research and practice in developing and enhancing SCRes from the extant literature. Among the techniques, Bayesian networks are the most topical and mature ones. Multi-agent intelligent systems and artificial neural networks are the second and third popular techniques in our sample.

Prediction, automated reasoning, optimization, decision support, clustering, and decision-making were identified as frequently utilized capabilities of AI and ML. Decision support is the most popular capability utilized in our sample; thus, we answer RQ3. Concerning RQ4, our sample identified visibility, flexibility, collaboration, resilient sourcing, SC configuration, velocity, and awareness as the critical antecedents of SCRes. Visibility is the most realized antecedent by the applications of AI techniques in our sample. To answer RQ5, we reviewed the state-of-the-art definitions of SCRes and identified that readiness, response, recovery, and growth are the phases of SCRes. However, our finding has revealed that AI techniques support only the first three phases of SCRes. Regarding RQ6, providing insights into risks and disruptions is the topper and helping to make effective decisions under uncertainties is the second most popular among the specific tasks investigated in our sample.

With regard to providing an answer to RQ7, we proposed a holistic framework that we developed based on the synthesized relationships from the analysis of the sample to help practitioners utilize the right and proven AI techniques to enhance resiliency in SCs. RQ8 was answered by drawing insights into future impactful research at the nexus of AI and SCRes. Answering the research questions systematically provided important implications for practice and policy and directions for future research. Hence, we can conclude that AI techniques have proven potential applications for developing and enhancing SCRes in this dynamic business environment.

7. Limitations

This paper has certain methodological and scope-related limitations. First, the results obtained from the SLR depend on the databases leveraged and the inclusion criteria applied that we justified in the SLR section. However, other studies with properly justified inclusion criteria and the consideration of sources other than peer-reviewed journals can still discover missed studies and provide further insights into the topic. Second, the study was limited to collecting only original empirical and analytical research to extract empirical evidence. However, considering other studies like conceptual and literature review works, thesis works, Book chapters, and conference papers can draw new and deep insights into the topic. Third, different organizational theories like dynamic capabilities theory, improvisational theory, resource-based view, and contingency theory are currently contributing to the development and enhancement of SCRes. Future SLRs can consider their potential in SCRes and at the nexus of AI and SCRes. Fourth, AI is not the only cutting-edge technology for developing and enhancing SCRes. Hence, future SLR can investigate other technologies like Blockchain, IoT, Digital twins, etc.. in achieving SCRes.

CRediT authorship contribution statement

Adane Kassa: Conceptualization, Methodology, Data curation, Investigation, Formal analysis, Project administration, Writing – original draft, Writing – review & editing, Validation. **Daniel Kitaw:** Conceptualization, Methodology, Investigation, Project administration, Supervision, Writing – review & editing, Resources. **Ulrich Stache:** Project administration, Supervision, Visualization, Validation, Writing – review & editing. **Birhanu Beshah:** Conceptualization, Methodology, Formal analysis, Project administration, Writing – review & editing, Validation. **Getachew Degefu:** Supervision, Validation, Project administration, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Appendix A:. Summary description of AI techniques

AI techniques /Algorithm	Description
Multi-agent intelligent systems (MAIS)	A subfield of distributed artificial intelligence (DAI) to solve distributed problems (Akerkar, 2019) by using independent agents (Marsh, 1992; Z. Zhang & Zhang, 2004). A complex control problem can be divided into several simple problems, being each control unit self-contained, processing its goals, skills, knowledge, and a set of rules that regulate its behavior. A multi agent system refers to a group of autonomous intelligent agents that collaborate(share information) to solve common tasks or make decisions that are beyond the individual capabilities or knowledge (Z. Zhang & Zhang, 2004) within a dynamic environment (Giannakis & Louis, 2011; Lo et al., 2008; Saraeian et al., 2019) in a decentralized autonomous planning systems (Marsh, 1992; Wooldridge & Jennings, 1995). MAIS integrates several AI techniques from different subfields like reasoning, knowledge representation, machine learning, planning, coordination, communication, etc.
Genetic algorithm (GA)	A global search heuristics algorithm based on the idea of "survival of the fittest" biological evolution and heredity (Tong et al., 2020). In AI and ML, search is used in both learning (from data or examples) and reasoning, and GA is used in this context (Shapiro, 2001; Sharma et al., 2020). It is used to find optimal solutions for difficult problems that would otherwise take decades (Akerkar, 2019). The algorithms iteratively select better solutions and uses them for generating new candidates in order to "evolve" the population (Y. Liu et al., 2020; Russel & Norvig, 2010).
Rough set theory (RST)	It was developed by (Pawlak, 1982) to classify and deal with imprecise, inconsistent, uncertain, or incomplete information and knowledge(Parmar et al., 2010; Pawlak, 1982; Qinghua et al., 2016), and to aid approximations in decision support (G. Li, 2007). Incomplete or inconsistent information can be encountered when the available feature set describing data samples does not suffice to discern between them, that is, the dataset contains elements having the same values for all features but different values for the related outcomes. It classifies objects into similarity classes (clusters) containing objects that are indiscernible with respect to previous occurrences and knowledge. Then, the similarity cases are employed to determine various patterns within the data (Bai et al., 2017; Parmar et al., 2010).
Fuzzy logic (FL)	It is a subset of the fuzzy set theory proposed by (Zadeh, 1965). It is a technique of reasoning that resembles human reasoning (Russel & Norvig, 2010) dealing with uncertainties in data, information and knowledge by summarizing data and focusing on decision relevant information (Klement & Slany, 1997; Luger, 2009; Serena et al., 2008). Uncertainty relates to the notions of imprecision, randomness, incompleteness, unreliability, vagueness, and fuzziness (Klement & Slany, 1997). In general terms, FL can handle ambiguity, impression, and ambiguity of objects (Min, 2010). The main reason for using FL in AI in general and expert systems in particular is that much of the information contained in knowledge-based systems is uncertain in nature (Kandel & Schneider, 1989).
	ML algorithms
Artificial neural networks (ANNs)	They simulate the structure and functionality of biological neural networks of the human brain in learning to perform specific tasks. The basic building block of an ANN is a neuron that is a simple mathematical model (function) having three simple sets of rules namely multiplication, summation, and activation. The weights of the network learn to reduce the error between prediction by the ANN and the true value provided by the training data.
Bayesian networks(BNs)	BNs are structured based on Baye's theorem and probability theory (Drury et al., 2017; Hosseini & Ivanov, 2020; Neil et al., 2005). The ability to perform inference and causal modeling under uncertain knowledge are one of their most powerful features (Fenton & Neil, 2019; Neil et al., 2005; Russel & Norvig, 2010).The BN structure and parameters are developed either based on domain knowledge (expert elicited) or by learning from data by implementing either supervised or unsupervised ML techniques (Huang et al., 2020; Heckerman, 2008; Hosseini & Ivanov, 2020). Baye's classifier, Dynamic and static Bayesian networks are the most frequently utilized types of BNs in AI and ML.
Decision tree (DT)	It is one of the simplest and yet the most successful machine learning algorithm (Joshi, 2020; Mohri et al., 2018; Russel & Norvig, 2010) that represents a function that takes as input a vector of attribute values and returns a single output value (decision) (Ni et al., 2020; Russel & Norvig, 2010; Toorajipour et al., 2021) DT displays possible consequences with different graphs and each node of the graph contribute to one specific feature (Ni et al., 2020). It falls under both classification and regression categories of ML tasks.
Random forest (RF)	To cope with the overfitting in a DT, the random forest (RM) algorithm was proposed (Joshi, 2020). RF fits many regression and classification trees to a data set, and then combines the prediction from all the trees (Cutler et al., 2007; Fukuda et al., 2014). The algorithms start with the selection of many bootstrap samples from the dataset. A classification and regression tree are fit to each of the bootstrapped samples, but at each node, only a small number of randomly selected variables are available for binary partitioning. The trees fully grow and each is used to predict the out-of-bag (OOB) observations (Cutler et al., 2007; Joshi, 2020; Ni et al., 2020).
Ensemble learning(EL)	EL is a general Meta approach in ML, which seeks superior predictive performance by combining the predictions from multiple algorithms. EL algorithms are general techniques in ML for combining several predictors to create a more accurate (Mohri et al., 2018; Sharma et al., 2020) and stronger one (Joshi, 2020). The idea of ensemble learning is to select a whole collection, or ensemble, of hypotheses from the hypotheses space and combine their prediction (Liakos et al., 2018; Russel & Norvig, 2010) and to reduce overfitting. Each learner in the ensemble of learners captures certain aspects of information contained in the data which is utilized to train it (Joshi, 2020).
Deep learning(DL)	It refers to a set of machine learning algorithms that learn multiple levels of representations (Araque et al., 2017) in deep architectures (Al-Jarrah et al., 2015). In the term "deep learning" methodology, the term "deep" enumerates the concept of multiple hidden layers through which the data is transformed (Dargan et al., 2020; Schmidhuber, 2015). DL was proposed to overcome the incapability of the shallow ANNs (Janiesch et al., 2021; P. Kim, 2017) to handle big amounts of complex data which are common in many routine applications of AI like natural speech, images, information retrieval and other human-like information processing (Akerkar, 2019; Dargan et al., 2020). Autoencoders, deep belief networks, convolutional neural networks, recurrent neural networks, and self-organizing maps are the most popular DL algorithms that have applications in many fields (Akerkar, 2019; Dargan et al., 2020; Joshi, 2020).
K Means algorithm (km)	K-means is an unsupervised ML algorithm for clustering problems in pattern recognition and image processing(Likas et al., 2003; Mucherino et al., 2009; Ni et al., 2020). It is a method for finding cluster structure(into k clusters) in a dataset that is characterized by the greatest similarity (homogeneity) with the same cluster and the greatest dissimilarity(heterogeneity) between different clusters (Mucherino et al., 2009; Sinaga & Yang, 2020).
Logistic regression (LR)	It is a supervised ML algorithm. LR is one of the most important statistical and data mining algorithms used by statisticians and researchers for the classification and analysis of binary and proportional response datasets (Agresti, 2008; Akerkar, 2019; Dreiseitl & Ohno-machado, 2003; Joshi 2020; Mohri et al., 2018; Maalouf, 2011). LR algorithm takes continuous data as input and categorical (mostly binary) data as response (output) variables (Borucka, 2020).

Appendix B:. Summary of articles with regard to AI techniques and SCRes

AT Algorithms	Source	AI/ ML Task	SCRes antecedents enhanced /discussed							Phase of SCRes supported				Specific SCRes task/ benefit	Industry type
			Visibility	Velocity	Flexibility	Awareness	SCND	Collaboration	Resilient sourcing	Readiness	Response	Recovery	Growth		
ANN	(Lorenc et al., 2021)	P	X			X	X			X				Provide insights into possible risk and disruptions	Transportation & logistics
ANN	(Lorenc et al., 2020)	P	PX			X				X				Provide insights into possible risk and disruptions	Transportation & logistics
ANN	(Silva et al., 2017)	P	X			X				X				Improving SC visibility	Manufacturing
ANN	(Raut et al., 2018)	P	X		X	X		X		X				Investigation the impact of integration	Manufacturing
ANN	(Protogerou et al., 2021)	P		X		X		X		X				Provide insights into possible risk and disruptions	Food & beverage
ANN	(Sharifnia et al., 2021)	O	X			X	X			X	X			To help effective decision making under uncertainties	Chemical
ANN	(El-Hiri et al., 2019)	O	X					X	X	X	X			Resilient suppler selection	Manufacturing
ANN	(Ma & Peng, 2014)	P	X	X						X				Provide insights into possible risk and disruptions	Service
ANN	(Nezamoddini et al., 2020)	O	X		X		X			X	X			To help effective decision making under uncertainties	Manufacturing
ANN	(Kochak & Sharma, 2015)	P	X		X					X				Provide insights into possible risk and disruptions	Manufacturing
ANN	(Guillermo-Muñoz et al., 2020)	P	X			X		X		X				Predicting level of integration	Textile & garment
ANN	(Fanoodi et al., 2019)	P	X		X					X	X			Provide insights into possible risk and disruptions	Humanitarian logistics
ANN	(Hae Lee et al., 2010)	P	X		X	X				X				Predicting SC flexibility	Manufacturing
BNs	(Garvey & Carnovale, 2020)	AR	X	X			X				X			Modeling the ripple effect	Manufacturing
BNs	(D.Liu et al., 2021)	O			X	X	X				X			Modeling the ripple effect	Manufacturing
BNs	(M. Liu et al., 2022)	AR					X			X				Modeling the ripple effect	Manufacturing
BNs	(Sakib et al., 2021)	P	X			X				X				Provide insights into possible risk and disruptions	Energy & Utility
BNs	(Hosseini et al., 2016)	AR	X							X	X	X		Measuring resilience	Chemical
BNs	(Anuat et al., 2022)	P	X				X			X				Provide insights into possible risk and disruptions	Energy & Utility

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AT Algorithms	Source	AI/ML Task	SCRes antecedents enhanced /discussed Visibility	Velocity	Flexibility	Awareness	SCND	Collaboration	Resilient sourcing	Phase of SCRes supported Readiness	Response	Recovery	Growth	Specific SCRes task/ benefit	Industry type
BNs	(Marvin et al., 2020)	P	X			X				X				Provide insights into possible risk and disruptions	Food & beverage
BNs	(Hosseini & Barker, 2016)	AR	X						X	X				Resilient supplier selection	Manufacturing
BNs	(Liang et al., 2022)	P	X			X				X				Provide insights into possible risk and disruptions	Transportation & logistics
BNs	(Yang & Liu, 2018)	P	X							X				Measuring vulnerability	Food & beverage
BNs	(Hosseini et al., 2020)	S	X			X			X	X				Modeling the ripple effect	Manufacturing
BNs	(L. Zhang et al., 2015)	AR	X							X				Provide insights into possible risk and disruptions	SMEs
BNs	(Ojha et al., 2018)	P	X							X				Modeling the ripple effect	Manufacturing
BNs	(Hossain et al., 2020)	P	X			X				X				Modeling the ripple effect	Transportation & logistics
BNs	(Nepal & Yadav, 2015)	AR	X					X	X	X				Resilient supplier selection	Chemical
BNs	(Anwar et al., 2022)	P	X			X				X				Measuring vulnerability	Food & beverage
BNs	(Lawrence et al., 2020)	P	X			X		X		X				Measuring vulnerability	Pharmaceutical
BNs	(Y. Lu et al., 2020)	AR	X			X				X	X			Provide insights into possible risk and disruptions	Chemical
BNs	(Jiao et al., 2020)	AR	X			X				X				Provide insights into possible risk and disruptions	Manufacturing
BNs	(Molina Serrano et al., 2018)	P	X			X				X				Provide insights into possible risk and disruptions	Transportation & logistics
BNs	(Hossain et al., 2019)	P	X			X		X			X	X		Measuring resilience	Transportation & logistics
BNs	(Boutselis & McNaught, 2019)	P	X			X				X				Provide insights into possible risk and disruptions	Transportation & logistics
BNs	(Kumar Sharma & Sharma, 2015)	P	X			X				X				Provide insights into possible risk and disruptions	Manufacturing
BNs	(Lockamy & McCormack, 2012)	P	X			X	X		X	X				Provide insights into possible risk and disruptions	Manufacturing
BNs	(Nannapaneni et al., 2016)	P	X							X				Measuring resilience	Manufacturing
BNs	(Brintrup et al., 2018)	P	X				X			X				Provide insights into possible risk and disruptions	Manufacturing

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AT Algorithms	Source	AI/ ML Task	SCRes antecedents enhanced /discussed Visibility	Velocity	Flexibility	Awareness	SCND	Collaboration	Resilient sourcing	Phase of SCRes supported Readiness	Response	Recovery	Growth	Specific SCRes task/ benefit	Industry type
MAIS	(Z. Liu et al., 2022)	DM	X				X	X			X			Provide insights into possible risk and disruptions	Manufacturing
MAIS	(Nair & Vidal, 2011)	DM	X		X	X	X	X		X	X			Provide insights into possible risk and disruptions	Manufacturing
MAIS	(Giannakis & Louis, 2011)	DS	X			X	X	X		X	X			Provide insights into possible risk and disruptions	Manufacturing
MAIS	(Biao et al., 2014)	DM	X				X	X			X	X		Provide insights into possible risk and disruptions	Service
MAIS	(Puche et al., 2019)	DS	X	X	X			X			X			Provide insights into possible risk and disruptions	Manufacturing
MAIS	(Kwon et al., 2011)	DM	X		X		X	X			X			Enhancing collaboration	Manufacturing
MAIS	(Mekki et al., 2016)	DS	X		X		X	X			X			To help effective decision making under uncertainties	Manufacturing
MAIS	(Giannakis & Louis, 2016)	DM	X	X	X		X	X			X			Enhancing responsiveness	Manufacturing
MAIS	(Ahmadpour et al., 2017)	DS	X					X		X				Provide insights into possible risk and disruptions	Manufacturing
MAIS	(Saraeian et al., 2019)	DS			X	X	X				X			Provide insights into possible risk and disruptions	Manufacturing
MAIS	(Hogenboom et al., 2015)	DS	X					X		X				To help effective decision making under uncertainties	Manufacturing
MAIS	(Dev et al., 2016)	DS		X	X		X				X			To help effective decision making under uncertainties	Manufacturing
MAIS	(Hajian Heidary & Aghaie, 2019)	O	X				X	X	X	X				To help effective decision making under uncertainties	Manufacturing
MAIS	(Blos et al., 2015)	DS	X		X	X				X	X			Provide insights into possible risk and disruptions	Manufacturing
MAIS	(J. Li & Sheng, 2011)	DS	X		X			X		X				Modeling information uncertainties	Manufacturing
MAIS	(Blos et al., 2018)	DS	X		X	X		X		X	X			Provide insights into possible risk and disruptions	Manufacturing
MAIS	(Fu & Fu, 2015)	DM	X			X		X		X				Enhancing collaboration	Manufacturing
DT	(B. Liu et al., 2021)	P	X			X		X		X				Provide insights into possible risk and disruptions	Manufacturing

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AT Algorithms	Source	AI/ ML Task	SCRes antecedents enhanced /discussed Visibility	Velocity	Flexibility	Awareness	SCND	Collaboration	Resilient sourcing	Phase of SCRes supported Readiness	Response	Recovery	Growth	Specific SCRes task/ benefit	Industry type
DT	(Ruiz-torres et al., 2022)	P	X						X	X				To help effective decision making under uncertainties	Manufacturing
DT	(M. Peng et al., 2014)	P	X		X					X		X		Provide insights into possible risk and disruptions	Humanitarian
DT	(W. Wang et al., 2021)	P	X			X				X				Provide insights into possible risk and disruptions	Manufacturing
DT	(Kamalahmadi & Parast, 2017)	P	X			X			X	X				Evaluating mitigation strategies	Manufacturing
DT	(Mogre et al., 2016)	DS	X			X				X				Evaluating mitigation strategies	Energy & utility
DT	(Ponnambalam et al., 2014)	P	X			X				X				Provide insights into possible risk and disruptions	Energy & Utility
SVM	(Ye et al., 2015)	P	X			X	X			X				Provide insights into possible risk and disruptions	Manufacturing
SVM	(Cheng et al., 2020)	P	X			X				X				Resilient supplier selection	Manufacturing
SVM	(L. Zhang et al., 2015)	P	X			X			X					Provide insights into possible risk and disruptions	SMEs
SVM	(Y. Liu & Huang, 2020)	P	X					X		X				Provide insights into possible risk and disruptions	Manufacturing
SVM	(Baştuğ & Yercan, 2021)	P			X	X					X	X		Measuring resilience	Trasportation & logistics
SVM	(Cao & Zhang, 2016)	P	X					X		X				Provide insights into possible risk and disruptions	Manufacturing
SVM	(G. Zhang et al., 2020)	P	X			X				X				Provide insights into possible risk and disruptions	Trasportation & logistics
Km	(Sabouhi et al., 2021)	Clu	X			X	X	X	X	X				Measuring resilience	Chemical
Km	(Raptou et al., 2022)	Clu				X					X	X		Measuring resilience	Food & beverage
Km	(Khayyam & Herrou, 2018)	Clu				X		X			X			Enhancing collaboration	Manufacturing
GA	(Esmaeili-Najafabadi et al., 2021)	O	X				X		X	X				Resilient supplier selection	Manufacturing
GA	(Yavari et al., 2020)	O	X		X		X			X	X			Provide insights into possible risk and disruptions	Food & beverage
GA	(Shekarian et al., 2020)	P	X		X		X				X			Enhancing responsiveness	Manufacturing

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AT Algorithms	Source	AI/ML Task	SCRes antecedents enhanced /discussed							Phase of SCRes supported				Specific SCRes task/benefit	Industry type
			Visibility	Velocity	Flexibility	Awareness	SCND	Collaboration	Resilient sourcing	Readiness	Response	Recovery	Growth		
GA	(X. Wang et al., 2022)	O	X		X		X			X	X			To help effective decision making under uncertainties	Manufacturing
GA	(Yan & Ji, 2020)	O	X		X		X			X	X			To help effective decision making under uncertainties	Transportation & logistics
GA	(D. Z. Liu & Li, 2021)	O	X		X		X			X	X			Enhancing collaboration	Manufacturing
GA	(Vali-siar et al., 2022)	O	X			X	X		X	X	X			To help effective decision making under uncertainties	Manufacturing
GA	(Y. Liu et al., 2020)	O				X	X			X	X			Provide insights into possible risk and disruptions	Manufacturing
GA	(Tong et al., 2020)	O				X	X			X	X			To help effective decision making under uncertainties	Manufacturing
GA	(P. Peng et al., 2011)	O	X		X		X				X			To help effective decision making under uncertainties	Manufacturing
FL	(Davoudabadi et al., 2019)	DS	X			X			X	X	X			Resilient supplier selection	Manufacturing
FL	(Hosseini-Motlagh et al., 2020)	O	X			X	X			X	X			Provide insights into possible risk and disruptions	Energy & utility
FL	(Reyna-castillo et al., 2022)	P						X				X		Measuring resilience	Manufacturing
FL	(Kumar & Anbanandam, 2019)	DS	X		X			X						Measuring resilience	Manufacturing
FL	(Yazdani et al., 2022)	DS	X											Measuring supply chain resilience	Food & beverage
FL	(Jiang et al., 2021)	RS	X			X				X				Measuring vulnerability	Transportation & logistics
RF	(Grbčić et al., 2020)	P	X			X				X				Provide insights into possible risk and disruptions	Energy & utility
RF	(R. Joshi et al., 2018)	P	X			X				X				Provide insights into possible risk and disruptions	Service
RF	(Islam & Amin, 2020)	P	X			X				X				Provide insights into possible risk and disruptions	Manufacturing
RST	(Amiri et al., 2022)	DS	X			X				X				To help effective decision making under uncertainties	Manufacturing
RST	(Parmar et al., 2010)	clu	X					X	X	X				Resilient supplier selection	Manufacturing
RST	(Daoping et al., 2015)	P	X		X	X		X		X				Enhancing collaboration	Manufacturing

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AT Algorithms	Source	AI/ML Task	SCRes antecedents enhanced /discussed							Phase of SCRes supported				Specific SCRes task/benefit	Industry type
			Visibility	Velocity	Flexibility	Awareness	SCND	Collaboration	Resilient sourcing	Readiness	Response	Recovery	Growth		
RST	(Bai et al., 2017)	DS	X			X	X			X				To help effective decision making under uncertainties	Transportation & logistics
DL	(J. Li et al., 2022)	P	X			X				X				Provide insights into possible risk and disruptions	Energy & utility
DL	(Kong & Li, 2018)	P	X		X	X				X				Enhancing responsiveness	Manufacturing
DL	(Wichmann et al., 2020)	P	X			X		X		X				Enhancing visibility	Manufacturing
DL	(Nikolopoulos et al., 2021)	P	X			X		X		X				Provide insights into possible risk and disruptions	Humanitarian
DL	(Shokouhifar & Ranjbarimesan, 2022)	P			X		X		X	X				Provide insights into possible risk and disruptions	Humanitarian
LR	(Stöber et al., 2021)	P	X			X					X	X		Provide insights into possible risk and disruptions	Food & beverage
LR	(Marley et al., 2014)	P	X			X				X				Provide insights into possible risk and disruptions	Manufacturing
EL	(Hosseini & Khaled, 2019)	P	X				X		X	X	X	X		Resilient supplier selection	Manufacturing
EL	(Brintrup et al., 2019)	P	X			X				X				Provide insights into possible risk and disruptions	Manufacturing
EL	(Cavalcante et al., 2019)	P	X			X				X				Resilient supplier selection	Manufacturing

Notes. LR: logistic regression, BNs: Bayesian networks, MAIS: multi agent intelligent systems, DL: deep learning, FL: fuzzy logic, GA: genetic algorithm, ANNs: artificial neural networks, DT: decision tree, SVM: support vector machine, RST: rough set theory, Km: k means algorithm, RF: random forest, EL: ensemble learning, P: Prediction, DS: Decision support, O: Optimization; AR: Automated reasoning, Clu: Clustering, DM: Decision making, SMEs: Small and medium enterprises

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