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IFAC PapersOnLine 58-19 (2024) 813–818

Artificial Intelligence Opportunities for Resilient Supply Chains

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Abstract: The need for supply chains to be resilient is increasingly being recognised, following recent disruptions caused by global socioeconomic crises. Supply chain resilience allows for sustainable growth and development through adaptive capabilities, principally including the ability to effectively respond to disruptions to maintain consistent operations. This paper explores the opportunities presented by Artificial Intelligence (AI) in enhancing supply chain resilience. We first conceptualise resilience through a 4-C model: context, capabilities, choices, and contingencies. We then explore a range of AI approaches and develop a research roadmap that attempts to map particular technologies holding potential to the 4-C model.

Keywords: supply chain resilience; artificial intelligence; explainability; industry 5.0

1. INTRODUCTION

Supply chain resilience (SCRes) has come to the forefront following recent realisation that disruptive events have the potential to seriously impact the functioning and continuity of operations with severe consequences. Resilience, in its essence, is the ability of an organisation to respond to disruptions and restore its original state with minimum delay. Supply chain (SC) disruptions can arise from a variety of sources including pandemics, catastrophic events such as natural disasters, terrorism, war, political, social, and environmental influences and so on (Pettit et al., 2019; Queiroz et al., 2022).

Supply chains are increasingly required to develop capabilities that can help them withstand and effectively respond to disruptions. SCRes capabilities are necessary for businesses to reap the multitude of benefits associated with resilience. These include improved risk management and risk reduction, agility and continuity in operations, sustainability gains, and competitive advantage (Ivanov, 2018). Adopting innovative digital technologies and quantitative decision-making solutions have emerged as one powerful way for building SCRes (Baryannis et al., 2018; Hosseini et al., 2019; Zamani et al., 2023). An emergent view is that reasoning and learning plays an important role and AI-driven innovative technologies are crucial for building and enhancing SCRes (Kassa et al., 2023; Modgil et al., 2022; Belhadi et al., 2021; Dubey et al., 2022). AI can empower resilient SC in recognising, analysing, reconfiguring, and activating operations quickly, among others (Modgil et al., 2022).

This work explores opportunities presented by AI for the purpose of making SC more resilient. To achieve this, we first propose a 4-C model of SCRes, specified as context, capabilities, choices, and contingencies. We then provide an overview of the full landscape of AI approaches that is currently available, ranging from symbolic AI to sub-symbolic AI, machine learning and deep learning. Finally, we then bring the two together in the form of an indicative research roadmap that maps some of the technologies presented to each of the four components of the 4-C model. With this roadmap, we intend to stimulate further research in particular areas of AI that remain under-explored in the context of SCRes and drive the development of bespoke solutions that SC stakeholders can leverage to address resilience issues.

The remainder of this paper is structured as follows. Section 2 presents an overview of related work on resilience and introduces the 4-C model. An overview of AI approaches across different paradigms is presented in Section 3, along with a brief summary of applications of AI in SC research. Section 4 then presents a roadmap for further research on AI for SCRes, indicatively highlighting approaches using graph-based AI, probabilistic modelling and reinforcement learning. Finally, Section 5 concludes and discusses implications of further research in this area.

2. RESILIENT SUPPLY CHAINS

According to Ponomarov and Holcomb (2009), SCRes encapsulates "the development of adaptive capabilities that could aid organisations in meeting the challenges posed by unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and functions". Resilient SC should have capabilities to withstand and adjust to disruptions, absorbing minor disruptions and mitigating major ones, and ensure consistent operations. SC may not always be disruption proof, and in scenarios where disruptive events occur, resilient SC should have in place measures and contingency arrangements to limit the impact of consequences such as

10.1016/j.ifacol.2024.09.195

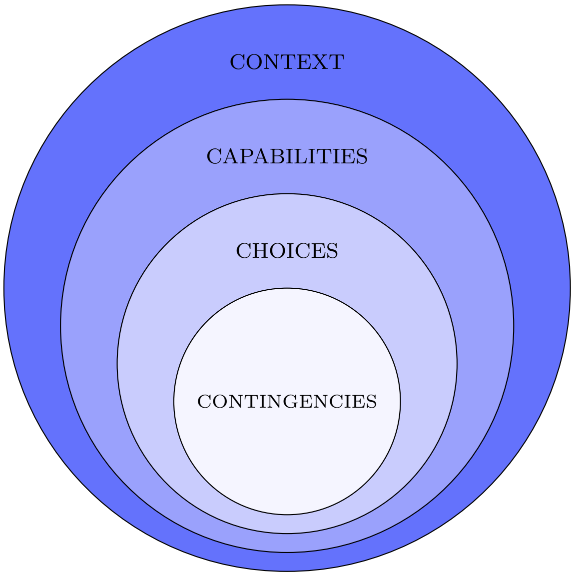

Fig. 1. The proposed 4-C model for Supply Chain Resilience

increased costs, reduced revenue, and decreased customer satisfaction.

In the definitions of SCRes put forward by several researchers (e.g. Ponomarov and Holcomb (2009); Xiao et al. (2012); Ivanov (2018)), aspects that are most prominent include adaptive capability, preparation for unexpected events, recovery from disruption, withstanding disruption, staying functional under disruption, ability to maintain control over performance variability, capability of sustained response to sudden and significant shifts in the environment, and ability of SC to cope with change. Central to these aspects are terms such as capability, adaptability, sensitivity, disruption, and staying functional. Ponomarov and Holcomb (2009) claim that resilient SC are less sensitive to disturbances and are more absorptive of SC disruptions. SCRes enables firms to ensure their products and services' continuous delivery to their customers Jafar Namdar and Pradhan (2018).

Phases of SC disruption can be viewed through a variety of lenses, each offering valuable insights. Two most common approaches are based on the impact and timeframe dimensions. Impact is addressed through a) prevention that proactively seeks to identify potential risks and vulnerabilities in the SC before they cause disruptions; b) mitigation that aims to minimise it; c) recovery that restores normal operations as quickly as possible; and d) adaptation that involves learning from the disruption and adapting the SC to be more resilient. The timeframe dimension has the following phases: a) onset, which marks the initial trigger of the disruption; b) escalation in which the disruption's impact grows and could cascade to multiple parts of the SC, c) protraction in which disruption continues for an extended period; and d) resolution which marks return to normalcy as the disruption subsides and the SC recovers. Associated with the two approaches is the conceptualisation by Scholten et al. (2020) of SCRes against disruptions: readiness (proactive, pre-disruption), response, and recovery (reactive, post-disruption). In general, the phases of SC disruption are often iterative, sometimes overlapping, and most importantly involve continuous improvement. Building a resilient SC is an ongoing process and involves: identifying potential risks; developing appropriate choices, solutions and contingency plans; investing in information processing technologies for real-time data and analytics, visibility and transparency; collaboration and appropriate SC relationships; and continuous monitoring and adaptations.

Drawing from the aforementioned insights gathered from literature, we propose to conceptualise SCRes as a 4-C model: Context, Capabilities, Choices, and Contingencies, as illustrated in Fig. 1. The SCRes *Context* consists of the circumstances that form the setting for SCRes and in terms of which it can be fully understood. SCRes context is multifaceted and can depend on stakeholder's perspectives. It includes, for example, the following: a) SC organisation, its resources, linkages and interconnectedness; b) the dynamic environment within which the chain operates, and the business focus, e.g. the type of products and/or services the chain offers. SCRes can indicatively be viewed from a microeconomic context, company and industry context, and resource impact context.

SCRes *Capabilities* are prominent and have received significant attention in literature. Resilience involves situational capability and can be acquired through continuous learning and adaptation from a series of disruptions (Belhadi et al., 2021). The situational capability can manifest across strategic, operational, and tactical levels of a SC. At the operational level, make-related activities are known to impact perceptions of strategies for resilience in the future. Highly significant to SCRes at the operational level are capabilities relating to visibility, collaboration, financial strength, and adaptability.

Of particular prominence in SCRes literature are studies adopting the theoretical lenses of Organisational Information Processing Theory, and those associated with the resource-based view, collaborative capability, and dynamic capabilities view (e.g. Dubey et al. (2022); Queiroz et al. (2022). Several studies argue that SC learning capability is key to improving resilience through the assimilation of knowledge from internal and external sources. In this regard, SC learning can offer useful strategic tools through, indicatively, evaluating prior experiences, observing current trends, and developing insights that help to enhance performance.

SCRes *Choices* and SCRes *Contingencies* collectively refer to the alternative options that an SC has at its disposal and according to its capabilities, in order to tackle the impact of SC disruptions. Choices may refer to identifying a range of alternative suppliers to manage uncertainty on the supply side, a range of policy options from just-in-case to just-in-time to address volatile demand and any other mechanism that has the ability to reduce the likelihood and impact of disruptions through appropriate prevention, avoidance or mitigation actions. Contingencies, on the other hand, may primarily delve into plans that are enacted in case response mechanisms are not successful in addressing the effects of a disruption.

AI is emerging as the forefront of technologies used for SCRes, due to its potential to reason with expert knowledge and learn from data in order to adapt decision making, promote SC innovation and develop rapid responses before, during and after a disruption. There are at least two viewpoints of AI in the SCRes literature: a) AI as a technological toolbox directly used to enhance SCRes outcomes; and b) AI as an organisational capability building technology that can be useful for innovation in disruption-prone environments. In this paper, we adopt the former and endeavour, in the next section, to present a complete overview of the current AI landscape that is not restricted to particular parts of the associated technological toolbox that may have received more attention, but rather encompasses the full range of AI capabilities available to SC stakeholders.

3. THE ARTIFICIAL INTELLIGENCE LANDSCAPE

The term “Artificial Intelligence” has broadly been used by researchers and practitioners to refer to systems that possess an element of intelligence in their decision making. The difficulty of defining human intelligence itself has led to a wide range of definitions for its artificial counterpart. In the context of this paper, we follow the definition of AI as a result of the thorough analysis of definitions of intelligence by Legg and Hutter (2007), and adapted by Baryannis et al. (2018) in the context of SC. This definition assumes two fundamental prerequisites to consider an approach as artificially intelligent: (1) the ability to autonomously decide on a course of action in order to achieve objectives; and (2) the ability to deal with a partially unknown environment.

This definition admits a wide range of approaches that range from symbolic AI and knowledge representation, to sub-symbolic and statistical AI, including machine learning (ML) and deep learning (DL). In the remainder of this section, we will attempt to unpick these different areas of AI and discuss major approaches within them and how they have been applied in the context of SC.

3.1 Symbolic AI

Symbolic AI broadly refers to AI approaches that invariably employ a high-level representation or model of knowledge relying on agreed upon abstractions using symbols. These representations are then used to reason about real-world problems to support decision making. Terms that are used synonymously to symbolic AI, include GOFAI (Good Old-Fashioned AI), knowledge-based AI or model-based AI. The defining characteristic of approaches that fall under the umbrella of symbolic AI is the specific language of symbols that is used for representation. The most commonly used languages are based on mathematics, with approaches ranging from mathematical programming, logic-based knowledge representation and reasoning and agent-based modelling. In the case of logic, many different variants have been explored to address issues with developing intelligent systems, from classical propositional and first-order logic to description logics and knowledge graphs, probabilistic logic and Bayesian networks, non-monotonic logic and fuzzy logic. Beyond logic, symbolic AI approaches have also included case-based reasoning, using precedents to make decisions, and evolutionary computation, which includes modelling approaches that are inspired by biology and evolution.

The main argument in favour of symbolic AI approaches is that they inherently afford a level of explainability that is normally not readily available in non-symbolic approaches which, at best may offer the ability to interpret outputs based on inputs. Note that we follow Antoniou et al. (2022) in distinguishing between interpretability and explainability, with the former being narrower than the latter, focusing on interpreting ML model outputs, without, however, being able to provide a full reasoning path from input to decision. Symbolic AI systems, especially rule-based ones (Baryannis et al., 2016), are more likely to be end-to-end explainable.

Another important benefit of symbolic AI approaches is their ability to work with less data. On the other hand, this is only possible provided that there is access to expert knowledge which can be encoded. Also, domains which are less structured and more uncertain are quite challenging for symbolic AI.

3.2 Sub-symbolic AI

Symbolic representation is considered high-level and was the dominant form of AI in its early decades, but schools of thought soon emerged that advocated so called sub-symbolic approaches at lower levels. Syb-symbolic AI today encompasses all approaches that rely on data (usually large amounts, often referred to as big data) in order to extract insights and make predictions that can, in turn, support decision making. Terms that are used synonymously to sub-symbolic AI, data-driven AI and machine learning. Machine learning approaches are quite wide-ranging and are commonly grouped into supervised, unsupervised and reinforcement approaches, based on learning with or without labels for the desired output, and learning iteratively through a feedback loop.

There is a wide range of machine learning algorithms falling under the sub-symbolic AI umbrella, including support vector machines, decision trees, regression, as well as ensemble approaches that combine multiple models. However, arguably the most popular approaches produce so-called connectionist models, or artificial neural networks. In recent years, versions of the latter that contain a significant number of internal layers have led to significant advances and the rise of deep learning as a dominant subfield. Deep learning has been quite successful in a range of areas, from computer vision and speech recognition, to natural language processing (Omar and Baryannis, 2020) and generative AI. The latter represents the latest revolution in AI that is characterised by a step change in the ability to generate text, images, audio and data that are high-quality and human-like, driven by latest advances, such as generative adversarial networks and transformers.

Regardless of the approach, the common benefit of syb-symbolic AI is the ability to produce results with minimal to no human input. This allows them to deliver insights that may go beyond collective expert knowledge and to successfully navigate unstructured and uncertain environments. However, this comes at the cost of limited to no explainability, as the complexity of the developed models can be too high for the human mind to easily comprehend. Additionally, most machine learning approaches especially

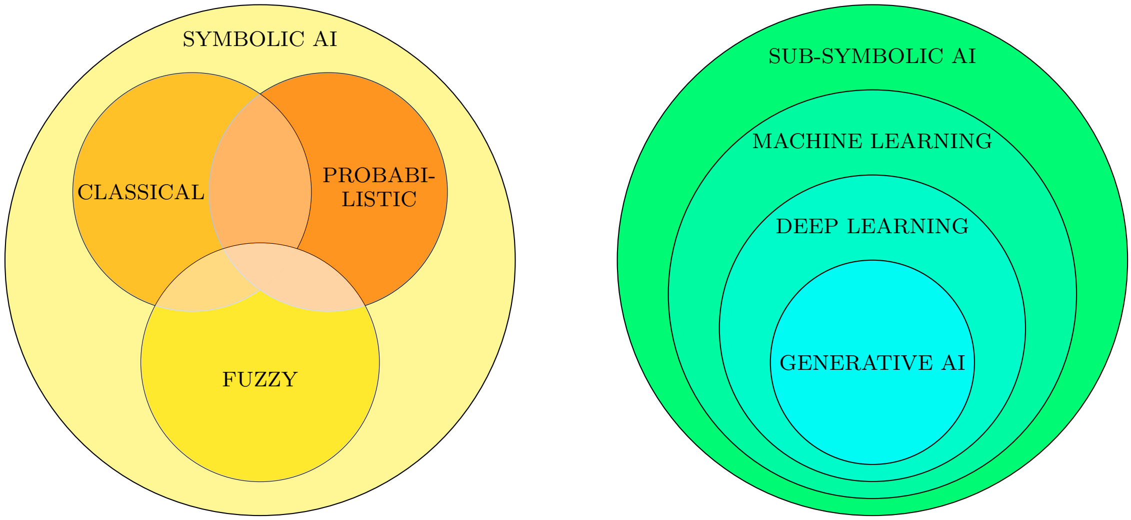

Fig. 2. Artificial Intelligence approaches and their interrelationships

deep learning ones depend on the availability of significantly large high-quality datasets.

Symbolic and sub-symbolic approaches exhibit high degrees of complementarity, with the former possessing desirable features that the latter lack, and vice-versa. This has led to an increasing focus on hybrid or integrated approaches that combine symbolic and sub-symbolic approaches. Examples include statistical relational learning and neurosymbolic approaches (Kosasih et al., 2023). There is also a growing body of literature that combines AI with approaches outside the AI spectrum, such as multi-criteria decision-making (Abdulla et al., 2023).

3.3 AI applications in supply chains

While AI has a long history spanning eight decades, it has only received significant attention from the SC community relatively recently. Coupled with the significant advancements in sub-symbolic AI summarised in the previous section, this has led to a proliferation of research in applying AI technologies to address both longstanding and emerging challenges within SC. In the remainder of this section, we briefly summarise the main areas within SC where AI has been applied and the particular approaches that have been explored. We adopt the application areas that were identified by Kosasih et al. (2023).

Demand Forecasting. Given the statistical nature of the demand forecasting problem and the statistical underpinnings of data-driven AI algorithms, there has been significant research in applying machine learning, deep learning and ensemble methods to forecast demand. A recent review by Mediavilla et al. (2022) identifies 23 research papers within a five year period (2017-2021) that use a range of approaches, from k-means clustering, logistic regression and decision tree classification to neural networks, random forests and boosting algorithms. These are employed for daily, weekly, monthly or quarterly forecasting with a range from 1 month to 14 years.

Supplier Selection. While supplier selection has traditionally been performed using Multi-Criteria Decision-Making (MCDM) approaches, there is an increasing body of work that explores AI approaches for ranking and selecting the best suppliers, in many cases combined with MCDM approaches. Chai and Ngai (2020) conducted a systematic review of the period 2013-2018 which identifies mathematical programming, fuzzy and rough sets, k-means clustering, genetic algorithms and most well-known machine learning based classification methods as ways to classify suppliers based on different criteria and decide which to select.

Inventory Management. A systematic review across a 10-year period (2012-2022) by Albayrak Ünal et al. (2023) highlights a rapid growth in research exploring AI solutions to inventory management problems, such as inventory control and policies and inventory visibility. The authors highlight computer vision, object detection and recognition and digital twinning as approaches within the AI spectrum that can assist in improving inventory management processes.

Risk Management. Surveys conducted by Baryannis et al. (2018) and Deiva Ganesh and Kalpana (2022) show that identifying, assessing, monitoring and responding to risks represent a major application area for AI approaches. Researchers have explored the use of data analytics in pinpointing risk indicators and drivers, network and simulation approaches to assess cascading risks and ripple effects and mathematical optimisation to develop response and recovery strategies.

Performance Evaluation and Others. In addition to the above SC management areas, AI has also indicatively been applied for: performance evaluation, using neural networks to classify the most important performance indicators among different stakeholders (Dumitrascu et al., 2020).

4. RESEARCH ROADMAP

The previous two sections discussed four main aspects of SC resilience under the 4-C model, on one side, and a range of AI technologies that can be leveraged to improve SC resilience, on the other side. In this section, we attempt to bring these together by proposing a research roadmap suggesting the exploration of particular AI technologies based on their alignment with the 4-C model. Note that the roadmap is meant to be indicative, not exhaustive: there are many more intelligent approaches to be explored than the ones that are highlighted next, but our analysis prioritises these due to their untapped potential.

Graph-based AI to capture resilience context. Understanding the multifaceted context of SCs and their environment requires a systematic approach to capture knowledge and expertise from relevant stakeholders, encode it in a model that can be consumed by intelligent systems and use these systems to extract additional contextual knowledge that may not be readily available. Knowledge graphs and graph neural networks (GNNs) are quite pertinent here, due to the inherent ability of graph models to capture complex interrelations between concepts. A recent line of work towards this direction is that of Kosasih and Brintrup (2022) and Kosasih et al. (2022) that explore knowledge graph reasoning and GNNs to discover hidden relationships between parts of a SC, improving the understanding of risk-related knowledge and, hence, contributing towards improved resilience. The explainability afforded by graph-based AI approaches is crucial to understanding resilience context and we envision further research in this direction, developing both general-purpose and sector-specific graphs to capture and reason with knowledge pertinent to resilience.

Probabilistic models to understand resilience capabilities. As explained in Section 2, understanding SC capabilities in relation to visibility, collaboration, adaptability, and so on, is fundamental in figuring out the scope within which resilience approaches can be explored. In this context, it is important to understand the range of factors that may support or hinder these capabilities, and Bayesian networks have already been shown to be capable of capturing uncertainties in this context, including but not limited to cascading risks, risk propagation and ripple effects (Hosseini and Ivanov, 2020). There is scope in this area to employ a wider range of probabilistic reasoning approaches, such as DeepProbLog(Manhaeve et al., 2018), which combines probabilistic inference with learning based on neural models.

Reinforcement learning to decide on resilience choices. The flexibility of reinforcement learning in adapting to various environments and optimising decisions through trial and error has already been leveraged in the context of SC risk management, e.g. to assist in identifying risks by progressively learning which news articles are relevant to a risk event (Aboutorab et al., 2022). In a similar vein, reinforcement learning can be used to sort through different choices that may be available in response to a risk, progressively learning which choices maximise resilience, ideally in combination with a human-in-the-loop approach, where experienced risk managers assist reinforcement learning algorithms to converge faster.

Industry 5.0 for human-centric contingency planning. Ivanov (2023) highlights data-driven SCs that are dynamically and structurally adaptable as the core tenet of Industry 5.0. Developing contingency plans in this context requires leveraging technologies in a way that retains humans at the centre of of decision making. Apart from human-in-the-loop approaches mentioned earlier, this can also be achieved, on one hand, by intelligent solutions that afford a level of interpretability or explainability to ensure they are understandable by humans and, on the other hand, by solutions that include generative and conversational AI (Ilya Jackson and Namdar, 2024) components to facilitate interaction with and input from humans.

5. CONCLUDING REMARKS

In conclusion, opportunities of AI technologies for resilient SCs remain under-explored, considering the relatively limited adoption of such technologies within SCs and the fast pace at which new technologies emerge. Viewing resilience through the lenses of the proposed 4-C model highlights the importance of understanding the context and capabilities of a SC and the range of choices and contingencies that are available to improve resilience. We expect models based on graph, probabilistic and reinforcement paradigms to play a significant role in supporting all three key Industry 5.0 pillars of resilience, sustainability and human-centricity.

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