The impact of multiagent systems on autonomous production and supply chain networks: use cases, barriers and contributions to logistics network resilience

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Abstract

Purpose – Academics and practitioners have long acknowledged the potential of multiagent systems (MAS) to automate and autonomize decision-making in logistics and supply chain networks. Despite the manifold promises of MAS, industry adoption is lagging behind, and the exact benefits of these systems remain unclear. This study aims to fill this knowledge gap by analyzing 11 specific MAS use cases, highlighting their benefits, clarifying how they can help enhance logistics network resilience and identifying existing barriers.

Design/methodology/approach – A three-stage Delphi study was conducted with 18 industry experts. In the first round, these experts identified 11 use cases of MAS and their potential benefits, as well as any barriers that could hinder their adoption. In the second round, they assessed the identified use cases with regard to their potential to enhance logistics network resilience and improve organizational productivity. Furthermore, they estimated the complexity of MAS implementation. In the third round, the experts reassessed their evaluations in light of the evaluations of the other study participants.

Findings – This study proposes 11 specific MAS use cases and illustrates their potential for increasing logistics network resilience and enhancing organizational performance due to autonomous decision-making in informational processes. Furthermore, this study discusses important barriers for MAS, such as lack of standardization, insufficient technological maturity, soaring costs, complex change management and a lack of existing use cases. From a theoretical perspective, it is shown how MAS can contribute to resilience research in supply chain management.

Practical implications – The identification and assessment of diverse MAS use cases informs managers about the potential of this technology and the barriers that need to be overcome.

Originality/value – This study fills a gap in the literature by providing a thorough and up-to-date assessment of the potential of MAS for logistics and supply chain management. To the best of the authors' knowledge, this is the first study to investigate the relevance of MAS for logistics network resilience using the Delphi method.

Keywords Multiagent systems, Automation, Autonomization, Digitalization, Autonomous systems, Delphi study, Resilience, Logistics network resilience, Productivity

Paper type Research paper

Introduction

Modern logistics and supply chain management (LSCM) is driven by the digitalization of processes and networks. In this regard, stable, efficient and resilient processes are of paramount importance and are a natural part of supply chain evolution (MacCarthy *et al.*, 2016; Miceli *et al.*, 2021). Among the plethora of challenges arising from the digitalization process, the automation of informational processes in LSCM is a core challenge, as acknowledged by both academic research (Dotoli *et al.*, 2019; Viale and Zouari, 2020; Frederico *et al.*, 2019; Nitsche *et al.*, 2021) and industry practice (Junge *et al.*, 2019; Kersten *et al.*, 2017). When equipped with enhanced decision-making abilities and artificial intelligence (AI), automated

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processes can evolve into autonomous processes, thereby bringing further value and enhanced resilience (Nitsche, 2021).

The ongoing COVID-19 pandemic has caused significant disruptions to supply chain networks (Sarkis, 2021) and sparked a debate over ways to increase supply chain resilience (Herold *et al.*, 2021). This might include increasing the speed of decision-making and reinforcing the ability of supply chains to recover from unpredictable disruptions more quickly (Ozdemir *et al.*, 2022). Therefore, in the wake of the COVID-19 crisis, the design of autonomous processes for managing logistics networks is becoming particularly important. Recent technological evolutions, in particular the increase in computational capacity and the growing availability of data, are crucial for enabling wide-scale automation and self-organizing logistics networks. These developments, in combination with technologies such as the Internet of Things (IoT) (Aryal *et al.*, 2018; Rejeb *et al.*, 2022), machine learning (ML) (Akbari and Do, 2021), blockchain (Treiblmaier, 2018b) and digital supply chain twins (Gerlach *et al.*, 2021; Calatayud *et al.*, 2019), have made autonomous systems in LSCM ever more realistic. Previously, the implementation of these technologies was hampered by technological shortcomings, but new concepts and applications have illustrated how they can be successfully integrated and deployed (Simchi-Levi and Wu, 2018; Helo and Hao, 2022; MacCarthy and Ivanov, 2022).

In this complex technological ecosystem, multiagent systems (MAS) are a highly important, yet under-researched, technological driver for enabling automation and autonomization (Dorri *et al.*, 2018). LSCM is a good match for the practical application of MAS, as supply chain processes require multiple decisions among a large number of actors, both within a company and among decision-makers of different firms. Previous examples demonstrate the positive impact of MAS on the automation of small-scale LSCM tasks, which play key roles in supply chain networks. For instance, MAS can be used to select suppliers based on ordering synergies (Yu and Wong, 2015), to establish collaborative supply chain management (Fu and Fu, 2015), to optimize process scheduling in the supply chain (Jiang *et al.*, 2018; Leusin *et al.*, 2018; Yu *et al.*, 2017) and to support decision-making in logistics networks (Blos *et al.*, 2018; Souza Henriques, 2019).

According to Sycara (1998), MAS have four defining characteristics:

1 limited information regarding each agent;
2 absence of a global control system;
3 decentralized data; and
4 asynchronous computation.

They enable optimization problems in subsystems to be solved in a short time compared with system-wide optimization (Karnouskos and Leitão, 2017; Wooldridge, 2009). As supply chains regularly comprise a variety of subsystems, their respective optimizations can yield substantial improvements overall. Through the digitalization of business processes, MAS can take over decision-making from humans and arrive at equally good or better solutions at greater speed (Müller and Fischer, 2014). In summary, MAS offer great potential for creating supply chains that are partially or fully autonomous (Ghadimi *et al.*, 2019; Fiedler, 2022).

It is important to differentiate MAS from related and partially overlapping concepts that are frequently used to support automation and autonomy in logistics and supply chain processes. To start with, the broad research field of AI has attracted significant attention in recent years since industrial users in particular expect complex problems to be solved quickly, proactively and, in some cases, independently of human decision-makers (Toorajipour *et al.*, 2021). Distributed artificial intelligence (DAI), a subfield of AI, provides solutions to problems that are too complex to be solved by one agent; thus, the associated computational load must be distributed among several agents, some of which might have divergent goals (Balaji and Srinivasan, 2010). Within the field of DAI, MAS offer one way to address complex decentralized problems. MAS consist of a finite number of agents; each agent has a specific goal and can determine whether or not this goal is met within its own context (Ferber, 1999). MAS can be understood as a set of agents that share information with each other to solve problems that are beyond the ability of a single agent (Balaji and Srinivasan, 2010). ML, which can be understood as a subset of AI, is defined as:

> [...] a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty (Murphy, 2012, p. 5).

ML depends on algorithms that can learn and improve from experience (Mitchell, 1997). In summary, MAS and ML are overlapping and complementary concepts. Individual agents within a MAS can be equipped with additional intelligence (including ML capabilities) to learn about future events (Iqbal *et al.*, 2016). ML algorithms are an important tool that agents can use to make decisions and increase autonomy. The usefulness of ML for solving complex MAS problems has been acknowledged in previous research (Panait and Luke, 2005).

Although MAS have been discussed in the academic literature for several years (Wooldridge, 2009), industry implementations of these systems remain scarce. Single use cases of the technology have been previously deployed in pilot projects (Müller and Fischer, 2014), yet the use of MAS is not widespread (Xu *et al.*, 2021), despite its postulated benefits (Jennings, 2000). Considering the proliferation of other forms of autonomy and digitalization in LSCM, such as autonomous vehicles, ML algorithms and self-organizing warehouses, it is high time to rigorously reassess the potential of MAS as an autonomous technology that can benefit LSCM. Therefore, in this paper, we scrutinize the application of MAS with the goal of identifying concrete use cases and their contribution to logistics network resilience and organizational performance. Specifically, this study addresses the following research questions (RQ):

RQ1. Which use cases in LSCM have the greatest potential to be operated autonomously with the help of MAS applications?

RQ2a. What potential lies in the autonomous execution of specific use cases?

RQ2b. How can MAS enable and support resilient logistics networks as well as improve productivity?

RQ3. What are the barriers to implementing autonomous processes with the help of MAS?

This paper is organized as follows. First, academic research on MAS is discussed, and how MAS can play an important role in creating resilient networks is illustrated. Subsequently, the research design is outlined, which consists of a three-stage Delphi study among 18 LSCM practitioners. In the results section, MAS use cases are first identified and then assessed according to their respective potential. Furthermore, potential barriers are pointed out. Several recommendations for future theory-based research are presented, as well as practical recommendations for managers. This study ends with a short conclusion that also illustrates several limitations and interesting avenues for future research.

Theoretical background

Automation and autonomy in supply chains

Increasing automation and autonomy shape the present development of LSCM and will continue to do so in the foreseeable future (Nitsche *et al.*, 2021). Automation has already been a key focus of the third industrial revolution, and autonomy is playing a leading role in the ongoing fourth industrial revolution, triggered in the wake of the IoT (Schwab, 2017). Both concepts, in essence, refer to processes happening without direct human intervention and tend to be used interchangeably. However, there is an important difference: automation refers to systems that are programmed by humans to act in an exactly specified way and under certain circumstances. In contrast, autonomous systems can act on their own and are able to change initially designed paths of action within boundaries defined a priori by designers (Wooldridge and Jennings, 1995; Wooldridge, 2002). Consequently, autonomous systems have greater flexibility and the ability to self-govern.

Although automation has been achieved in many processes in recent decades, autonomy in production or logistics networks has not yet lived up to its initial promise. When it comes to the differentiation between automation and autonomy, various authors have developed their own taxonomies over the years (Sheridan and Verplank, 1978; Miller and Parasuraman, 2007; Johnson *et al.*, 2009). Some suggest classifying a system according to its level of autonomy, which typically ranges from full human control to a fully functional autonomous system that works without any human interference. Dumitrescu *et al.* (2018) propose five evolutionary stages in the autonomy of technical systems that range from remotely controlled systems to fully autonomous systems. At each stage, the amount of human user control is reduced, whereas the level of control by the system, its decision-making and ML gradually increase, leading to autonomous systems that are capable of solving complex problems and interacting with other systems without the need for direct human interaction. The advanced stages of this evolutionary process are closely linked to the deployment of AI, which leads to systems that have agency of their own (Baryannis *et al.*, 2019). Recent advancements in AI have made the vision of fully autonomous systems increasingly realistic (Baryannis *et al.*, 2019). As AI can still face computational boundaries due to the complex nature of many problems, DAI has been suggested as a solution that would divide the computational load across a network of smaller agents. MAS therefore offer a goal-oriented solution for agent collaboration within the field of DAI (Balaji and Srinivasan, 2010).

Multiagent systems

Based on Wooldridge and Jennings (1995), Wooldridge (2002, p. 5) defines an *agent* as "a computer system that is *situated* in some environment, and that is capable of *autonomous action* in this environment in order to meet its design objectives." Any control system can therefore be seen as an agent, and the more complex the environmental control system becomes, the more complex and comprehensive the decision structures become. Taken together, individual intelligent agents can become part of a larger system, labeled as MAS. Such a decentralized system consists of multiple autonomous agents that each pursue their individual objectives and execute activities in parallel (Wooldridge, 2009). They can solve complex problems by dividing them into simpler subproblems and offering companies features such as decentralization, modularity, flexibility and robustness (Skobelev and Trentesaux, 2017), which help to increase the resilience of the overall system (Vistbakka and Troubitsyna, 2021). Different levels of autonomy within MAS exist, ranging from machines that are able to solve simple mathematical functions to fully autonomous individual agents that evolve over time through ML (Dorri *et al.*, 2018; Moyaux *et al.*, 2006).

MAS have existed for several decades, and previous research has already confirmed their importance in areas such as real-time manufacturing through the modeling of competitive manufacturing systems, the capturing of manufacturing systems' evolutionary development and the designing of rational agents, which together allow for improved qualitative analysis and the development of simulation frameworks as well as real-life applications (Dominguez and Cannella, 2020; Lee and Kim, 2008).

MAS have gained renewed attention following the rise of data-driven technologies at the beginning of the current decade. The overall number of MAS implementations is increasing, and numerous application areas have been identified, including scheduling, coordination between enterprises, information sharing, order fulfillment processing, collaborative production planning, provider selection, remanufacturing and resilience (Dominguez and Cannella, 2020). However, the technology has not yet reached its predicted levels of use (Karnouskos and Leitão, 2017; Xu *et al.*, 2021). Existing studies on specific industries, such as the oil and gas industry, have found that several companies already apply MAS systems, but existing implementations strive to solve rather well-defined supply chain problems, such as logistics planning or process optimization. In contrast, implementations for more complex problems covering the whole supply chain are rare (Hanga and Kovalchuk, 2019).

Although there are considerable benefits from MAS, they also have weaknesses that inhibit their practical deployment (Dorri *et al.*, 2018). A major issue is that decentralized systems only provide local optimization and, when combined, may underperform compared with a centralized solution (Treiblmaier, 2018a). The high interdependency of the different agents makes finding an optimal solution difficult, and a great number of interactions between agents can also lead to long computation times. Problems that cannot be divided into subproblems are also unsuitable for MAS. Implementation and monitoring are costly, and the output of the system can be incomprehensible and unpredictable, as MAS can lead to emergent and unpredictable behavior (Jennings, 2000). These downsides result in six barriers, as summarized by Karnouskos and Leitão (2017), which hinder the widespread implementation of MAS in industry. These are change management – describing the complex process of MAS adaptation, lack of technological maturity, costs for development, maintenance and implementation, lack of standardization, problems finding suitable and feasible practical applications and the ability to measure the total benefits of the system.

As an evolving technology, the widespread industrial adoption of MAS depends on how well these barriers can be dealt with. Although several benefits can be relatively easily shown at the level of proof-of-concept, showing true business value in the long run is much harder (Bergenti *et al.*, 2004). Furthermore, the business benefits of MAS are notoriously difficult to quantify in advance. The technology requires acceptance by all relevant stakeholders, which is particularly difficult to achieve in tightly controlled, hierarchical industrial settings. To ensure this acceptance, it is therefore crucial to identify and evaluate specific MAS use cases and to understand the barriers hindering their adoption.

Resilience and the role of multiagent systems

In general, resilience can be defined as the capability of a supply chain to return to normal operations or even to an improved state after being disrupted (Christopher and Peck, 2004; Pettit *et al.*, 2010). Building on this core objective, a broad field of research has emerged, and several definitions have been developed that highlight various characteristics of resilience (Shishodia *et al.*, 2021). An overview of resilience definitions in logistics and supply chain research is given in Table 1. To achieve resilience, proactive strategies can be established to ensure that the probability of disruptions is lowered, but reactive strategies also have to be in place to increase an organization's capability to react to any disruptions (Tukamuhabwa *et al.*, 2015). Although the proactive part is of importance, a major portion of resilience research focuses on the reaction to disturbances. What most definitions have in common is the ability to recover from disruptions and return to normal operations. In this regard, the speed of this process is crucial to becoming resilient (Brandon-Jones *et al.*, 2014; Sheffi, 2005; Tukamuhabwa *et al.*, 2015).

Pettit *et al.* (2010) list several vulnerabilities in the supply chain (i.e. turbulence, deliberate threats, external pressures, resource limits, sensitivity, connectivity, supplier/customer disruptions) and derive important capability factors (e.g. flexibility, capacity, efficiency, adaptability, collaboration) that can be leveraged to address these vulnerabilities. MAS in LSCM can help alleviate several of these issues by allowing lengthy and complex processes, which often include negotiations with other entities, to be run autonomously in a faster and more efficient way. Besides gains in the productivity of processes, MAS also offer the potential to react to unforeseen changes in a network in a timely manner and leverage the knowledge stored in the network as opposed to tacit knowledge in individual units.

As a contribution to logistics network resilience, MAS can increase organizational flexibility through modularity and are able, through decentralization, to offer new solutions that cannot be found in purely centralized systems (Huhns and Stephens, 1998). Moreover, MAS reduce the need for computational power, as only subsystems need to be optimized. In the wake of Big Data, highly complex centralized systems are consuming ever more resources (Schwartz *et al.*, 2020). In this regard, MAS offer an effective way to design efficient distributed computer systems (Huhns and Stephens, 1998). Additionally, the division into subsystems makes the programming of MAS relatively easy for developers owing to the reduced complexity of the system. One resulting benefit is the ease of making modifications, as a modular system makes it easier to change a single agent, thereby reducing configuration costs and increasing system reusability. Finally, the multidimensionality of MAS simplifies problem-solving in complex environments, and the combination of decentralization and modularity lends itself to situations that are likely to change frequently (van Parunak, 1998; Treiblmaier, 2018a).

Given the core characteristics of autonomous MAS, it can be concluded that they can support companies in increasing their organizational productivity and making their networks more resilient. Furthermore, gaining independence from individual human knowledge has become an important driver for LSCM, especially during the COVID-19 pandemic (Modgil *et al.*, 2022a; Modgil *et al.*, 2022b; Nitsche and Straube, 2021). During this pandemic, the need for more resilience in future supply chains became evident, and process automation is now seen as one important cornerstone in achieving it (Kiers *et al.*, 2022). Process automation can be seen as another evolutionary step in the industrial evolution that substitutes humans with machine labor and, in doing so, reduces the number of jobs needed in the industry (Schmidpeter and Winter-Ebmer, 2021; Petropoulos, 2021).

Table 1 Resilience definitions in logistics and supply chain management research

Source	Definition/understanding
Brandon-Jones *et al.* (2014, p. 58)	Supply chain resilience is defined as the ability of a system to return to its original state within an acceptable period of time after being disturbed
Ponomarov and Holcomb (2009, p. 131)	The adaptive capability of the supply chain to prepare for 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 function
Sheffi (2005, p. 2)	In the corporate world, resilience refers to the ability of a company to bounce back from a large disruption – this includes, for instance, the speed with which it returns to normal performance levels (production, services, fill rate, etc.)
Tukamuhabwa *et al.* (2015, p. 8)	The adaptive capability of a supply chain to prepare for and/or respond to disruptions, to make a timely and cost-effective recovery, and therefore progress to a post-disruption state of operations – ideally, a better state than prior to the disruption

Methodology

In this explorative study, we chose a Delphi method because of its ability to attain and develop knowledge among a group of experts in a particular field of interest (Melnyk *et al.*, 2009; Okoli and Pawlowski, 2004). The experts were tasked with making predictions on the future development of MAS in their respective work areas and providing contextual information regarding their predictions (Alarabiat and Ramos, 2019). Their input was aggregated and analyzed anonymously by the researchers, and, in line with the tenets of a Delphi study, the results were sent back to the experts for revaluation. Bias was prevented by the absence of interactions among the individual experts, which also increased the accuracy of the forecasting (Okoli and Pawlowski, 2004). In summary, the Delphi method provided the ideal tool to account for the different geographical locations of the experts, objectively gain group consensus on single topics while avoiding dominant respondent bias, and extract knowledge from highly qualified individuals.

Previous Delphi studies in LSCM research were successfully used to systematically extract practitioners' knowledge, with the goal of predicting and assessing developments in industry practice (Hohn and Durach, 2021; Durach *et al.*, 2017; Darkow *et al.*, 2015). Following previous authors' recommendations, we placed special emphasis on recruiting a heterogeneous group of experts from different areas of LSCM to ensure creativity, avoid bias from likeminded answers and gain a broad view (Alarabiat and Ramos, 2019) of this under-researched field. We chose a three-round Delphi study design, which is a design that is generally regarded as being sufficient for gaining conclusive data (Okoli and Pawlowski, 2004); additional rounds would potentially lead to substantial dropout rates (Kache and Seuring, 2017). The selection of experts took place between April and May 2020. The first round of the study was conducted in June 2020. In August 2020, the experts assessed the different use cases with regard to the potential of MAS identified during the second stage. In the subsequent third stage in October 2020, the experts received aggregated group answers to update their own answers. The empirical study concluded by communicating the preliminary findings to the participants in the first half of 2021.

Expert selection

Selecting the right experts is crucial for the success of the Delphi method, as participants who are highly qualified in a subject contribute the best possible insights and predictions for a research topic (Alarabiat and Ramos, 2019). To assemble a suitable group of industry experts, potential candidates from research and industry with known backgrounds in LSCM as well as autonomous technologies were contacted and asked if they considered themselves knowledgeable regarding MAS or, if this was not the case, to forward the request for participation in the Delphi panel to more suitable colleagues. Although there were no geographical restrictions, the participants were required to be able to complete the questionnaires in English or German. A group of 18 participants took part in all three rounds. Our number of participants slightly exceeds the recommended number of 10–15 experts for Delphi studies to gain meaningful results (Delbecq *et al.*, 1975; Adler and Ziglio, 1996; Alarabiat and Ramos, 2019). To spark creativity and allow for well-rounded opinions, the Delphi panel also included two consultants and two academic researchers.

Table 2 shows the characteristics of the Delphi panel participants, including their country of origin, industry type, number of employees, annual turnover, management level and years of experience in LSCM. On average, the study participants had 13 years of professional experience, which considerably exceeds the recommended domain experience of at least five years (Durach *et al.*, 2017).

Delphi study design

After confirming their qualifications of relevance to autonomous systems, the experts were briefed about the goals and the planned rounds of the Delphi study, which are detailed in the sections below (see Figure 1).

First round: The aim of the first round of the Delphi study was threefold. First, the experts were tasked with identifying and describing specific use cases for MAS in LSCM. These use cases should be complex and ideally included interactions with other supply chain participants, as well as exhibiting a high potential for autonomization. Second, the experts needed to name potentials that they would expect from an MAS implementation and that they would use to evaluate a specific application. Third, they identified barriers that hinder the widespread implementation of such MAS. The experts were asked to answer each question openly and to name as many use cases, potentials and barriers as they could think of. To synthesize the results, Q-methodology was applied to each question individually (Ellingsen *et al.*, 2010). This method enables a structured synthesis of a variety of answers and has previously been applied in LSCM research to synthesize large numbers of qualitative answers (Durach *et al.*, 2015; Nitsche and Durach, 2018). This was done by writing down each use case mentioned by a study participant on an individual card. Subsequently, two researchers individually performed the Q-methodology process, reading one card after another and either opening up a new use case group in case no thematically similar use group already existed or placing it into an existing and similar group of use cases. By executing this procedure, each researcher individually came to a synthesis of use cases that were presented to the other researcher. Afterwards, the similarities in assignments were identified and differences discussed to find a common understanding. As a result, a set of 11 use cases was synthesized that provided the basis for the further assessment of the potential of the use cases in the subsequent rounds.

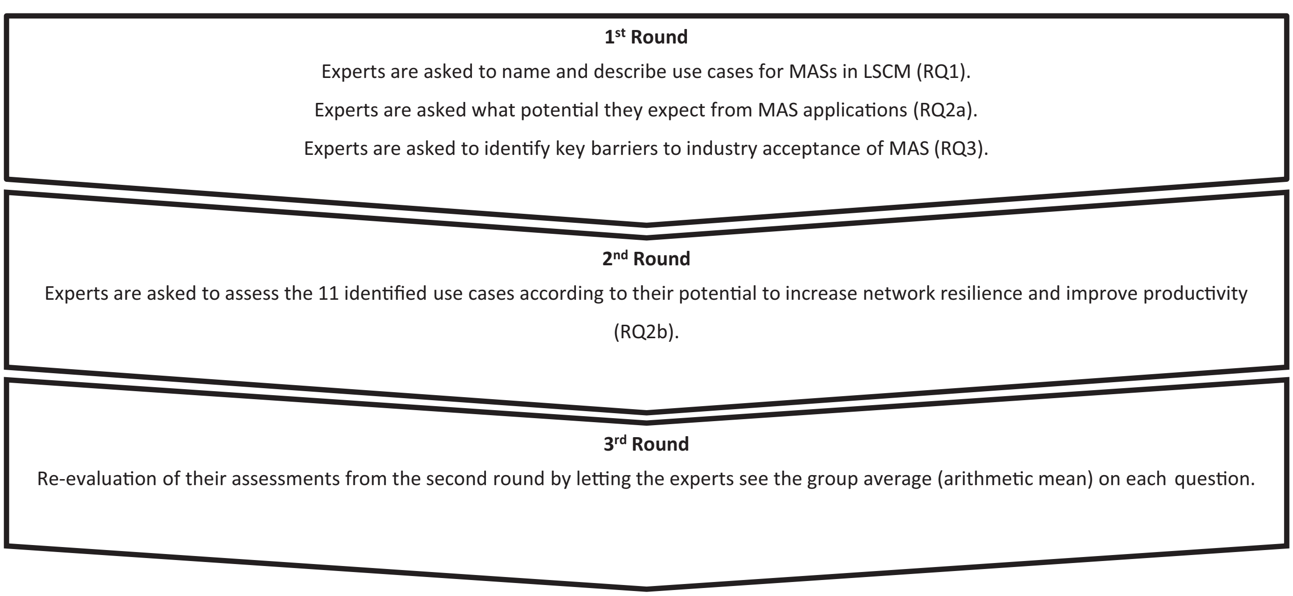
Second round: The goal of the second round was to assess the potential of the identified MAS use cases. Building on the results of the first round, the potential of each MAS use case was identified in the synthesis as either improving the resilience of the logistics and supply chain network or increasing organizational productivity. Additionally, we asked for a thorough assessment of the implementation complexity of each use case. In the second and third rounds, the 11 use cases identified were assessed using a five-point differential scale with endpoints 1 (low) and 5 (high) using the following three assessment criteria:

1 Potential for logistics network resilience (PLNR): The potential of a use case to increase the capability of a logistics/supply chain network to go back to regular operational functioning within a tolerable time interval after being disrupted.

Table 2 Sample demographics of the Delphi study

#	Country of origin	Industry type	No. of employees	Annual turnover	Management level	Years of experience
1	Netherlands	Manufacturing, automotive	>10,000	5–10bn €	Department manager	20
2	Germany	Consulting	<50	<10 m €	General manager	30
3	Brazil	Manufacturing, machinery/equipment	>10,000	5–10bn €	Team leader	25
4	Germany	Consulting	<50	<10 m €	Self-employed	20
5	Germany	Manufacturing, consumer goods	1,000–2,500	500–1,000 m €	Team leader	15
6	USA	Manufacturing, automotive	>10,000	5–10bn €	Department manager	10
7	Germany	Manufacturing, Automotive	>10,000	>10bn €	Team member	3
8	Germany	Manufacturing, automotive	>10,000	>10bn €	Department manager	6
9	Germany	Manufacturing, automotive	>10,000	>10bn €	Team member	3
10	Germany	Manufacturing, automotive	>10,000	>10bn €	Department manager	9
11	Cyprus	Manufacturing, chemicals and pharmaceuticals	250–500	50–250m €	Department manager	25
12	China	Logistics service provider	>10,000	>10bn €	Department manager	14
13	Germany	Logistics service provider	>10,000	>10bn €	Department manager	15
14	Germany	Manufacturing, aviation	>10,000	>10bn €	Team member	6
15	Germany	Manufacturing, automotive	>10,000	2.5–5bn €	Department manager	15
16	Australia	Research	1,000–2,500	500m−1,000 m €	Team member	10
17	France	Research	<50	<10 m €	General manager	5
18	Netherlands	Construction	250–500	50–250m €	Team leader	2

Figure 1 Research procedure for the three-stage Delphi study



2 Potential for productivity increase (PP): The potential of a use case to perform at least one organizational process more efficiently (e.g. faster or at lower cost).
3 Reduction of the complexity of implementation (CI): A decrease in the level of resources needed to deploy a project.

Third round: In the third round, the experts were given the aggregated results for each of the three metrics (i.e. PLNR, PP and CI) applied to assess each use case and were given the chance to adjust their initial answers based on this new information and to provide additional information to outline their decisions. Based on the results of this final round, we calculated important statistics for each use case to determine whether a group consensus had been reached. Such consensus is the case if the interquartile range (IQR) lies beneath a certain threshold. A consensus confirms the results and indicates high forecast accuracy (Hahn and Rayens, 1999; Raskin, 1994).

Results

In the following sections, we present our results in three parts, addressing each RQ consecutively. First, we identify and describe promising LSCM use cases (RQ1); second, we assess the potential of each of these use cases and how they can benefit organizations and be leveraged to create resilient and productive networks (RQ2a/b) and, third, we present and discuss relevant barriers to MAS implementation (RQ3).

Identification of promising MAS use cases

Table 3 outlines the 11 use cases (UC) that the experts identified as having the most potential for MAS-supported automation. For all use cases, it was considered beneficial to include multiple entities with partially different target systems in decisions related to problem-solving. These use cases illustrate the broad applicability of MAS. In UC1, search agents check databases to discover suitable suppliers for required tasks and materials. Interested suppliers can register in the databases to be visible to search agents. Once the agent finds a suitable supplier, it notifies the responsible employee or another agent to initiate a contract process. In UC2, renegotiating expiring contracts or creating new ones can be automated by letting agents take the place of negotiators. These agents are configured to represent the goals of individual companies. For a more complex problem, agents from different companies can come together to achieve an optimal collaborative planning scenario. UC3 describes how agents can be used to monitor demand and coordinate purchasing. All involved agents are in constant communication with one another, in accordance with the metrics agreed. Demand and stock are constantly evaluated, and new orders are generated automatically. In UC4, agents check truck load sizes, optimal transport routes and available transport offers for specified routes. Should a match with a third-party logistics (3PL) or fourth-party logistics (4PL) provider occur, an agent can automatically book the optimal transportation solution. UC5 illustrates how two separate agents can optimize production and transport plans in accordance with one another, finding the optimal solution for the entire supply chain. Should one of the two subsystems be disrupted, the agents can work together to create an automated, viable solution in real time. In UC6, an agent constantly monitors whether the current production plan is still optimal, based on new information that can be added in real time to the system. Should such data lead to a new optimal plan, a production agent is informed, who checks the plan for feasibility before implementing it as an updated production plan. In UC7, different agents take into account staff availability, workload and flexibility to optimize personnel scheduling. The information is regularly passed on to another agent responsible for generating an optimal schedule. UC8 involves different agents that track the demand and availability of intralogistics components and match them accordingly, which includes the scheduling of forklifts and automated guided vehicles (AGVs). In UC9, an agent regularly updates the list of outgoing orders, sorting them by urgency. This information is given to another agent, which plans the sequence of commissioning and outbound goods. In UC10, an agent scans databases, such as news sites, for disruptive events. Relevant instances are reported to an event management agent, which then reconfigures the supply chain to limit the events' impacts and implements the new optimal solution. Finally, in UC11, each agent becomes part of the supply chain and can be used to create a simulation to optimize and verify solutions for the whole value network.

As described in the introduction, MAS are used when separate entities need to be involved in complex decision-making processes that require automation. Participants were aware of the crucial role of ML in solving complex MAS problems; this role

Table 3 Use cases for MAS implementation in LSCM

No.	Use case	LSCM domain
UC1	Automated partner/supplier search based on predefined parameters	Partner search and negotiations
UC2	Automated negotiations with suppliers including contract negotiations	Partner search and negotiations
UC3	Automated inbound supply planning and purchasing of materials	Supply planning
UC4	Automated transport planning including scheduling/booking	Supply planning
UC5	Automated combination and optimization of transport and production plans	Supply planning
UC6	Automated rescheduling and production plan optimization including dynamic lot sizing	Production planning
UC7	Automated personnel scheduling (in-house, warehouse/production)	Warehouse operations
UC8	Automated in-house planning and scheduling of intra logistics components	Warehouse operations
UC9	Automated order processing/prioritization of orders in finished goods warehouses	Warehouse operations
UC10	Automated risk/event management, identification of disruption risks and rescheduling/planning of new transport routes	Risk management
UC11	Simulation of supply chain networks to identify potential for optimization	Strategic planning

was also explicitly included in the definitions of the use cases. The extent to which the agents should be equipped with ML capabilities or whether predefined rules are sufficient was not explicitly prescribed for each use case. However, due to the complexity of the use cases, it can be assumed that their automation would frequently require intelligent agents that can learn and adapt over time.

Assessment of MAS use cases

To answer RQ2a and RQ2b pertaining to the different potentials of the respective use cases, as well as the applicability of these use cases to the strengthening of supply chain resilience and productivity, the experts used the assessment criteria PLNR and PP, as presented above. Additionally, we asked about the CI. The results can be found in Table 4, which is ordered by the resilience potential (PLNR) of the respective use cases. For each case, the arithmetic mean of the assessment criteria is shown, as well as the IQR and the convergence rate (CV). The IQR is used to measure the consensus of the expert group and is calculated by subtracting the results of the first quartile (25%) from the third quartile (75%). The CV is the decrease in standard deviation between the rounds of the Delphi study, in this case, between rounds two and three. A negative CV indicates a convergence toward a group consensus. Furthermore, we calculated the difference between the scores of the PP and the PLNR and weighed these scores against the CI. These deltas can be used to assess and compare the relative benefits of the corresponding use cases. Those with positive scores can be seen as high-value use cases and should be prioritized when it comes to MAS implementation in practice, as their potential benefits (e.g. increases in either productivity or resilience) outweigh the CI. It should be noted that a use case does not necessarily have to address both benefits; rather, LSCM managers need to start thinking about and prioritizing applications in light of their respective demands to determine whether the goal of autonomizing the process concerns either increases logistics network resilience or productivity. Although Table 4 illustrates that all use cases have above-average assessment scores for each of the assessment criteria, the results still diverge, depending on the nature of the use case itself.

Concerning the potential of PLNR, automated risk and event management is the most promising use case. However, every use case that automates material flow achieves a high score, as MAS allows for the rescheduling of material flows in real time and swift responses to unforeseen events. Notably, automated supplier negotiations (the only MAS that received a score below 3 for PLNR) are not seen as very relevant to resilience, as they are regular, singular events with limited potential for automation.

When it comes to productivity increases, the use cases that exhibit the highest potential are those that relate to automated rescheduling and production planning, synchronized transport and production planning and inbound supply planning and purchasing. Since production and transport are at the core of any supply chain and require substantial coordination effort, they benefit the most from autonomous processes. In comparison, automated negotiations are also not highly ranked for PP, since negotiations have a distinct social component and can be hard to automate, which is especially true if two or more parties are pursuing conflicting goals.

The CI is highest for those processes that deal with a lot of data or involve multiple different parties. The automated rescheduling of production plans and their synchronization with transportation are examples of such complex problems. In comparison, in-house activities, such as automated order processing in warehouses and the planning of intralogistics, are comparatively low in complexity. These use cases can be used to test and gain experience for companies starting out with deploying MAS, as they offer sufficient potential while simultaneously having low implementation complexity.

The deltas show that swift implementation is not desirable for all use cases from a resilience or productivity perspective, as their benefits may be simply too low or the complexity too high. These include automated rescheduling and production plan automation (UC6), the simulation of supply chain networks for optimization purposes (UC11), automated personnel scheduling (UC7) and automated supplier negotiations (UC2). The optimization of transport and production plans (UC5) as well as inbound supply planning and purchasing (UC3) score positively when it comes to organizational productivity but negatively from a resilience perspective. Automated risk/event management (UC10) is the only use case that has a negative score from a productivity perspective, but has a positive resilience assessment. Two cases have two positive deltas, identifying them as applications that should be prioritized by companies wanting to implement MAS solutions. These include automated transport planning (UC4) and automated order processing/prioritization (UC9).

We defined a threshold value for the IQR of ≤25% for the three criteria (PP, PLNR and CI) to test consensus in group opinion, which is in line with the recommendations of previous Delphi studies (Hahn and Rayens, 1999). Given the use of a five-point scale, consensus is thus reached if IQR ≤ 1.0. In total, consensus was achieved for 29 out of 33 predictions (88%), which is an above-average group consensus for a Delphi study, as most results vary between 22% and 85% (Hahn and Rayens, 1999).

Barriers to MAS use cases

To answer RQ3, the participants were tasked with naming the relevant barriers to the implementation of MAS. Four main barriers emerged, which we summarize in a qualitative manner:

Standardization: Current MAS applications are highly customized solutions implemented by single companies. Consequently, standardization has not been achieved yet, and one-size-fits-all solutions are not readily available on the market. This makes the scalability of current MAS applications very difficult, and connection with third parties is also impeded by the lack of widespread standards. Even though there have been efforts to standardize MAS, these have mainly come from academia and do not specifically consider industrial requirements.

Technological maturity: This barrier addresses the technological complexity of solutions and the readiness of these technologies for wider use. The experts indicated that companies may doubt the technological readiness of MAS; thus, a MAS solution can always be questioned, as the problem-solving process is complex and may not always be transparent. As a result, potential use cases might be discarded or canceled due to their complexity.

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Table 4 Assessment of MAS use cases in LSCM ordered by logistics network resilience potential

Use case	Short description	PLNR	IQR_{PLNR}	CV_{PLNR} (%)	PP	IQR_{PP}	CV_{PP} (%)	CI	IQR_{CI}	CV_{CI} (%)	$\Delta_{PP\text{-}CI}$	$\Delta_{PLNR\text{-}CI}$
UC10	Automated risk/event management	4.2	1	−9.6	3.2	1	0.0	4.1	1	−33.3	−0.9	0.1
UC4	Automated transport planning	4.1	0.8	0.0	4.3	0.8	0.0	3.8	1	−10.5	0.5	0.3
UC6	Automated rescheduling and production plan optimization	4.1	0.8	−9.6	4.4	1	−12.9	4.5	1	−27.2	−0.1	−0.4
UC5	Automated combination and optimization of transport and production plans	4.0	0	−33.3	4.4	1	−20.8	4.3	1	−7.4	0.1	−0.3
UC3	Automated inbound supply planning and purchasing	3.8	0.8	0.0	4.3	1	0.0	3.9	0	−20.9	0.4	−0.1
UC11	Simulating supply chain networks for optimization purposes	3.8	1	−24.7	3.8	1	−6.8	4.0	1	−2.5	−0.2	−0.2
UC1	Automated partner/supplier search	3.6	1	−7.5	3.4	1	−9.4	3.4	1.8	0.5	0	0.2
UC7	Automated personnel scheduling	3.6	1	−20.4	3.9	0.8	−4.6	4.0	0	−13.4	−0.1	−0.4
UC9	Automated order processing/prioritization	3.6	1	−22.0	3.9	0	−4.5	3.1	0	−11.2	0.8	0.5
UC8	Automated in-house planning of intra logistics components	3.4	1	−21.7	4.0	1.5	−4.4	3.4	1	−16.4	0.6	0
UC2	Automated negotiations with suppliers	2.9	1.5	−10.1	3.5	1	−14.7	4.0	1.8	−13.0	−0.5	−1.1

Notes: PLNR = potential of logistics network resilience; PP = potential of productivity increase; CI = complexity of implementation; IQR = interquartile range; CV = convergence rate

Most companies have no or only a few MAS experts who are qualified to develop these complex solutions and dispel doubts about the technology's maturity. However, the growing number of academic MAS publications and the proliferation of industry projects indicate that MAS might reach a sufficient level of maturity in the foreseeable future that will then be acknowledged by industrial actors.

Costs: In addition to the high costs for software acquisition and development, deployment, management and maintenance, personnel training and hardware acquisition, the generation of high-quality data can be very expensive, a problem that is not exclusive to MAS. Setting up the master data or migrating it from legacy systems can consume a lot of effort and time. Automated data acquisition needs to be implemented in the entire process so that the whole MAS system can function fully autonomously. These requirements can easily lead to soaring costs.

Change management: Decision-makers and management are often unaware or skeptical of MAS applications, which can be partly attributed to the barriers discussed above. Furthermore, MAS might lead to a loss of control because of decentralization and autonomization. Apart from the previously mentioned need for successful MAS projects as positive role models for decision-makers, systems need to be designed in a way that allows for human interaction and intervention, at least in the first years of MAS application. This would prevent a feeling of fully handing over control to an automated system and could help to increase trust in the technology. Employees may also fear being replaced by an MAS solution. Good change management is therefore essential, with employees being involved in the development and implementation of MAS. They also need to be prepared to take on new tasks when their current work is replaced by automated processes. During change management, it is important to pay particular attention to the behavioral factors that prevent employees from supporting technological change. Personal attributes, values and fears must be addressed; otherwise, this barrier can lead to a situation in which a technologically mature solution has been developed but cannot be implemented. On a broader scale, this also raises the issue of finding employment opportunities for humans, who are increasingly being replaced by technology.

Discussion and implications

MAS have gained a reputation for providing suitable solutions for the development of complex systems that demand flexibility, robustness, adaptation and responsiveness (Barbosa *et al.*, 2015). Despite promising perspectives, few industrial applications have been discussed in the literature, which makes it difficult to convince industry stakeholders of the benefits and technological maturity of this technology (Leusin *et al.*, 2018). The results of this study indicate numerous potential benefits for MAS in logistics for several use cases, which is in line with the findings of previous research on the general potential of MAS (Skobelev and Trentesaux, 2017). At the same time, the inherent complexity of each of those use cases was confirmed, which matches the general sentiment in the academic literature regarding the cost of implementing MAS solutions in industrial applications (Leitão and Karnouskos, 2015). Our findings provide several academic and managerial implications that can guide future research and provide value for MAS implementation in practice.

Theoretical implications

In this study, we investigate the current and future development of MAS in LSCM and identify and assess possible use cases. In a rigorous three-round Delphi study, a total of 18 experts compiled a comprehensive list of use cases, which presents a starting point for other researchers to focus on one or several of the identified cases or to add further applications to the list. More in-depth knowledge of the impacts and benefits of MAS applications in LSCM can reduce the CI and lower the threshold for further industry integration.

We approached the assessment of the cases from the viewpoint of resilience theory, which, in a network setting, refers to the capability of a supply chain to return to normal operations or even to an improved state after being disrupted (Christopher and Peck, 2004; Pettit *et al.*, 2010). In this regard, our study makes an incremental contribution to previous research by identifying capability factors that can be leveraged to address supply chain vulnerabilities, with the goal of increasing resilience (Pettit *et al.*, 2010). MAS might, by definition, be unable to identify black swan events in advance, but they can offer increased flexibility when such events occur and enable companies to react to unforeseen events more quickly, thus supporting faster recovery. Our findings identify those MAS use cases with the highest potential to increase logistics network resilience, namely, automated risk/event management, transport planning, rescheduling and production plan optimization and combination/optimization of transport and production plans. Furthermore, we also take into account the implementation complexity of all use cases and have been able to pinpoint applications that might be advantageous for companies to try out first. Future theory-based research can build on our findings by:

- taking a behavioral viewpoint and investigating adoption antecedents and consequences of a specific implementation; or
- taking a design-oriented perspective and helping to create solutions that help companies to make their own networks more efficient.

As indicated above, the implications of our findings may have both intended and unintended consequences for the organization itself and its workforce. The main focus of our study was the investigation of how MAS can help improve an individual organization's performance or strengthen the resilience of the network it is operating in, but the change processes that accompany these digital transformation processes must not be neglected. In this regard, the theory of organizational learning (Crossan *et al.*, 2011) and organizational behavior theories (Miner, 2003) can help to get a better understanding of how organizations and their workforce might respond to the changes that are induced by MAS. Moreover, our findings can help to identify technologies that might impact organizational structure and processes in the not-too-distant future.

Another theory-building outcome of this study is the confirmation and refinement of previous research on MAS implementation barriers (Karnouskos and Leitão, 2017). Future research needs to focus in more detail on ways to overcome these barriers and enable easier MAS implementations. Barriers always need to be considered for specific scenarios and can potentially be removed as the industry matures and knowledge of MAS becomes more widespread. Some of these barriers take the form of obstacles resulting from digitalization in LSCM in general (Agrawal *et al.*, 2019).

Managerial and societal implications

This study has several important implications for practitioners. Management can use the suggested list of MAS application scenarios to identify and assess implementation opportunities within their own supply chains. The assessment of the respective use cases gives practitioners guidance on which MAS cases to start with. If a company has no prior experience with MAS, use cases with a low CI and reasonable profits might be recommended to first try out the technology. The assessment criterion (i.e. delta) that we used to measure the difference between the expected benefits and implementation complexity also provides interesting insights for practice, since managers with little experience in MAS can identify those use cases that promise high benefits in relation to their expected complexity. Examples include the automation of in-house transport planning and order processing.

It is to be expected that with growing experience in the field of MAS, companies will be able to maximize the benefits and lower the costs of implementation over time. In case organizational subsystems have already been implemented that use MAS, developers in the company will have earned relevant experience, and management and employees will have gained trust in the technology. When implementing MAS, it is also advisable for management to keep a close eye on the barriers presented in our study, especially the lack of standardization, missing industry experience and unpredictable costs. Furthermore, managers need to establish change management processes that not only take into account the interests of a company's shareholders but also its employees. Our list of barriers can thus help to enable mindful implementation, show management which challenges are likely to arise and give them some ideas on how to adequately address these.

Even though our study focuses on the potential of MAS for increasing resilience in logistics and supply chain processes, the societal implications of these changes must not be neglected. In general, optimized supply chain processes contribute to societal welfare and value generation, supporting the more effective and efficient use of existing resources (MacCarthy and Ivanov, 2022). However, the autonomization of previously manual processes could have a detrimental impact on employment levels and lead to deskilling in supply chains. The use cases developed by the Delphi panel illustrate that many of these processes are currently very labor-intensive and are conducted manually, with little technological assistance. Autonomizing such processes will have direct implications for the workforce and raise various questions that have not yet been adequately investigated. Several authors already highlighted the significance of the human factor in the introduction of AI systems (Dora *et al.*, 2022; Dwivedi *et al.*, 2021; Hoberg *et al.*, 2020; Klumpp and Ruiner, 2022). However, most current research focuses on the technical implementation of specific UCs, as demonstrated in the literature reviews by Pournader *et al.* (2021), Riahi *et al.* (2021) and Toorajipour *et al.* (2021). So far, few articles have investigated the employment implications of AI systems in general and MAS systems in particular.

In highly digitalized and partially autonomous supply chains, the competence profiles of logistics managers will need to change. It is currently unclear to what extent systems can run autonomously or when employees will need to intervene in systems whose decision-making processes can only be understood to a limited extent. Consequently, Hoberg *et al.* (2020) point out that, despite technological advancements, it is unlikely that human decision-making will ever be completely eliminated. For the supply chains of the future, Hoberg *et al.* (2020) favor a combination of the unique capabilities of human decision-makers with AI-based guidance to enable complex problem-solving.

Conclusion, limitations and future research

The goal of this Delphi study among 18 LSCM practitioners is to identify MAS application scenarios, their potentials and barriers to MAS implementation. Eleven distinct use cases were identified that ranged from processes that were internal to general and more complex ones that involved multiple stakeholders along the supply chain. Subsequently, those use cases were assessed by the Delphi panel according to three assessment criteria: PLNR, PP and CI. The expert assessment of these criteria offers practitioners guidance when implementing MAS. Our findings highlight use cases with either substantial potential benefits, a low level of implementation complexity or, in some cases, both. For the majority of assessments done through this Delphi study, a group consensus was reached, leading to a solid basis for further research and helpful guidance for managers.

This study has several limitations, particularly due to the use of the Delphi method and the associated study design. The composition of the expert panel and the qualitative nature of the evaluation create some limitations as well. First, the heterogeneity of the Delphi panel can potentially lead to shortcomings. For instance, a more homogenous panel would be able to go into more detail on use cases for a particular industry sector. Practitioners should keep this in mind, as specific use cases might be of high importance to certain industries, whereas others might be of less importance to these industries. However, since there has been little research on the assessment of the potential of MAS use cases in practice, we decided to set up a heterogeneous group to ensure broad insights from various viewpoints when creating the list of potential cases. Therefore, this assessment has to be understood as a first indication of the potential benefits of MAS in practice, while acknowledging that it needs further refinement if industry-specific insights are sought. Second, the selected experts all came from companies that were already interested in MAS applications or even had experience in developing them. It is to be expected that these are among the frontrunners in MAS implementation and will therefore be among the first companies to implement MAS in the years to come. It is likely that, on a broader scale, autonomous processes will be implemented by the end of the decade. Third, the qualitative nature of the assessment criteria can be seen as a potential shortcoming because quantitative criteria would have led to higher precision in the study results. However, the early state of the implementation of MAS solutions makes quantitative analysis difficult. Although lacking precise, quantitative insights, our study provides the first qualitative overview of the potential and costs of MAS implementation. Finally, we acknowledge that the technology itself is constantly developing and that all findings are based on the current state of the art. Future applications might offer more advanced solutions for existing problems pertaining to performance and resilience.

This leads to our call for future research. The results of the study indicate that autonomy in LSCM processes is, with the help of MAS, on the rise and can become an important technological driver in the industry within the current decade. Since the full-fledged implementation of MAS has only become possible with the rise of Industry 4.0, the coming years offer a wide variety of new research areas for MAS applications. More in-depth research is therefore needed on the use cases identified in this study. Future research needs to focus on particular industry sectors or on participants at specific tiers in the supply chain (e.g. raw material suppliers, transporters). Furthermore, additional examples can be added to the list as new applications arise and MAS proficiency increases. Although the experts in our panel indicated that these use cases have significant potential for increasing resiliency, further empirical research is needed to substantiate this claim. In addition, as more companies gain experience with MAS, this will provide a solid basis for a quantitative evaluation of MAS use cases and enable a better evaluation of the benefits and potentials of autonomous processes in the supply chain.

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