Computers & Industrial Engineering 181 (2023) 109344

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

The future of industry 4.0 and supply chain resilience after the COVID-19 pandemic: Empirical evidence from a Delphi study

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ARTICLE INFO

Keywords:
Supply chain Resilience
Supply Chain Risk
Industry 4.0
Digital supply chain
COVID-19 pandemic
Delphi study

ABSTRACT

The COVID-19 pandemic has caused major supply chain disruptions and unveiled the pressing need to improve supply chain resilience (SCRES). Industry 4.0 (I4.0) is a promising lever; however, its future in supply chain risk management (SCRM) is highly uncertain and largely unexplored. This paper aims to evaluate I4.0′s potential to improve SCRES in a post-COVID-19 world. Based on current literature and multiple workshops, 13 future projections on potential I4.0 application areas in SCRM were developed. A two-round Delphi study among 64 SCRM experts with digital expertise was conducted to evaluate and discuss the projections regarding their probability of occurrence until 2030, their impact on SCRES, and their desirability. A fuzzy c-means algorithm was applied to cluster the projections based on the expert assessments. The expert evaluations led to three clusters on I4.0 application in SCRM: Four projections on generating data, increasing visibility, and building digital capabilities received considerable approval and are reliable to improve SCRES in 2030. Four projections enabling data sharing and processing were predominantly supported and demonstrated realization potential for 2030. Finally, five projections that require major supply network adaptations were deemed unlikely to improve SCRES in 2030. This paper answers several research calls by presenting empirical evidence on the pathway of I4.0 implementation in SCRM following the COVID-19 pandemic. Moreover, it evaluates a holistic set of technologies and indicates prioritization potentials to achieve SCRES improvements.

1. Introduction

Over the last few years, companies have faced increasing challenges from supply chain disruptions (SCDs) (Paul & Chowdhury, 2020). The reason is twofold: From an internal perspective, firms across industries have outsourced and globalized their operations for competitiveness and cost optimization reasons, which has led to longer, more complex, and more vulnerable supply chains (SCs) (Hohenstein, Feisel, Hartmann, & Giunipero, 2015). In this context, SC members are not just interconnected operationally but also financially (Wu, Zhang, Pan, & Dolgui, 2021), which further increases vulnerability. From an external perspective, disruptive events, including natural disasters and political interventions, have increasingly affected operations (Lechler, Canzaniello, Roßmann, von der Gracht, & Hartmann, 2019). Practical consequences from SCDs include higher costs, sales losses, and declining customer satisfaction up to a damaged brand (Basole, 2014). Despite these experiences and the recognition that resilience to SCDs reveals the potential for competitive advantage (Hohenstein et al., 2015), many companies failed to prepare for the next "black swan" (Van Hoek, 2020), which became apparent when the COVID-19 outbreak hit the fragile SC environment in 2020. Many firms have faced tremendous challenges along their SCs, including simultaneous supplier failures, production capacity restrictions, and demand uncertainties (Ivanov, 2020). Company leaders have therefore expressed their intentions to increase resilience in their SCs for mitigating future SCDs (van Hoek, 2020). In this context, supply chain resilience (SCRES) refers to an SC's "ability to be prepared for unexpected risk events, responding and recovering quickly to potential disruptions to return to its original situation or grow by moving to a new, more desirable state" (Hohenstein et al., 2015, p. 108).

Abbreviations: AI, Artificial intelligence; AM, Additive manufacturing; BC, Blockchain; BDA, Big data analytics; CV, Convergence rate; D, Desirability; EP, Expected probability; FCM algorithm, Fuzzy c-means algorithm; I, Impact on SCRES; I4.0, Industry 4.0; IoT, Internet of things; IQR, Interquartile range; RQ, Research question; SC, Supply chain; SCD, Supply chain disruption; SCM, Supply chain management; SCRES, Supply chain resilience; SCRM, Supply chain risk management.

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https://doi.org/10.1016/j.cie.2023.109344

Available online 26 May 2023

Dasaklis, Pappis, and Rachaniotis (2012) already claimed that information management plays a crucial role during an epidemic. However, scholars report that traditional information systems are too weak to support SCRES holistically (Pettit, Croxton, & Fiksel, 2019). With innovative Industry 4.0 (I4.0) technologies evolving, a new opportunity to strengthen SCRES through generating, exchanging, and processing information has emerged (Ali & Gölgeci, 2019; Ivanov, Dolgui, & Sokolov, 2019). Although the literature consents that successful supply chain risk management (SCRM) will rely on digital technologies in the future (Ivanov et al., 2019; van Hoek, 2020), the road map following the COVID-19 pandemic remains unclear (Ivanov, 2020).

Theoretical concepts to assess I4.0′s maturity in supply chain management (SCM) have been developed but not yet applied (Frederico, Garza-Reyes, Anosike, & Kumar, 2019). De Oliveira and Handfield (2019) and Bragazzi (2020) thus reported that I4.0 is still in its infancy, its implementation level is mostly unclear, and several challenges for its successful realization persist. Companies remain uncertain about how to launch digitalization initiatives; they hesitate to replace their complex legacy systems and still doubt the economic benefits of I4.0, preventing application at scale (Ghadge, Er Kara, Moradlou, & Goswami, 2020; Nguyen, Chen, & Du, 2020; Stank, Esper, Goldsby, Zinn, & Autry, 2019). Missing legal frameworks further complicate quick realization initiatives (Nguyen et al., 2020). A lack of resources and capabilities, as well as data privacy, security, and accuracy concerns, also hinder implementation (Ghadge et al., 2020; Handfield, Jeong, & Choi, 2019; Horváth & Szabó, 2019). Moreover, I4.0′s different technologies and application areas require identifying and prioritizing the most promising ones (Frederico et al., 2019; Ivanov et al., 2019).

Nevertheless, scholars have reported occasional SCRES improvements from pioneering digitalization projects during the COVID-19 pandemic. For instance, Javaid et al. (2020) claimed that healthcare SCs have benefited from digital technologies, including effective product allocation and timely delivery. In this context, Bragazzi (2020) noted that additive manufacturing (AM) has helped to create additional production capacities to overcome medical supplies scarcity. In an automotive context, Belhadi et al. (2021) reported that big data analytics (BDA) and the Internet of Things (IoT) have been critical enablers for choosing reliable suppliers and determining manufacturing capacities and safety stock levels during the pandemic.

Scholars expect the exceptional circumstances during the COVID-19 pandemic and the positive I4.0 experiences to be catalysts for SCRM digitalization (Craighead, Ketchen, & Darby, 2020), which implies further SCRES enhancement (Belhadi et al., 2021). However, the discussed challenges of implementing I4.0 in SCRM at scale persist. When and how companies will follow the scientific call and broadly leverage I4.0 solutions to enhance SCRES thus remains uncertain. Already before the COVID-19 pandemic, scholars stressed these pressing questions (Hofmann, Sternberg, Chen, Pflaum, & Prockl, 2019). Overall, the current literature lacks comprehensive and empirical foresight for the post-COVID-19 maturity of I4.0 technologies in SCRM, which indicates a significant research gap at the intersection of I4.0 and SCRES. Using expert knowledge through a Delphi study is recommended to assess future scenarios with high uncertainty (Rowe & Wright, 1999; Winkler, Kuklinski, & Moser, 2015). We therefore leveraged the Delphi method and asked 64 SCM digitalization experts to assess 13 projections, which enabled us to answer the following research question (RQ):

RQ: Given the experiences during the COVID-19 pandemic, how will I4.0 technologies impact SCRES until 2030?

This paper is organized as follows: First, we review relevant literature and introduce the projections that the Delphi panel evaluated. Second, we describe our research methodology. Third, we present our quantitative and qualitative results and discuss them based on our RQ. Finally, we derive conclusions and implications for theory, practice, and policy-making, highlight limitations, and propose future research directions.

2. Literature review and projection development

The literature widely discusses different levers to enhance SCRES, with most scholars referring to agility (including visibility, velocity, and flexibility), collaboration, SCRM culture, and SC (re-)engineering (Christopher & Peck, 2004; Hohenstein et al., 2015). In this context, digital innovations have the potential to improve SCRES levers (Ivanov et al., 2019). Since legacy information technology widely lacks the possibility of increasing SCRES (Pettit et al., 2019), many scholars see great potential in I4.0 (Ali & Gölgeci, 2019). With the COVID-19 pandemic profoundly compromising SCs, the debate on using I4.0 solutions to enhance SCRES has gained further momentum (Chowdhury, Sarkar, Paul, & Moktadir, 2020).

I4.0 is based on the idea of connected and autonomously interacting machines, products, and processes within and across company boundaries (Ivanov et al., 2019). It offers the opportunity to capture, transfer, and analyze information within reasonable timelines (Stank et al., 2019). Hofmann et al. (2019, p. 945) stated that I4.0 “will change how supply chains are designed and operated,” referring particularly to better possibilities for coordinating material, information, and financial flows. In this context, scholars claim that I4.0 directly supports traditional resilience levers and thus enhances SCRES (e.g., van Hoek (2020), Belhadi et al. (2021), Modgil, Gupta, Stekelorum, and Laguir (2021)). Following a systematic literature review, Spieske and Birkel (2021) recently presented comprehensive evidence on the positive relationship between I4.0 and SCRES levers. To give some literature examples, Stank et al. (2019) described that accelerated and more transparent information flows lead to more visibility and velocity in the SC. Paul and Chowdhury (2020) noted that sharing accurate and up-to-date information with SC partners also improves collaboration. The SC (re-)engineering lever can be supported through automatically generated SC maps (Wichmann, Brintrup, Baker, Woodall, & McFarlane, 2020). Nevertheless, certain boundaries for I4.0 to support SCRES exist. For instance, a risk management culture relies predominantly on management engagement, internal collaboration, and employee training (Chunsheng, Wong, Yang, Shang, & Lirn, 2020) rather than technological advancement. Establishing organizational routines and procedures to manage SCDs effectively is another activity driven by traditional organizational learning mechanisms (Scholten, Sharkey Scott, & Fynes, 2019). Cross-company relationship management and trust are other SCRES areas that I4.0 can support (Dubey, Gunasekaran, Bryde, Dwivedi, & Papadopoulos, 2020; Ivanov et al., 2019) but still strongly rely on personal interaction (Ralston & Blackhurst, 2020).

To discuss I4.0′s various technologies and application areas with topic experts, we developed 13 projections for 2030. We built on a review of current studies at the intersection of I4.0, SCRES, and the human factor in SCRM and contextualized them with the challenges of the COVID-19 pandemic.

The COVID-19 pandemic has unveiled major visibility insufficiencies in today’s global and complex SCs (Z. Xu, Elomri, Kerbache, & El Omri, 2020). When internal, supplier, or transportation malfunctions have caused a disrupted flow of goods, companies have struggled to quickly determine points of failure (Craighead et al., 2020). Moreover, externalities such as infection patterns and governmental interventions have developed dynamically and affected SCs over a long period (Craighead et al., 2020). Remaining informed of restrictions while steering global operations has therefore been a major challenge. Due to these experiences, companies have reported focusing on improving visibility (van Hoek, 2020). In this context, scholars consider SC digitalization a central lever (Stank et al., 2019). With the IoT and artificial intelligence (AI), two promising I4.0 solutions for enhancing visibility are evolving. First, the IoT refers to a network of machines and products equipped with digital technology to interact with one another, humans, or other digital systems autonomously (Queiroz, Pereira, Telles, & Machado, 2021). Monitoring devices implemented in such networks bear great potential to collect real-time data and improve objectivity and accuracy (Birkel &

Hartmann, 2020). Application areas include item location, inventory tracking, and metrics determination (e.g., temperature and pressure measurement) (Er Kara, Oktay Fırat, & Ghadge, 2020; Kaur & Prakash Singh, 2021). This technology is especially powerful since it enables a shift from a partial and sequential to a complete and instant information supply (van Hoek, 2020). Visibility gains through the IoT can enhance process risk and overall risk knowledge, as well as the resulting mitigation strategies (Birkel & Hartmann, 2020). Second, in an SCRES context, "AI" is the umbrella term for digital solutions, which can autonomously and successfully decide on the next action in a partially unknown SC environment (Baryannis, Validi, Dani, & Antoniou, 2019). These solutions include all techniques that support a system's continuous learning and adaptive decision-making capabilities (Baryannis et al., 2019; Queiroz et al., 2021). AI relies on past behavior or underlying data (Stank et al., 2019). A prominent area for applying AI in SCRES is screening external real-time information, including news feeds and social media, for quicker risk identification and assessment (Chae, 2015; Handfield, Sun, & Rothenberg, 2020). In this context, AI's application is not limited to structured data, as recent progress in natural language processing techniques reveals (Wichmann et al., 2020). Potential outcomes include but are not limited to visual risk maps and country risk scores (Handfield et al., 2020). Given the visibility challenges during the COVID-19 pandemic and both technologies' potentials, we introduce our first two projections:

- o *P.1 (2030)*: *Internet of Things implementation has been heavily extended to improve data availability and accuracy for SCM decision-making [IoT data].*
- o *P.2 (2030): Artificial intelligence applications have been widely implemented to leverage external real-time information sources for risk identification and assessment [AI external data].*

Even when data has been available, processing and gaining actionable insights from it has been a major challenge during the COVID-19 pandemic (Nikolopoulos, Punia, Schäfers, Tsinopoulos, & Vasilakis, 2021). Apart from enhancing data quantity and quality, improved data processing and sharing are also required to build visibility. SC data availability in organizations has increased exponentially in recent years (Vieira, Dias, Santos, Pereira, & Oliveira, 2019). Evolving data and process mining solutions can help to leverage the large, steadily growing, and primarily unstructured SC data treasure that many companies already possess more effectively for SCRM (Choi, Wallace, & Wang, 2018; Er Kara et al., 2020). Visibility, and thus SCRES, can be enhanced by quickly analyzing this data (Dubey et al., 2021; Oliveira & Handfield, 2019). In this context, van Hoek (2020) recommends sharing data and important findings with SC partners. Cross-company data and communication platforms can enable such data exchange (Chen, Dui, & Zhang, 2020). In a final expansion stage that includes all SC members actively contributing data, these platforms can lead to real-time end-to-end SC visibility, significantly increasing SCRES (Ivanov & Dolgui, 2021). Furthermore, SC partners' additional information can be used to implement digital SC twins, representing the real-time SC network state and enabling the simulation of alternative disruption scenarios and SCRM measures (Hosseini, Ivanov, & Dolgui, 2019; Ivanov & Dolgui, 2021). Such stress test simulations can be valuable decision support systems for SCRM managers (Ivanov & Dolgui, 2021). Based on this discussion, we formulated another three projections:

- o *P.3 (2030): Real-time aggregation of available internal and external data has been significantly intensified to improve SC visibility within organizations [data aggregation].*
- o *P.4 (2030): Cross-company data platforms have been widely established to enable real-time end-to-end supply chain visibility [cross-company data platforms].*
- o *P.5 (2030): Digital supply chain twins have been widely established to improve accurate disruption scenario simulation and alternative SCRM measure assessment [digital SC twins].*

Another I4.0 technology to address visibility constraints in SCs while increasing collaboration is blockchain (BC) (P. Xu, Lee, Barth, & Richey, 2021), an open and cryptographic peer-to-peer network that stores transactional information on decentralized but identical digital ledgers (Li et al., 2020). Since all parties involved in a transaction have timely access to equal data, SC visibility regarding assets' provenance, location, or ownership status (Ivanov & Dolgui, 2021), as well as information authenticity and security, can be improved (Li et al., 2020; P. Xu et al., 2021). Container shipping is among the first sectors to benefit from the BC visibility and security improvements (Nguyen et al., 2020). These advancements translate into enhanced communication, trust, and therefore collaboration across company borders (Dubey et al., 2020; Kumar, Raut, Narwane, & Narkhede, 2020) and improves all steps (i.e., risk identification, assessment, and management) of the SCRM process (Kopyto, Lechler, von der Gracht, & Hartmann, 2020). However, most BC solutions in SCM have not reached maturity, and fundamental challenges remain, including a lack of scalability, incompatibility with legacy systems, and immature regulatory frameworks (Dubey et al., 2020; P. Xu et al., 2021). We therefore introduce our sixth projection to evaluate BC's future in building SCRES:

- o *P.6 (2030): Blockchain adoption has been substantially increased to improve trusted and reliable information exchange [BC information exchange].*

Apart from visibility, the COVID-19 pandemic has also revealed velocity and flexibility insufficiencies in SCRM. Companies have been overstrained due to the high number of incidents that require attention and decision-making in their SCs. For instance, infection prevention measures that restrict the number of personnel per area have led to capacity constraints for blue- and white-collar workers (Z. Xu et al., 2020). Digital technologies also offer solutions to these challenges. Baryannis et al. (2019) claimed that an increasing share of SCRM decision-making can be transferred to autonomous software, allowing humans to focus on more complex SCRM problems (Ralston & Blackhurst, 2020). Moreover, cyber-physical systems are becoming a credible option to reduce dependency on humans in manufacturing processes. These systems integrate physical infrastructure with AI to self-manage operations, allowing companies to facilitate or even replace physical human labor with autonomous robots and vehicles (Queiroz et al., 2021; Stank et al., 2019). Cost improvements in robotic development and manufacturing, as well as enhanced operational performance, reveal a bright future for this technology (Stank et al., 2019). Finally, cloud solutions have emerged in recent years, enabling data access and exchange between decentralized locations (Oliveira & Handfield, 2019). These applications form the foundation for white-collar workers to use company resources remotely and ensure business continuity in times of SCDs. From this discussion, we derived three more projections:

- o *P.7 (2030): Autonomous software has assumed responsibility for most decision-making in SCRM to achieve better mitigation results [autonomous decision-making].*
- o *P.8 (2030): Autonomous robots have replaced a significant share of physical labor to reduce human resource dependency during supply chain disruptions [autonomous robots].*
- o *P.9 (2030): Remote working and digital collaboration have been implemented at scale to ensure business continuity during supply chain disruptions [remote working].*

In addition, the COVID-19 pandemic has disrupted several companies' inbound flows, making SC (re-)engineering a prominent topic.

Infection prevention measures and actual COVID-19 cases have recurrently affected supply bases and transportation, leading to capacity constraints (Ivanov, 2020). Border crossing restrictions and personnel shortages have also impacted transportation (Z. Xu et al., 2020), which has led to severe uncertainty for several companies, even causing production stoppage (van Hoek, 2020). Nevertheless, firms can build on I4.0 solutions to strengthen their supply base. AI and BDA offer possibilities to automize and improve the efficiency and accuracy of supplier selection and regular audits (Cavalcante, Frazzon, Forcellini, & Ivanov, 2019). Based on internal and external data, predictive models can be used to evaluate purchasing markets and develop hedging strategies (Handfield et al., 2019). In this context, suppliers' maturity to quickly report delivery capabilities should also be evaluated since companies can benefit from digitalization only if their entire SC can provide critical data (Kaur & Prakash Singh, 2021; Queiroz et al., 2021). Furthermore, AM – a technology that creates products by successively printing layer upon layer – offers alternatives for designing an SC more resiliently and overcoming certain risks (Durach, Kurpjuweit, & Wagner, 2017; Zhang, Wu, Tang, Feng, & Dai, 2020). Scholars expect this technology to reduce the number of production steps, suppliers, and transportation links, resulting in more localization and flexibility enhancements (Dolgui, Ivanov, & Sokolov, 2020; Stank et al., 2019). These AM characteristics also indicate lead time and velocity advantages, which constitute a major SCRES lever (Kaur & Prakash Singh, 2021; Paul & Chowdhury, 2020), especially during emergency situations (Bragazzi, 2020). Given these impressions, we introduce three additional projections:

- o *P.10 (2030): Supplier selection and evaluation have been based exclusively on big data analytics and artificial intelligence [supplier selection and evaluation].*
- o *P.11 (2030): Suppliers not offering real-time information about short-term delivery capabilities have been replaced [supplier replacement].*
- o *P.12 (2030): Additive manufacturing has been established at scale to increase supply and manufacturing flexibility strongly [AM flexibility].*

Scholars consider an organization's risk sensitivity and culture decisive for successful SCRM, including the right capabilities to manage SCRM-related activities (Grötsch, Blome, & Schleper, 2013). In this context, digital skill sets to implement and operate all the discussed technological innovations have gained importance in recent years (Zouari, Ruel, & Viale, 2020). However, many firms still struggle to develop these employee capabilities, making a lack of skills and experience a primary barrier for SCRM digitalization (Hofmann et al., 2019). As companies must thus address this talent gap internally and externally, we developed our final projection:

- o *P.13 (2030): Digital capabilities have been established as a core skill requirement for SCRM external hires and internal upskilling [digital capabilities].*

3. Research methodology

3.1. The Delphi technique

The Delphi technique's main goal is to predict future developments (Linstone & Turoff, 1975; von der Gracht, 2008). It is an empirical method building on expert judgments to drive structured group communication and consensus-building on a specific topic (Linstone & Turoff, 1975; von der Gracht, 2012). Expert assessments can be provided on a quantitative (e.g., Likert scale rating) or qualitative (e.g., comment with reasoning) basis (Scheibe, Skutsch, & Schofer, 1975). Its round-based approach allows interaction among participants, individual reassessment of estimates, and ongoing reflection of answers (Rowe & Wright, 1999; von der Gracht, 2008).

The Delphi technique offers four major advantages. First, it is a well-established approach for studying future scenarios with high uncertainty (Winkler et al., 2015), particularly in SCM (von der Gracht, 2008). Second, the Delphi method is an accurate approach to exploring contexts with insufficient empirical data, where expert knowledge provides the only reliable source of information (Rowe & Wright, 1999). Third, the Delphi approach allows drawing on informed opinions from diverse experts (Hirschinger, Spickermann, Hartmann, von der Gracht, & Darkow, 2015), leading to higher accuracy than individual evaluations such as semi-structured interviews and other forms of group evaluations (von der Gracht, 2008). Fourth, the method's guaranteed anonymity prevents negative group dynamics such as bandwagon and halo effects (Linstone & Turoff, 1975; Rowe & Wright, 1999).

3.2. Delphi study design

The present foresight study was conducted using a two-round web-based Delphi format and built on a comprehensive projection development process. It follows the four steps depicted in Fig. 1 and is described in detail in the following sub-sections.

In the context of this study, the Delphi method's four main advantages presented in the previous section were all decisive. First, the COVID-19 pandemic continues to cause severe disruptions more than one year after it began to affect SCs globally. Triggered by this crisis, scholars expect significant structural changes in SCs and foresee a considerable role for I4.0 technologies in this transformation (Ivanov & Dolgui, 2021; van Hoek, 2020). However, due to this crisis's novelty and the I4.0 research context, it is highly uncertain how these structural changes will be realized and which I4.0 technologies will be prioritized to improve resilience (Dolgui & Ivanov, 2020). The Delphi method has proven to be a reliable instrument for predictive research in various contexts related to disruptive technological change (Lechler et al., 2019; Roßmann, Canzaniello, von der Gracht, & Hartmann, 2018; Rowe & Wright, 1999). Therefore, the approach is well suited to answer our future-oriented RQ on how I4.0 technologies will impact SCRES after the COVID-19 crisis. Second, due to the COVID-19 pandemic's recency, reliable, large-scale quantitative information is scarce. Therefore, expert knowledge is currently the only reliable source of information for future predictions. Third, a variety of stakeholders who have been affected by the COVID-19 pandemic and are engaged in the transition toward a more digitalized SCRM could be included in this study. This setting allows drawing from first-hand experience with the COVID-19 crisis and comprehensive subject matter knowledge to create a holistic future scenario on I4.0-enabled SCRM, which the literature currently lacks (Ivanov, 2020). Fourth, the anonymity benefit ensured participants a protected environment to be able also to share negative experiences and consequences of the COVID-19 pandemic with other experts without disclosing sensitive information such as their firm affiliation.

3.3. Step 1: Projection development

In our study, participants were asked to evaluate future-oriented statements. The systematic development of those projections is crucial for the value, validity, and reliability of the Delphi study (Warth, von der Gracht, & Darkow, 2013). First, an opening workshop with the research team and three experienced SCM practitioners from different industries was held. All practitioners reported that the experiences of the COVID-19 crisis triggered a reevaluation of digital support for SCRM in their organizations. The group also agreed that a comprehensive foresight study on SCRM through I4.0 would be valuable for updating the current theoretical thinking and practical guidance on digitalization pathways. Second, relevant influencing factors on how I4.0 technologies can affect SCRES were collected to build a basis for projection formulation. Multiple sources were leveraged to ensure methodological rigor and completeness. The sources included (1) an extensive review of academic and practitioner literature, (2) a creative workshop with four researchers, and (3) five semi-structured interviews with senior SCM executives. Third, a projection formulation workshop was conducted.

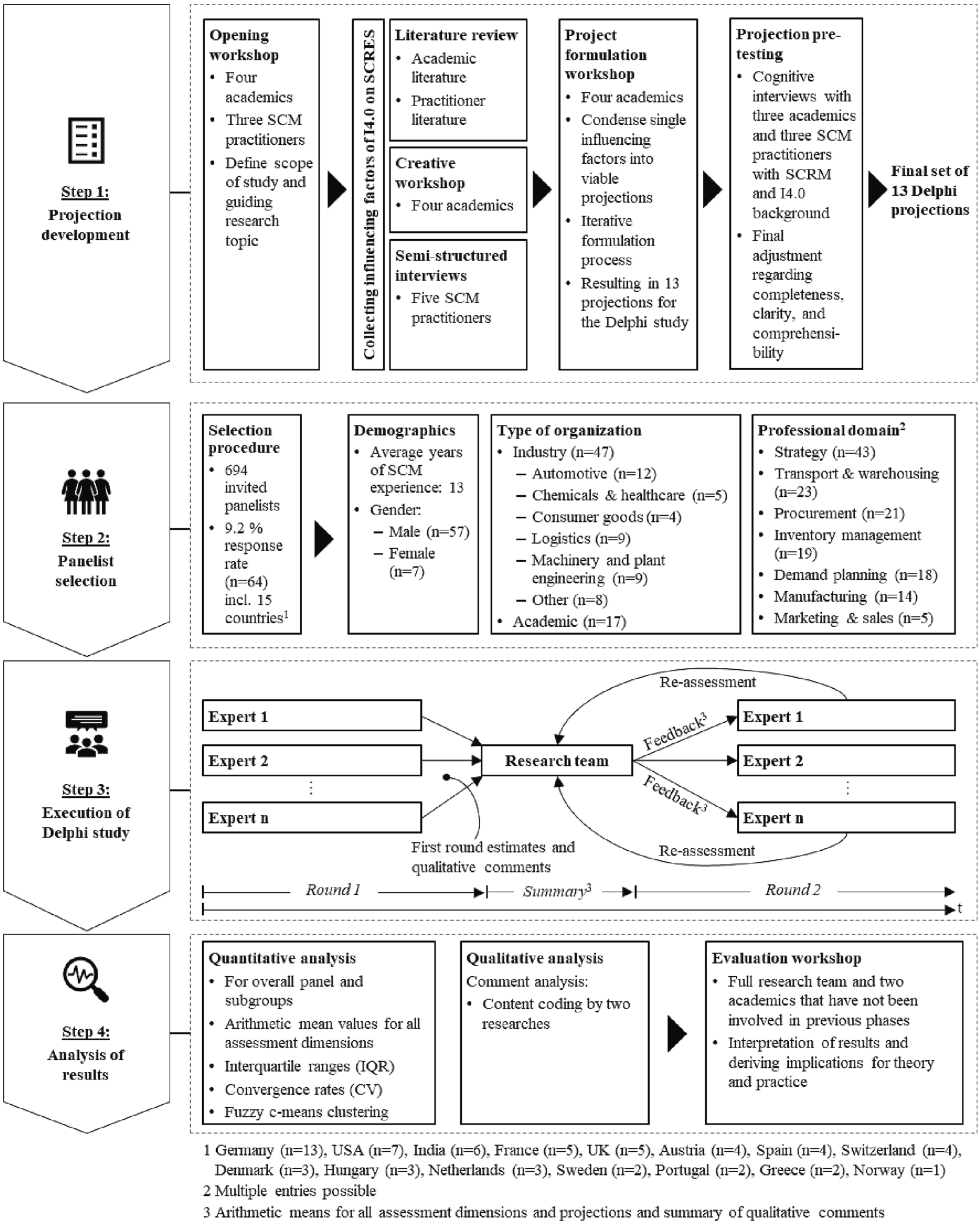

Fig. 1. Structure of the Delphi process applied in the study.

Delphi projections were drafted, repeatedly revised, and reflected against their theoretical foundations. Commonly accepted guidelines regarding formulation (Linstone & Turoff, 1975; Mitchel, 1996; Rowe & Wright, 1999) and word count (Salancik, Wenger, & Helfer, 1971) were considered to ensure validity and reliability. Following Mitchel's (1996) recommendations, the number of projections was limited to 13 to increase the response rate and reduce the likelihood of sparse completion. Consistent with previous Delphi studies in the SCM field (Darkow, Foerster, & von der Gracht, 2015; Keller & von der Gracht, 2014), the projections were formulated with a 10-year time horizon until 2030 to increase creativity and novel thoughts. Finally, the formulated projections were pre-tested via cognitive interviews with three academics and three SC managers with in-depth methodological or subject-specific knowledge on SCRM. These interviews helped to ensure the study's robustness and validity by cross-validating the projections and testing for completeness and comprehensibility (Warth et al., 2013).

3.4. Step 2: Panelist selection

The selection of expert panelists significantly influences a Delphi study's reliability (Spickermann, Zimmermann, & von der Gracht, 2014). One must ensure both deep subject matter expertise and diverse perspectives to achieve the most accurate results (Rowe & Wright, 2011). For an unbiased selection process, we followed Spickermann et al. (2014) and defined selection criteria, including the type of organization, present work position, academic status, and supposed level of expertise on SCRM and digital technologies. We identified 694 experts, including both SCRM experts from academia and industry representatives with SCRM responsibilities, and invited them to participate in our study. Overall, 64 experts participated in both rounds. This number is higher than or comparable to many recent Delphi studies in SCM research (Durach et al., 2017; Gossler, Wakolbinger, & Burkart, 2020; Lechler et al., 2019). The final panel represents 15 countries and comes from a diverse background of industry (73%) and academia (27%), as well as various professional domains (see the third row of Fig. 1). Heterogeneity of expert backgrounds is recommended in Delphi literature to prevent various potential biases (Rowe & Wright, 2011; Winkler & Moser, 2016). Overall, we achieved a response rate of 9.2%, which, given the seniority of the identified experts and the long processing time, is considered adequate and comparable to similar studies' response rates (Hirschinger et al., 2015; Lechler et al., 2019).

3.5. Step 3: Execution of the Delphi study

In the first Delphi round, all panelists were asked to assess each of the 13 projections for the year 2030. Consistent with previous Delphi studies (Keller & von der Gracht, 2014; Lechler et al., 2019; Roßmann et al., 2018), the following assessment dimensions were selected:

- EP: The expected probability of occurrence on a scale from 0% to 100%
- I: The impact on SC performance in the case of an SCD[1], based on a five-point Likert scale (very low = 1, low = 2, medium = 3, high = 4, and very high = 5)
- D: The desirability of occurrence, based on the same five-point Likert scale

To foster qualitative data gathering, we asked panel members to add written comments to their quantitative assessments for each dimension (Tapio, Paloniemi, Varho, & Vinnari, 2011). After the first round, descriptive statistics (i.e., means and interquartile ranges per dimension) for all predictions were derived, and the qualitative comments were summarized. These results were shared with all participants as input for the second round, in which panelists could reevaluate their assessments and add additional qualitative comments. To explore the existence of a non-response bias among the panelists, we compared the early (initial 10) and late (last 10) responders in both rounds of the survey for all assessment dimensions. As a Shapiro-Wilk test on normality ($p < 0.05$) revealed a non-normal distribution of the sample for each of the dimensions (see Appendix A), we conducted a Wilcoxon-Mann-Whitney test to explore the differences between the two respondent groups. The test revealed no significant differences ($p < 0.05$) between early and late responders across both rounds and all dimensions (see Appendix A). The presence of a non-response bias can thus be rejected.

3.6. Step 4: Analysis of results

Mean values were determined for the EP, I, and D of each projection after the second round (Keller & von der Gracht, 2014; Warth et al., 2013). Two additional indicators were calculated for each projection's EP: The convergence rate (CV) describes the difference in standard deviation for the EP from the first to the second Delphi round and provides information on overall assessment changes. A negative CV signifies that participants reevaluated their judgments after reviewing their fellow panelists' quantitative and qualitative arguments and veered toward the group opinion (Rowe & Wright, 1999), which indicates that the group-based consensus-building process worked as intended. The interquartile range (IQR) can be used to evaluate a projection's level of agreement and is generally accepted as an objective and rigorous indicator for measuring consensus in a Delphi study (von der Gracht, 2012). Consistent with several previous Delphi studies in the SCM field, a threshold of IQR ≤ 25 was set to define consensus (Keller & von der Gracht, 2014; Lechler et al., 2019; Roßmann et al., 2018; Warth et al., 2013). This threshold indicates that at least 50% of all estimations fall within a range of 25 percentage points on the 0%–100% scale for the EP (von der Gracht, 2012).

Following various recent Delphi studies in the SCM field (Hirschinger et al., 2015; Roßmann et al., 2018), we used a fuzzy c-means (FCM) algorithm to assign each projection to a designated cluster according to its EP, I, and D. We thus established a systematic scenario structure to discuss quantitative results and contextualize the written statements (Tapio et al., 2011), which enables a more focused and objective interpretation of the experts' judgments.

To systematically analyze the participants' qualitative comments, we applied a coding procedure based on Corbin and Strauss's (2015) for each projection. The written statements were classified according to their sentiments toward the projection: supportive (arguing for a high rating), negative (arguing for a low rating), balanced/neutral (providing pro and contra arguments or more general statements), or non-applicable (if the comment was incomprehensible). To reduce investigator bias, two researchers with experience in content analysis coded each statement individually. Any divergence was discussed until a consensus was reached, thus improving inter-rater reliability. The arguments were incorporated into the discussion of long-term quantitative expert judgments.

To conclude the analysis, the entire research team and two additional academics, who had not been involved in the study, conducted a full-day workshop to review the Delphi study results and inform the discussion section of this paper.

4. Results and discussion

4.1. Quantitative Delphi results

The left side of Table 1 presents the experts' average judgments for each projection, the IQRs, and the CVs, while the right side reveals the results of coding the experts' written statements. We found a wide EP range from 38% for P.10 (supplier selection and evaluation) to 89% for P.9 (remote working). The impact was projected high ($I \geq 3.5$) for 10 of the 13 projections, with P.3 (data aggregation) and P.4 (cross-company data platforms) rated highest ($I \geq 4$). In contrast, the impact of P.6 (BC information exchange) was rated lowest ($I = 2.9$). The respondents also assessed eight projections as highly desirable ($D \geq 3.5$). Only P.10 (supplier selection and evaluation) indicates a desirability rating below 3, suggesting that experts consider it a threat.

We observed convergence in ratings across all projections from round 1 to round 2, which confirms that the Delphi method worked as

[1] SCRES assessment dimension, in line with SCRES definitions (e.g., Hohenstein et al.(2015), Hosseini et al.(2019).

Table 1
Quantitative results from the expert panel and sentiment analysis of qualitative comments per projection.

		Quantitative results					Qualitative comments' trend				
No.	**Projection**	EP [0–100%]	IQR [0–100]	CV [-100%-100%]	I [1–5]	D [1–5]	Supportive	Negative	Balanced/ Neutral	n/a	**Sum**
P.1	IoT data	73%	*20.3*	−26%	3.8	4.1	64	9	23	3	**99**
P.2	AI external data	60%	40	−10%	3.5	3.7	38	21	38	2	**99**
P.3	Data aggregation	78%	34.3	−14%	4.5	4.6	55	3	20	1	**79**
P.4	Cross-company data platforms	64%	30	–22%	4.4	4.3	36	6	34	2	**78**
P.5	Digital SC twins	57%	31.8	−11%	3.8	3.9	32	9	26	–	**67**
P.6	BC information exchange	48%	30.8	−12%	2.9	3.1	22	36	31	–	**89**
P.7	Autonomous decision-making	53%	34.3	−17%	3.5	3.3	12	5	51	–	**68**
P.8	Autonomous robots	57%	40	−13%	3.5	3.2	13	12	44	2	**71**
P.9	Remote working	89%	*17.5*	−8%	3.8	4.2	37	7	15	–	**59**
P.10	Supplier selection and evaluation	38%	34.8	−11%	3.1	2.9	5	22	44	1	**72**
P.11	Supplier replacement	47%	40	−11%	3.4	3.3	12	12	45	–	**69**
P.12	AM flexibility	50%	37	−10%	3.5	3.5	16	14	36	–	**66**
P.13	Digital capabilities	80%	*22*	−7%	3.8	4.1	38	1	6	–	**45**
Sum							**380**	**157**	**413**	**11**	**961**

Note: EP: Expected probability; I: Impact; D: Desirability; CV: Convergence (i.e., decrease in standard deviation).

intended (Rowe & Wright, 1999). Overall, standard deviation decreased by 13.2% from round 1 to round 2 and fell between 7% and 26% across all projections, revealing a high convergence level to group consensus (Roßmann et al., 2018; Rowe & Wright, 1999). Applying the previously defined threshold of IQR $\leq$ 25, we conclude that consensus was reached for three projections (P.1, P.9, and P.13).

Since further insights can be derived from reviewing the differing assessments of subgroups, we classified our panel into industry ($n = 47$) and academia ($n = 17$) subgroups. As a Shapiro-Wilk test confirmed a non-normal distribution for each of the three dimensions in both rounds ($p < 0.05$), we also conducted a Wilcoxon-Mann-Whitney test to assess differences between responses for each of the projections in the subgroups (see Appendix A). The results demonstrate that EP and D assessments for P.10 (supplier selection and evaluation) and D for P.11 (supplier replacement) differed significantly ($p < 0.05$). No other significant deviations were found among the subgroups. This is an interesting result as the academia panelists are rather distinct, having no or very little industry experience with most of their careers spent in research institutions. Hence, the little variation in results from both subgroups further strengthens the Delphi results' credibility and validity as the experts attained comparable estimates regardless of their backgrounds (Kopyto et al., 2020; Roßmann et al., 2018).

Leveraging the FCM approach regarding EP, I, and D, we determined three projection clusters with four to five projections each (see Fig. 2).

Cluster 1 comprises four projections with high ratings across dimensions (EP > 70%, I > 3.5, D > 3.5). Two projections with an EP over 80% directly affect conditions and requirements for employees. Panelists believe that companies will make digital capabilities a requirement for SCRM personnel (P.13) and expect remote working to become a core lever to ensure business continuity (P.9). P.9 and P.13 also yielded the lowest conversion rates among all projections (-7% and −8%, respectively) and an IQR $\leq$ 25, which indicates that participants are particularly confident in their foresight and have reached consensus.

Cluster 2 comprises four projections evaluated with EPs between

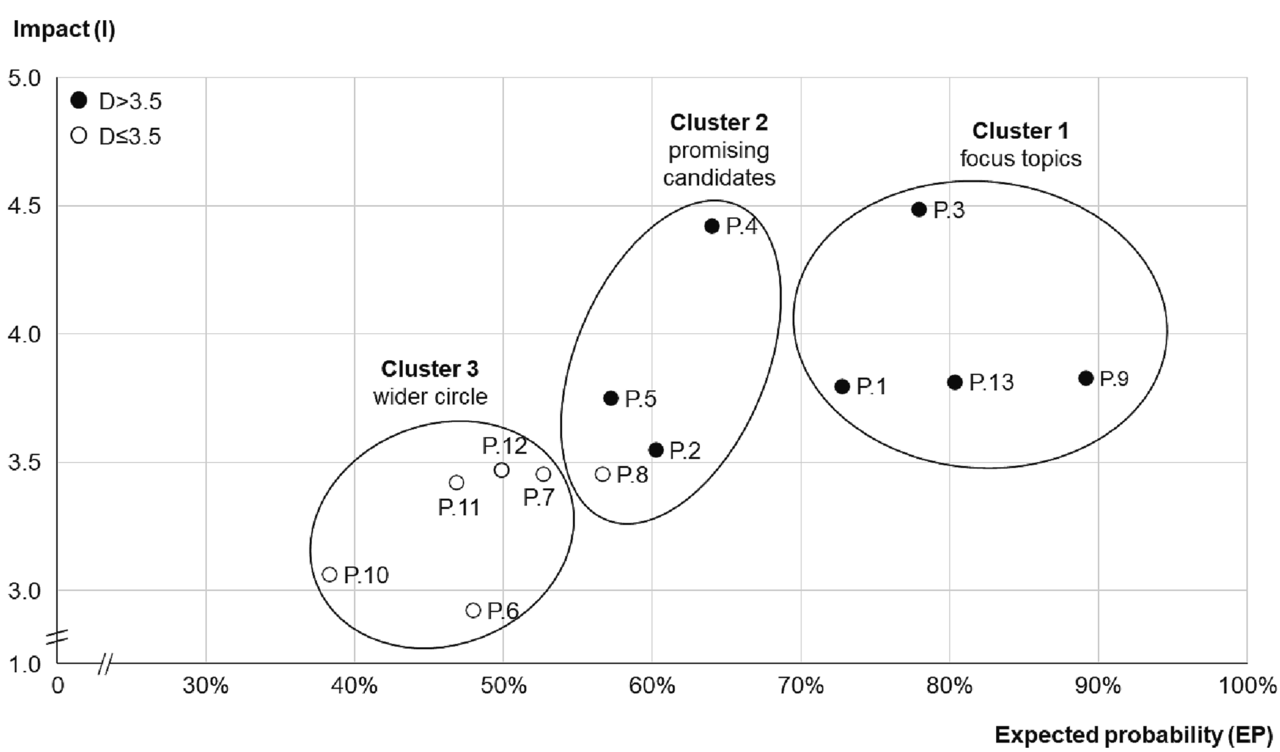

Fig. 2. Classification of projections based on FCM method.

57% and 64%, suggesting slightly positive tendencies regarding their realization until 2030. All four projections have thus been controversially rated and discussed (IQR > 31). In terms of impact and desirability, three projections show average ratings between 3 and 4, while P.4 indicates ratings above 4.

Cluster 3 comprises the last five projections. With comparably low occurrence (EP < 55%), impact (I ≤ 3.5), and desirability (D ≤ 3.5) scores, these statements were considered little relevant until 2030. This cluster also includes the least probable and desirable projection (P.10: EP = 38%, D = 2.9) and the least impactful one (P.6: I = 2.9). However, it is essential to note that all statements were discussed controversially, and some experts still see high probability and impact potential for all statements, as IQRs > 25 indicate.

4.2. Qualitative results

The experts provided 961 written statements (see right side of Table 1), which equals an average of 15 comments per participant. Moreover, 75% of all participants submitted at least one comment, which suggests a high level of interaction. In the following, we present the experts' qualitative reasoning for their quantitative evaluations along the three clusters.

4.2.1. Cluster 1: Focus topics

Digital capabilities (P.13). Panel members expect that ensuring the digital capabilities of the workforce will be crucial in 2030. They stressed P.13′s desirability, highlighting that digital-savvy employees will be more capable of data-driven decision-making, leading to an enhanced SCRM culture, including earlier and more precise risk identification and mitigation. One panel member stated that "none of the concepts mentioned in this study can be implemented and maintained without digital skill sets." Some panelists even argued that implemented I4.0 applications could be harmful to SCRES if employees administered them without digital experience. Some panelists believe that this projection will become a reality even before 2030, and the trend will accelerate due to the COVID-19 crisis. However, a continuous lack of digital talent within companies and on the labor market has recurrently been cited by the experts as a significant barrier to realizing P.13.

Remote working (P.9). During the COVID-19 pandemic, remote working has become integral across SCs to ensure business continuity. Papanikolaou and Schmidt (2020) found that organizations with higher remote working capability have revealed significantly greater robustness against COVID-19-related disruptions. Panelists suppose that remote working capabilities will improve faster coordination for pandemics. Specifically, it should accelerate an organization's reaction speed for white-collar workers and enable more flexible contingency planning. Some experts have also mentioned that more decentralized and digital interactions will allow for significant cost savings, which can safeguard critical cash flows in an SCD. Although remote working capabilities are currently mostly considered a reactive measure, our results suggest that having such options in place will be an SCRM capability in itself and safeguard business continuity during future disruptions. Nevertheless, experts deem P.9′s impact contingent on the SCD; while remote working represents an effective SCRES lever in a pandemic such as the COVID-19 crisis, it might not prove as decisive in a more decentralized disruption, such as a financial shock.

IoT data (P.1). COVID-19 has exposed the critical need for more visibility throughout SCs, and panelists expect that the IoT will be highly leveraged in 2030 to improve SCRES through higher data availability and accuracy for SCRM decision-making. Participants see the technology at the center of SC executives' agendas even now. Moreover, panelists connect the anticipated increase in IoT adoption to the expected trend toward more regionalization and increased safety stocks induced by COVID-19. They argue that managing higher and more globally dispersed stock levels will require even more visibility regarding products' statuses and locations. Compared to other projections in Cluster 1, P.1 indicates a relatively low expected occurrence. This assessment can be explained by participants cautioning against the IoT's high required investments, which constitutes a significant implementation barrier. Participants also stressed the IoT's potential incompatibility with other technologies in a company's digital infrastructure as IoT implementation requires considerable adaptation to companies' hardware and legacy systems.

Data aggregation (P.3). Delphi panelists expect that aggregating existing external and internal data in real-time for improved SC visibility and risk identification will be established in 2030. The panel further considers this projection the most impactful and most desirable of all, which indicates a significant influence on future SCRM. Explaining the high likelihood of occurrence, experts consider this projection a continuation of an ongoing trend. Many panelists have stressed that data aggregation would be an essential baseline for technology-enabled decision support systems and enhanced visibility to detect disruptions such as those caused by COVID-19 earlier. It should be an initial priority before more advanced solutions are implemented. Panelists who were more critical of P.3 indicated that company silos and fragmented data systems often constrain holistic data aggregation. These organizational barriers must be overcome before effective collection and processing does become possible.

4.2.2. Cluster 2: Promising candidates

Cross-company data platforms (P.4). Participants highlighted that COVID-19 forcefully revealed how often SC visibility still ends at the boundaries of a company's operations. Panelists particularly stressed that data platforms will play a key role in addressing future disruptions by reducing information silos, offering more SC collaboration opportunities, and accelerating decision-making in crises, emphasizing such platforms' scalability. Furthermore, the participants expressed only moderate confidence that P.4 will be realized in 2030, thus differing from their trust in the other high-impact, high-desirability projections of Cluster 1. They stressed significant implementation barriers for cross-company data platforms, including SC partners' reluctance to share information, high initial investment costs, and incompatible legacy systems. They highlighted the technology's security to protect company-specific data and intellectual property as a prerequisite for platform-based cross-company collaboration. Panel members also cited power dependence as an obstacle to realizing this projection.

AI external data (P.2). Participants generally agreed on AI's importance for screening external real-time information sources to enhance the visibility lever by identifying and assessing risks for a company's SC (Handfield et al., 2020). In this context, frequent reference to social media data was made. While its large volume makes it difficult for humans to monitor, it is expected to provide quick insights in the case of disruptions. As the panel emphasized, AI could recognize pandemic-related risks and others with similar global effects earlier. AI will also prevent human bias in risk assessment, which is essential in high-impact/low-probability disruptions. However, as the average EP of 60% and an IQR of 40 indicate, participants were undecided on whether this technology will be widely established in 2030. Critical panelists stressed AI's low maturity, which makes it vulnerable to false positives. Moreover, some experts warned that companies might get carried away by inflated expectations and forestall implementing more fundamental digital solutions that should be prioritized initially. Some panelists therefore argued that companies should spend their limited resources on other digitalization projects or using AI on internal data first.

Digital SC twins (P.5). Most experts consider digital SC twins a powerful instrument for SCRM. As one participant stated, "current decision-making in risk management includes many assumptions." Establishing digital twins will address and reduce this lack of accuracy in simulations, thus improving SCRES through three main levers, as the panelists noted: First, precise simulations will help to establish more resilient SC designs proactively before a disruption occurs. Second, these advanced simulation capabilities will enable more proactive risk identification, assessment, and mitigation, which – according to several panelists – has been lacking during the COVID-19 crisis. Third, from a reactive perspective, firefighting will require fewer resources and be quicker. Nevertheless, although SC data availability has significantly increased within organizations (Vieira et al., 2019), panelists are skeptical that digital twins will be established in 2030 since their full capabilities depend on unrestricted cross-organizational SC visibility, end-to-end data aggregation, and data sharing between all stakeholders. The experts thus reported that enabling prerequisites such as projections P.1, P.3, P.4, and P.13 must be achieved first.

Autonomous robots (P.8). The projections' aggregated EP, I, and D responses indicate no clear inclination to replace physical human labor with autonomous robots for improved SCRES. Although some panelists expect the experiences during the COVID-19 crisis to trigger a conscious effort for more production automation, they consider all SC risks too diverse to be handled autonomously. While they pointed out positive risk-mitigating effects of robots during pandemics and for operations with little variability, the experts also highlighted the SCRES-improving capabilities of humans. For instance, they emphasized humans' higher flexibility and improvisation capacity, which they agreed is more important during SCDs than under normal operations. Furthermore, robots must be reprogrammed for every risk-mitigating modification of processes, which may cost valuable time during disruptions. Panelists generally concluded that full automation is undesirable for SCRM, with one panelist stating that "robots can be even harmful." Overall, the experts see potential in robots for reducing certain risks but mainly believe they will be employed for cost, efficiency, or lack of skilled labor reasons, not SCRM-motivated ones.

4.2.3. Cluster 3: Wider circle

BC information exchange (P.6). Panelists were skeptical about BC's potential to enhance collaboration, particularly trust and reliability, between SC entities until 2030. Most experts argued that current poor BC implementation and understanding levels will hinder significant SCRM improvements. Nevertheless, in addition to the speed of adoption, the technology's general advantageousness was questioned. Experts also pointed out that less advanced data exchange systems will suffice in many situations, and only a limited number of truly beneficial use cases for BC exist. Experts therefore cautioned against overengineering with BC as a far more advanced solution than required for the problems to be solved. Incidentally, several experts revealed that a lack of SC collaboration has not been apparent during the COVID-19 pandemic. Therefore, BC's possibilities for strengthening this SCRES lever might thus be more advantageous for SCDs other than a pandemic. Moreover, missing regulatory guidelines and required high investments were discussed as further implementation barriers. Especially the second challenge was repeatedly stressed to explain BC's low desirability. We also observed a higher occurrence rating (EP = 52%) and a consensus among academic participants (IQR = 22), which demonstrates more optimism about BC within this group.

Autonomous decision-making (P.7). The projection on autonomous SCRM decision-making received the highest probability score in this cluster. Nevertheless, many experts highlighted that humans will still assume the most important decisions in SCRM in 2030. The unforeseeable spectrum of SCDs and liability regulations that require human involvement were discussed as the main reasons. For more critical instances going beyond operational day-to-day and low-impact activities, panelists expect digital technologies to support rather than replace human decision-making. According to most panelists, a high number of time-consuming SCRM activities overstrained employees in 2020; comprehensive support from more digital solutions would have been highly welcomed. A potential use case is thus intelligent software presenting next-best-action options, providing the human decision-maker with a reliable basis for quickly assessing and choosing between different mitigation options. Such applications can free up employee capacity for more complex tasks, which can be highly valuable, as recent experiences during the COVID-19 pandemic revealed.

Supplier selection and evaluation (P.10). Participating experts were rather open to general automation in SCRM decision-making (P.7) but rejected the specific option of basing supplier selection and evaluation exclusively on quantitative analyses. Although several panelists are convinced that AI's and BDA's relevance will increase and improve the SCRES (re-)engineering lever, they widely stressed the importance of soft factors in supplier audits and negotiations. In this context, they referred explicitly to cultural proximity, buyers' experience and gut feelings, relational trust, and personal impressions from site visits. Panelists also indicated that overly digitalized selection processes and the corresponding loss of interpersonal skills could ultimately harm collaborative buyer–supplier relationships. Nevertheless, participants presented two forms of hybrids in supplier selection. Panelists believe that supplier pre-selection and commodity material procurement will soon be managed exclusively by intelligent software. Remarkably, the Wilcoxon-Mann-Whitney test revealed significant deviations in occurrence and desirability ratings between panelists' organizational types. Contrasting industry, academia reached consensus (IQR = 10) for a much lower probability rating (EP = 29%) and noted less desirability (D = 2.4). This result indicates a significant and fairly manifested disconnect between industry and research on the future of digital procurement support, possibly caused by the lack of practice exposure of the academia panelists to the applications in question.

Supplier replacement (P.11). (Re-)engineering the SC by replacing suppliers not able or willing to share data on short-term delivery capability was controversially discussed. Overall, experts expect considerable SCRES improvements from ensuring higher supplier visibility. They revealed that certain SC partners' extended data sharing during the COVID-19 pandemic has helped to detect bottlenecks in the SC and quickly identify alternative sources in the case of supplier capacity constraints. However, P.11 has a comparably low expected probability, resulting from different priorities in supplier selection criteria, as the panelists confirmed. They believe that companies will continue prioritizing a supplier's cost and quality characteristics over potential visibility benefits. Moreover, they stressed that some suppliers possess certain unique value propositions, which translates into great negotiation power. If these firms refuse more transparency – a scenario most panelists anticipate – customers will have to accept these suppliers' business conditions and renounce visibility ambitions instead of replacing these players.

AM flexibility (P.12). The projection on AM's potential to improve SC flexibility received comparably high impact and desirability scores. Experts explained their ratings by highlighting AM's advantages regarding commodity and spare part supply, lead times, and local backup capacities. Additionally, different panelists mentioned the technology's potential to reduce supplier numbers and tiers. In this context, experts claimed that higher AM adoption would have helped to manage the COVID-19 pandemic by reducing supplier dependency. To illustrate, many panelists referred to successful ad-hoc AM applications during COVID-19, such as the decentralized 3D printing of personal protective equipment for hospitals and other care facilities to decrease supplier dependence and cope with considerable shortages. Although sound reasons for advancing the technology further exist, panelists indicated that they doubt implementation at scale will occur until 2030. Three main reasons were discussed: First, supply network adoptions would be significant, requiring more time. Second, several companies' parts portfolios are too complex to be produced predominantly by AM. Experts rather see high-risk mitigation potential for niche industrial use cases, such as spare part production. Third, the required investments and operational costs would be too high to scale AM, based on today's technological status.

4.3. Discussion

The presented quantitative and qualitative results reveal that several

I4.0 technologies will be widely established in 2030 and considerably benefit resilience levers such as agility, collaboration, SC (re-)engineering, and SCRM culture. This overall finding validates various scholars' conceptual arguments that future SCRES will increasingly depend on I4.0 after COVID-19 (e.g., Ivanov et al., 2019; van Hoek, 2020) and indicates that the positive relationship between I4.0 and SCRES confirmed for previous literature (Spieske & Birkel, 2021) will only strengthen in the future.

By interpreting the results for individual clusters and projections, we can deduce more specific confirmations and contradictions in relation to existing literature. Various "focus topics" and "promising candidates" enable data collection, exchange, and enhanced transparency. The prioritization of such technologies is consistent with Zouari et al. (2020), who found that digital connectivity and systems that foster information sharing strongly influence SCRES and act as an enabler for more advanced digital tools. The results further empirically confirm arguments by Ivanov and Dolgui (2021) and Horváth and Szabó (2019), who claim that such solutions are the base requirement for end-to-end visibility and further SC collaboration to increase SCRES. While experts concur with the literature that AI will build on this foundation and offer far more precise and faster SC disruption prediction capabilities than humans (Baryannis et al., 2019), wide-reaching maturity lies beyond a 10-year horizon. The high rating and supportive qualitative reasoning for the remote working (P.9) and digital capabilities (P.13) propositions are consistent with observations of Zouari et al. (2020), who demonstrated that an organization's digital maturity, including its employees' digital competencies and systems connectivity, has a more substantial positive effect on SCRES than the adoption of specific digital tools. The fact that experts made clear that they do not expect fully automated decision-making and supplier selection (P.7 and P.10), as sometimes advocated in literature (e.g., Cavalcante et al., 2019), reinforces the notion that human capabilities and assessments will continue to play an essential role in future SCRM. This supports previous research claiming that mostly routine activities will be automated (e.g., Ralston & Blackhurst, 2020) and contradicts scholars' claims that several relationship-based decision-making criteria such as personal experience, trust, and gut feeling will be less critical (Ocampo, Abad, Cabusas, Padon, & Sevilla, 2018). Furthermore, experts' evaluations of the BC (P.6) and the AM (P.12) projections refute some aspects attributed to these technologies by previous works. While several participants referred to BC's visibility and velocity benefits as a more promising way of enhancing SCRES, they contradicted previous research (e.g., Min, 2019; P. Xu et al., 2021) by denying significant collaboration improvements. Previous foresight research on AM claimed a considerable impact of the technology on a broad scope of processes in various industries within the next five to ten years (Durach et al., 2017). The results of this Delphi study rather point to a longer time to maturity (beyond 2030) and a more limited scope of beneficial use cases. In conjunction with the evaluation of other projections in Cluster 3, all referring to the (re-)engineering lever, we can infer that far-reaching digitalization initiatives demanding considerable supply network adaptations are unlikely to occur after the COVID-19 pandemic.

5. Conclusion

The COVID-19 crisis has put SCRM to the test in a wide array of industries. Moreover, since "the supply chain will be [only] as good as the digital technology behind it" (Ivanov et al., 2019, p. 838), scholars have increasingly called for I4.0 solutions to mitigate SCDs (Chowdhury et al., 2020). Given the experiences during the COVID-19 pandemic, we analyzed the momentum of digitalization and the future role of I4.0 in strengthening SCRES.

We built on existing I4.0 and SCRM literature and developed 13 projections on how I4.0 technologies will impact SCRES for 2030. Conducting a Delphi study, we surveyed 64 SCRM experts from industry and academia, who assessed and discussed the future-oriented projections according to each one's probability of occurrence, impact, and desirability. Our analysis includes quantitative and qualitative approaches and employs the FCM algorithm to ensure transparency in the experts' evaluations. Important implications for theory, practice, and policy-making were derived from the results.

5.1. Implications for theory

First, our paper is one of the primary studies that integrate multiple I4.0 technologies in SCRES-related foresight research. We followed the calls of Zouari et al. (2020) and Ivanov et al. (2019), who demanded empirical and more holistic investigations into different I4.0 solutions in SCRM. Whereas most studies at the intersection of I4.0 and SCRES are conceptual or have a narrow empirical focus (e.g., focusing on specific case studies), ours offers extensive quantitative and qualitative evidence from a broad range of experts. Second, our findings reveal that all investigated I4.0 technologies improve SCRES and are expected to be increasingly established until 2030. Thus, we can empirically confirm the claims that SCRM practices' future success will increasingly depend on I4.0 (Ivanov et al., 2019; Ivanov & Dolgui, 2021). This development is relevant for any kind of future SCD, including but not limited to pandemics. At the same time, we contribute a nuanced perspective on I4.0 for SCRM by showing that the human factor will remain crucial in SCRM in 2030. While SCRES benefits of technologies such as BDA and AI are clearly acknowledged, fully-automated risk management processes or decision-making are not be expected and human judgement will remain critical. Connecting behavioral perspectives such as stakeholder or principal-agent theory with the I4.0-SCRM literature might therefore be advantageous to accompany the transition. Third, while significant implementation progress can be expected, our analysis also reveals that the full range of I4.0 technologies will not yet be mature in 2030. We found that visibility-enabling levers, including IoT applications and real-time data exchange, and SCRM culture-related levers, such as digital workforce capabilities, represent base requirements for digital SCRM. These technologies will have initial priority as they build the necessary baseline for more sophisticated digital SCRES-improving approaches. Furthermore, our analysis suggests that the future road map for SCRES-enabling I4.0 technologies continues much beyond the 2030 horizon. On a different note, the comparatively low ratings and qualitative data for the "wider circle" cluster indicate that applicable use cases for the included I4.0 technologies have not been developed or their benefit is not sufficiently convincing. Particularly BC and AM revealed a more limited application scope than claimed in previous literature. Finally, we provide empirical foresight for the post-COVID-19 path and the maturity of I4.0 technologies in a SCRES context, thus offering the research community insights into how the intersection of SCRM and I4.0 must be conceptualized after COVID-19.

5.2. Implications for practice

From a managerial perspective, our study results offer both tactical and strategic guidance. First – and most importantly – our study confirms the benefits of I4.0 application in SCRM and encourages practitioners toward accelerated SC digitalization. Therefore, managers should assume a holistic perspective and consider I4.0 technologies' potential to improve resilience when deciding on implementing digital solutions in their SCs. Second, we identified that several SCRES-improving I4.0 solutions face similar implementation barriers. Common challenges include high investment costs, a lack of digital capabilities, a lack of compatibility with legacy or fragmented data systems, and organizational silos within and between companies. Managers are thus advised to design their companies' digitalization processes holistically and enable various I4.0 technologies by addressing common barriers together. Third, with this study's results, practitioners can prioritize implementing I4.0 technologies in a more nuanced fashion. By clarifying the future road map of I4.0 support for SCRM, we enable managers to compare the expected development to their companies' I4.0 maturity and inform their decision-making frameworks for future digitalization initiatives. Finally, managers can deduct from our study that not all impactful and desirable changes through I4.0 technologies must involve the structural reconfiguration of internal processes and applications. For instance, practitioners can considerably increase their digital SCRM activities' effectiveness by focusing on common enabling prerequisites, such as IoT implementation for data availability and accuracy, data visibility and internal and external information sharing, establishing cross-company data platforms, and fostering digital capabilities. Our results suggest that these comparatively mature technology levers can improve SCRES as well as or even better than more advanced applications such as AI, BC, and digital twins.

5.3. Implications for policy

Our study confirms a significant contribution of I4.0 technologies to SCRES by 2030. It must be in public authorities' interest to support measures that can mitigate the negative consequences of disruptive events such as the COVID-19 pandemic. Several policy implications can thus be drawn from our results. First, we demonstrated that visibility-enhancing digital solutions can build an essential foundation for improving SCRES. Policymakers should therefore incentivize or even enforce more information sharing among companies while ensuring trust in data protection. Such efforts could include establishing comprehensive and harmonized data security standards, common but anonymized industry databases, or minimum information sharing requirements. Second, policymakers should consider subsidy programs for I4.0 solutions for SCRM. As Delphi participants recurrently discussed, high investments are among the most severe barriers to implementing I4.0 at scale. Third, policymakers should aspire to create the appropriate legal frameworks for these transformative technologies, enabling companies to capture the benefits of I4.0 for SCRM while ensuring the required legal certainty. Finally, governments should support the rapid buildup of digital capabilities as it represents a core requirement for the success of I4.0 for better SCRM. Such measures could include more holistic financial support for research and education programs at universities or comprehensive re-skilling of the labor market.

5.4. Limitations and future research

As with any scientific paper, this study's limitations provide opportunities for further research. First, it empirically confirms several use cases of I4.0 technologies for SCRES improvement but lacks insights into their precise implementation. We encourage researchers to investigate implementation practices of I4.0 in SCRM empirically, for instance, using an in-depth single-case study approach. Second, while our study qualitatively identifies the projections' main implementation barriers, we have not investigated their interrelations, levels of influence, or ways to overcome them. Future research is particularly important for projections of the "promising candidates" and "wider circle" clusters as panelists expect a considerable impact on SC performance and major implementation challenges. Third, our study design fostered individual assessments of the investigated I4.0-related SCRM solutions. As our experts' comments revealed, further understanding of their interdependencies could increase SCRM performance. Fourth, the Delphi panel is mainly comprised of experts from European countries and the USA. Similar studies with respondents from other geographies, particularly Asia given its critical contribution to global SCs, might yield varying results due to alternate economic and regulatory environments. Fifth, the study compared evaluations of industry and academia subgroups with no significant deviations besides projections on digital enablement of supplier assessment and management. While the little variations indicate alignment between the two groups, scholars should aim for higher exposure to practice on the dissent topics and initiate stronger academia-industry exchange. Finally, we consciously limited the number of projections in our sample to ensure completion of the survey, even though other unexplored topics exist and should be investigated.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

Alexander Spieske: Conceptualization, Data curation, Investigation, Methodology, Validation, Visualization, Project administration, Writing – original draft. **Maximilian Gebhardt:** Conceptualization, Data curation, Investigation, Methodology, Validation, Project administration, Writing – original draft. **Matthias Kopyto:** Conceptualization, Data curation, Investigation, Methodology, Validation, Writing – original draft. **Hendrik Birkel:** Conceptualization, Investigation, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing. **Evi Hartmann:** Conceptualization, Methodology, Supervision, Validation, 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.

Appendix

Appendix A. . Results of statistical tests.

1. Shapiro-Wilk test on normality

Dimension	*p*-value
EP	0.0000000000002405*
I	<0.00000000000000022*
D	<0.00000000000000022*

Note: *$p < 0.05$ allows to reject the null-hypothesis on a normal distribution of the expert assessments.

2. Wilcoxon-Mann-Whitney test on non-response bias

Dimension	*p*-value
EP	0.238
I	0.647
D	0.104

Note: *p < 0.05 allows to reject the null-hypothesis that two samples belong to the same population (here: comparison of initial 10 and last 10 responders' (=approximation for non-responders) assessments).

3. Wilcoxon-Mann-Whitney test on subgroup differences

No.	Projection	Dimension	*p*-value
P.1	IoT data	EP	0.669
P.1	IoT data	I	0.928
P.1	IoT data	D	0.987
P.2	AI external data	EP	0.885
P.2	AI external data	I	0.661
P.2	AI external data	D	0.511
P.3	Data aggregation	EP	0.371
P.3	Data aggregation	I	0.366
P.3	Data aggregation	D	0.520
P.4	Cross-company data platforms	EP	0.855
P.4	Cross-company data platforms	I	0.212
P.4	Cross-company data platforms	D	0.402
P.5	Digital SC twins	EP	0.958
P.5	Digital SC twins	I	0.697
P.5	Digital SC twins	D	0.705
P.6	BC information exchange	EP	0.293
P.6	BC information exchange	I	0.425
P.6	BC information exchange	D	0.705
P.7	Autonomous decision-making	EP	0.168
P.7	Autonomous decision-making	I	0.411
P.7	Autonomous decision-making	D	0.753
P.8	Autonomous robots	EP	0.891
P.8	Autonomous robots	I	0.182
P.8	Autonomous robots	D	0.645
P.9	Remote working	EP	0.523
P.9	Remote working	I	0.060
P.9	Remote working	D	0.419
P.10	Supplier selection and evaluation	EP	0.029*
P.10	Supplier selection and evaluation	I	0.785
P.10	Supplier selection and evaluation	D	0.039*
P.11	Supplier replacement	EP	0.849
P.11	Supplier replacement	I	0.576
P.11	Supplier replacement	D	0.024*
P.12	AM flexibility	EP	0.311
P.12	AM flexibility	I	0.472
P.12	AM flexibility	D	1.000
P.13	Digital capabilities	EP	0.969
P.13	Digital capabilities	I	0.876
P.13	Digital capabilities	D	0.942

Note: *p < 0.05 allows to reject the null-hypothesis that two samples belong to the same population (here: comparison of academic and industry experts' assessments).

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