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Does digitalising the supply chain contribute to its resilience?

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Abstract:

Purpose: Supply chain resilience (SCR) is a key concept for managers who wish to develop the capacity to enhance the ability of their supply chain (SC) to cope with unexpected turbulence. Digital SC tools are often seen as a solution that provides greater visibility, anticipation and collaboration (SCR capability factors). The purpose of this paper is to investigate the link between SCR and SC digitalisation.

Design/methodology/approach: The results were analysed using an ordinary least squares (OLS) regression model based on a sample of 300 managers in the field of SC management.

Findings: SC digitalisation is characterised by the degree of digital maturity and the adoption of digital SC tools. Both the degree of digital maturity and the adoption of digital tools have a positive impact on SCR but the degree of digital maturity is stronger, especially among the smaller companies.

Research limitations/implications: The findings do not indicate which tools most contribute to SCR.

Practical implications: Managers should reflect on the need to continue digitalising their SCs and focus primarily on digital maturity degree, rather than digital SC tool adoption, if they want greater SCR in the current uncertain environment.

Originality/value: This is the first study to focus on assessing the impact of digitalisation on SCR by considering several digital SC tools at the same time. Validation of the hypotheses model confirms the positive impact of SC digitalisation on SCR for researchers and managers.

Keywords: Digital Supply Chain, Supply Chain Resilience, Digital Maturity, Digital Tool Adoption

1. Introduction

SC digitalisation emerges in an era in which real-time communication and coordination is pursued while many risks arise (e.g. cybersecurity, Tang and Veelenturf, 2019; Corallo *et al.*, 2020) which may hinder SC resilience (SCR; Colicchia *et al.*, 2019). It implies increasingly mature processes, organisation or even competences (Schumacher *et al.*, 2016; Schuh *et al.*, 2017; Colli *et al.*, 2019) along with digital tools adoption to support data-driven SCM (Büyükoçkan and Göçer, 2018). According to Frank *et al.* (2019), digital tools refer to technologies that provide intelligence and connectivity. SC digitalisation is attracting significant attention and the ‘digital SC’ (DSC) is the hottest buzzword in the industry (Büyükoçkan and

Göçer, 2018). The stakes are now focused on SC digitalisation in a business environment that is now more turbulent than ever (Ivanov *et al.*, 2019a) with financial, economic, ecological and social risks. Of course, digitalisation can be viewed as a solution to managing SC risks (Ivanov and Dolgui, 2019a; Ivanov *et al.*, 2019b) but the ongoing ‘wave’ of digitalisation also creates new dynamics that are often difficult to follow in companies (McKinsey & Company, 2015; Deloitte, 2017), leading to new challenges for businesses and society. In such an environment, resilience is desirable in companies. To the best of our knowledge, only a few studies have provided new insights into the impact of digital tools on SCR (Papadopoulos *et al.*, 2017; Ivanov, 2018; Dubey *et al.*, 2019). Given the paucity of research on the topic (Garay-Rondero *et al.*, 2019), this study aims to answer the question: *What is the relationship between supply chain digitalisation and supply chain resilience?*

Following Sheffi’s (2015) and Sheffi and Rice’s (2015) seminal study, Yao and Fabbe-Costes (2018) characterised SCR as a dynamic SC capability that is necessary when dealing with an uncertain business environment. More precisely, Yao and Fabbe-Costes (2018, p. 260) define SCR as follows: “*Resilience is a complex, collective, adaptive capability of organisations in the supply network to maintain a dynamic equilibrium, react to and recover from a disruptive event, and to regain performance by absorbing negative impacts, responding to unexpected changes, and capitalising on the knowledge of success or failure*”.

One key issue in operationalising the concept of SCR is the way data are collected and analysed (Evrard Samuel and Ruel, 2013). Analysed data can help SC managers to make the right decisions and build the capabilities included in the SCR concept: for example, visibility, anticipation and collaboration (Pettit *et al.*, 2013). To this end, digital tools can be useful: the Internet of Things, big data analytics, artificial intelligence (AI), radio-frequency identification (RFID), smart sensor technology, etc. (Schoenherr and Speier-Pero, 2015; Büyüközkan and Göçer, 2018; Ivanov and Dolgui, 2020). Despite the growing adoption of digital tools, research on their possible impacts on SCR is still in its infancy, and most of the research on this topic has focused on the impact of a single digital tool on SCR (e.g., Papadopoulos *et al.*, 2017; Dubey *et al.*, 2019). However, when companies start to digitalise their SC, they may implement several digital tools at the same time (Frank *et al.*, 2019).

Despite some encouraging first results on the interplay of SCR with some

digital tools (see the example of Procter & Gamble during COVID-19 outbreak era¹ and the study from Ivanov, 2020), Pettit *et al.* (2019) recommend further research. Addressing this gap in the literature is of utmost importance, as the emergence of new digital tools alters traditional ways of working and creates disruption across SC processes. This managerial reality needs to be explored by researchers to provide better understanding of the phenomenon. This article contributes to theory by exploring the impact of the adoption of several DSC tools at the same time on SCR, in line with the complex reality of digitalisation projects in the business world (Issa *et al.*, 2018). The contribution of the degree of digital maturity to SCR has also never been measured before, whereas this study demonstrates its predominance.

2. Theoretical background

2.1. Digital supply chain management and digital tools adoption

2.1.1. Towards a digital supply chain management mechanism

The SCM has gradually become a strategic function that creates competitive advantages for companies and their network of SC entities. One key to its success lies in improving management of the SC information flow (Christopher, 2016). Many companies invest in digitalising their SCM in order to respond to the growing demand for products that are better adapted to consumer needs (customisable and of good quality). SC processes must adapt to these trends and be increasingly interconnected (Issa *et al.*, 2018). Digitalisation has an impact on overall SC processes (Richey *et al.*, 2016): manual tracking systems and paper-dominated order processing systems are increasingly considered obsolete.

Stank *et al.* (2019) introduced a theoretically grounded digitally dominant paradigm framework to help guide future SCM research. They argue that “seeing” (enhanced visibility), “thinking” (improved analytics) and “acting” (heightened operational flexibility and reduced cycle time) are essential elements of SC digitalisation.

Büyükozkan and Göçer (2018, p. 165) define a DSC as “*an intelligent best-fit technological system that is based on the capability of massive data disposal and excellent cooperation and communication for digital hardware, software, and networks to support and synchronize interaction between organizations by making services more valuable, accessible and affordable*”

¹<https://www.supplychainbrain.com/blogs/1-think-tank/post/31166-how-digital-solutions-are-creating-more-resilient-supply-chains> (6th July 2020)

with consistent, agile and effective outcomes". SCs have thus become increasingly data-driven. Since digital tools disrupt traditional supply chains, some distinct characteristics are potentially associated with every DSC. Büyüközkan and Göçer (2018) list these factors as Speed, Flexibility, Global connectivity, Real-time inventory, Intelligence, Transparency, Scalability, Innovativeness, Proactiveness and Eco-friendliness. These characteristics are traditionally the objectives of mature SCM².

The digital tools support companies in transforming their traditional SC operations in order to better anticipate and respond to stakeholders' demands in real time. However, the companies implementing these tools require a degree of digital maturity.

2.1.2. Degree of digital maturity

Companies facing digitalisation challenges need methods and assessment tools that support the operationalisation of the process. Maturity models provide an effective way of measuring the quality of the processes (Wendler, 2012). The main aim of existing digital maturity models is to assess the digital maturity stage of companies and guide them to the next stage through a set of activities (Colli *et al.*, 2019).

Capability Maturity Model Integration (CMMI) (Chrissis *et al.*, 2003) has frequently been used by the information technology (IT) industry to support its evolution and produce a set of best practices (Wendler, 2012). Researchers have also broadened the applicability of the model to promote development in other industrial fields. Issa *et al.* (2018) considered the CMMI, which links the level of maturity to company performance, to be the most widely recognised model and both used and then improved the model. They define four levels of maturity, where Level 1 is "No Industry 4.0" and Level 4 is "Inter-organisational level (cross value chain/SC partners)".

It is important to translate a maturity model into a tangible model for companies wishing to make an accurate assessment of their digital approach. To this end, Schumacher *et al.* (2016) defined nine dimensions for assessing Industry 4.0 maturity and they classify them in two groups. The first group concerns the basic enablers (products, customers, operations and technology) and the second is about organisational aspects (strategy, leadership, governance, culture and people). The definitions of dimensions as proposed by the authors are quite unclear and can easily be confused (example: strategy, governance and culture).

² A table presents the main digital tools listed in the literature as contributing to improving SCM is available upon request

Schuh *et al.* (2017) identified four maturity dimensions: Organisational structure, Resources, Information systems and Culture. However, their proposal lacks a dimension relating to the “capture of valuable information from data” Colli *et al.* (2019, p. 6), which is needed to gain useful business insights and make appropriate decisions. To address this gap, Colli *et al.* (2019, p. 5) used Schuh *et al.* (2017) as a basis for putting forward a new digital maturity assessment approach that defines five dimensions for measuring digital maturity in an SCM context: Governance, Technology, Connectivity, Value creation and Competences. Each dimension is assessed on six stages, from none to integrated.

Many authors (Schumacher *et al.*, 2016; Schuh *et al.*, 2017; Colli *et al.*, 2019) highlighted the need of these dimensions for a company to adopt digital tools. Low maturity degree is one of the biggest challenges to be faced in a DSC tools adoption project (Raj *et al.*, 2020). More precisely, the governance dimension which represents the digital awareness, and engagement on different hierarchical levels in the company is perceived as a prerequisite element which, as such, enables the acquisition and the adoption of digital tools.

Digital competences are a key to success and thus training is necessary (Petrillo *et al.*, 2018). Being digitally competent means having the ability to search for information, to understand it, to be critical about what is retrieved and to be able to communicate with others using a variety of digital tools (Stank *et al.*, 2019). It also appears to be the case that enhanced connectivity, along with sufficient IT security and elements needed for data transmission inside and outside the organisation, supports DSC tools adoption (Lee and Lee, 2015; Gunasekaran *et al.*, 2016). Companies need models to generate and capture value from data. Digital tools adoption reflects the extent to which digital technologies are available and adopted and used by all key stakeholders so they add value to their activities (Schumacher *et al.*, 2016; Colli *et al.*, 2019).

Therefore, the following hypothesis is presented:

H1: The digital maturity degree (DMD) contributes positively to digital tools adoption (DTA) in an SC.

2.2. Supply chain resilience and digitalisation

In this subsection, we review the literature relative to different frameworks describing SCR capabilities and we build a model with a set of three hypotheses that can be used to better understand the link between SC digitalisation and SCR.

2.2.1. Supply chain resilience capabilities

Fiksel (2006) defined resilience as a company's ability to survive, adapt and grow in the face of turbulent change. The SC environment contains many uncertainties that create vulnerability. One solution is to mobilise the SCR concept. The notion of resilience applied to SCs appears particularly useful in analysing the potential for adaptation of interconnected physical and informational flows that are continually subject to hazards. Christopher (2016) believes that resilience refers to the ability of an SC to cope with unexpected turbulence. Thus, he explains that a resilient SC must be able to identify the following characteristics in order to adapt to an uncertain business environment:

- Network-wide recognition of the most vulnerable parts of the SC; and
- Recognition of the need to maintain a stock of strategic resources or excess capacity in order to be able to respond to sudden events.

Whereas Christopher (2016) presents two key features of a resilient SC, Pettit *et al.*'s (2010, 2013) research is more specific. The authors drew up a taxonomy of the different capability factors a SC should build in order to be resilient. The 14 main capabilities are as follows: flexibility in sourcing, flexibility in order fulfilment, capacity, efficiency, visibility, adaptability, anticipation, recovery, dispersion, collaboration, organisation, market position, security, and financial strength.

Pettit *et al.*'s (2010, 2013) taxonomy provides a basis for understanding the capabilities that need to be developed for a company to become resilient. Other classifications exist, such as those by Yao and Fabbe-Costes (2018), which lists five capacities: absorption, response, capitalisation, anticipation and improvisation, and Ponomarov and Holcomb (2009), which includes elasticity, amplitude, hysteresis, malleability and damping. This classification of capabilities and sub-capabilities offers an exhaustive assessment of SCR in empirical studies.

2.2.2. The advantages digitalization on supply chain resilience

Some researchers have recently analysed the relationship between digital tools and SCR (Ivanov and Dolgui, 2019b; Pettit *et al.*, 2019; Lezoche *et al.*, 2020). Ivanov and Dolgui (2019b) consider the impact of digitalisation on the resilience of operations and SCs as a complex issue. They highlight the value of the descriptive and predictive use of data analysis in gaining visibility and better forecast accuracy, as well as improving the activation of contingency plans. In the same

vein, Zhang and Zhao (2019) show that big data enhances SCR by improving visibility. Cloud computing and blockchain technology improve visibility, anticipation and adaptability, which can foster SCR (Pettit *et al.*, 2019).

A survey of the above studies showed that there is a need to mobilise all SCR capabilities (as defined by Pettit *et al.*, 2010, 2013) using several digital tools at the same time. Despite their first encouraging results on the interplay of SCR with some digital tools, Pettit *et al.* (2019) recommend further research on the topic. In short, the lack of a clear understanding of these elements has contributed to ambiguity in clarifying the interplay between DSCs and SCR.

We also contribute to the literature by assessing the DMD with regard to digital tools adoption. To the best of our knowledge, no research to date has attempted to link the degree of digital maturity with SCR, or the link between a bundle of digital tools and SCR. Amann and James (2015) suggest that more investigations should be pursued in order to better understand the relationships between resilience and digital maturity. ‘Value creation’ appears to be one of the characteristics for measuring SC digital maturity (Schumacher *et al.*, 2016; Colli *et al.*, 2019), and this is essential to increase delivery competence, knowledge management and customer service to quickly recover from a disruption (Tukamuhabwa *et al.*, 2015). ‘Governance’ is also a key construct for SC digital maturity (Büyüközkan and Göçer, 2018; Colli *et al.*, 2019), and it supports the effective information sharing which facilitates the rapid access to the appropriate resources necessary for recovery (Tukamuhabwa *et al.*, 2015). In addition, ‘connectivity’ is a key point in assessing SC digital maturity (Akdil *et al.*, 2018; Büyüközkan and Göçer, 2018; Colli *et al.*, 2019), and it supports resilience capabilities as visibility and collaboration, which can spot potential disruptions (Tukamuhabwa *et al.*, 2015) and SC collaboration (Pettit *et al.*, 2010, 2013). Finally, digital ‘competences’ are recognised as key assets for measuring SC digital maturity as it allows a critical and creative use of information collected from different sources. (Akdil *et al.*, 2018; Büyüközkan and Göçer, 2018; Colli *et al.*, 2019). These competences foster a SCR and better anticipate unexpected disruptive events.

H2. Digital maturity degree (DMD) contributes positively to supply chain resilience (SCR).

As academics analyse the positive impact of specific digital tools on some aspects of SCR components, we present Table 1 as a summary of those impacts linked to the classification of SCR capabilities proposed by Pettit *et al.* (2010, 2013).

Digital tool	SCR capabilities (Pettit et al., 2010, 2013)	Impact on SCR	References
Big data (BD)	Visibility Security	Enhances SCR by improving visibility and agility. BD help to trace the roots of disruptions and observe disruption propagation in order to select short-term stabilisation actions based on a clear understanding of what capacities and inventories are available. BD can improve SC risk management and be used to determine how best to achieve SCR in the face of disaster.	Papadopoulos <i>et al.</i> (2017); Ivanov <i>et al.</i> (2019); Zhang and Zhao (2019)
Artificial intelligence (AI)	Anticipation	Data analytics, AI and additive manufacturing play an important role in the adaptation to changing requirements to satisfy system stability and agility.	Salkin <i>et al.</i> (2018)
Machine learning (ML)	Anticipation Security	ML have been applied to detect bottlenecks, high-risk tasks and events in order to achieve adequate production rescheduling. ML contributes to supplier selection as a risk mitigation strategy that could assist optimisation and resilience management models.	Dolgui <i>et al.</i> (2018)
Augmented and virtual reality (VR)	Collaboration Adaptability	VR has an impact on SCR as it simplifies the user experience and collaboration between stakeholders. Enterprises require the assistance of virtual and physical technologies to provide rapid adaptation for their businesses and operations. VR enables the evaluation of autonomous planning rules in accordance with system robustness.	Ganzarain and Errasti (2016)
Mobile devices and wearables (MDW)	Collaboration Adaptability	“... can receive, transmit process related data in advance and allow users to address issues as they cope with in real time decision making. Using mobile technologies, issues can now be recognized and dealt with faster as information moves with a higher velocity in the right position.”	Salkin <i>et al.</i> (2018, p.16)
Robotics and automation (ROBOT)	Efficiency Security	Participates in SCR, as it improves efficiency, scalability and security.	Hofmann <i>et al.</i> (2020)
Internet-of-things platforms (IoT)	Efficiency Collaboration Market position	Changes the processes or the ways of doing work. IoTs are not just about new smart devices, but, more significantly, they mean productivity improvements and uninterrupted connectivity of economies all over the world. IoTs have an impact on efficiency, market position and collaboration.	Salkin <i>et al.</i> (2018)
Cloud computing (Cloud)	Efficiency Collaboration Flexibility in sourcing Visibility	As a consequence of advancements in technologies, such as decreasing reaction times, manufacturing data will increasingly be practised in the cloud systems that provide more data-driven decisions. Cloud service platforms are based on real-time data analytics. Crowdsourcing help multiple sources.	Schumacher <i>et al.</i> (2016); Salkin <i>et al.</i> (2018)
Blockchain	Efficiency Visibility Collaboration	Has great potential in the areas of SC traceability and transparency. Blockchain can help to build, execute smart contracts and create trading-partner visibility and more efficient collaboration. This	Koonce (2016); Somapa <i>et al.</i> (2018); Min (2019); Dolgui <i>et al.</i> (2020)

		helps to trace the roots of disruptions in order to observe disruption propagation.	
Advanced human-technology interfaces (AHTI)	Collaboration Visibility Market position	AHTI play a key role in social interactions, serve as gateways between humans and digital tools.	Oyekan <i>et al.</i> (2017)
Advanced smart manufacturing technologies i.e., 3D printing (SMT)	Adaptability Efficiency	3D printing is an inevitable tool for delivering compatible parts in the shortest time before production operations are disturbed by breakdowns.	Salkin <i>et al.</i> (2018)
Location detection technologies i.e., RFID (LDT)	Recovery Collaboration	Helps SC managers in time recovery following disruptions. RFID can be used to communicate disruptions to other tiers and help revise initial schedules.	Ivanov <i>et al.</i> (2014)
Collaborative technologies i.e., ERP, APS, EDI and workflow (COLLAB)	Adaptability Collaboration	Long-term and permanent relationships in SCs and loyalty in the supplier-customer relationship provide benefits to the SC by making it more resilient to crises and demand fluctuations.	Sheffi and Rice (2005); Schumacher <i>et al.</i> (2016)
Smart sensors (SS)	Efficiency	The arrays of sensors enable stock levels to be monitored continuously and make warehouse management more efficient.	Büyüközkan and Göçer (2018)
Self-driving vehicles (SDV)	Efficiency Collaboration	SDV is capable of sensing its environment and navigating without human input. Seamless human-machine interactions increase operational efficiency.	Büyüközkan and Göçer (2018)

Table 1. Impacts of the main digital tools that contribute to the SC on SCR

As shown in Table 3, digital tools play an important role in SCR and, therefore, the following hypothesis is presented:

H3. Digital tools adoption (DTA) contributes positively to supply chain resilience (SCR).

The conceptual model is presented in Figure 1.

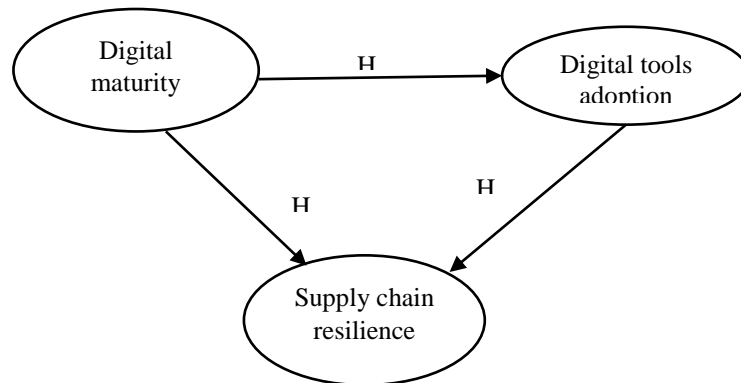


Figure 1. Hypotheses model

3. Research design and methodology

3.1. Measurement instruments

As shown in Figure 1, the model contains two second-order constructs: digital maturity degree and SCR.

Digital maturity degree. To measure DMD, items were developed based on the literature review and then refined through face and content validity as recommended by DeVellis (2016).

Since no survey-based literature was found to measure this construct, we've looked at several frameworks (e.g. Colli *et al.*, 2019; Schuh *et al.*, 2017; Schumacher *et al.*, 2016). We have retained the framework proposed by Colli *et al.* (2019) with its five dimensions to measure digital maturity degree in the SCM context: governance, technology, connectivity, value creation and competences. We consider that this framework is the most relevant one to our study. Then, we explored further in the literature to make a better understanding of dimensions and created items. In this way, for the DMD construct, we proposed five first order constructs with 33 items.

According to DeVellis (2016), when items are reviewed by experts in the domain of interest, it helps to validate the scale content and maximise item appropriateness. In order to evaluate the content validity of the DMD scale, we conducted a test with a researcher specialised in questionnaire design, together with two SC researchers and five professionals in SCM. This pre-

test was carried out face to face in order to discuss the relevance of the scale. The experts helped us to categorise the different dimensions of DMD: variables such as “governance” and “competences” concern practices needed to prepare the implementation of digital tools; the “value creation” and “connectivity” variables are inputs to manage data and to make more efficient use of the data provided by digital tools. With regard to the implementation and adoption of digital tools, only the “technology” variable concerns assets or, in this case, digital tools. The experts we consulted noted that this categorisation would help us to see that governance, connectivity, value creation and competence might be seen as essential factors that enable digital tools adoption. The majority of the experts also suggested separating the “technology” dimension, since it can be measured according to the level of adoption, ranging from 1 to 5: (1) not started, (2) basic, (3) developing, (4) intermediate, and (5) advanced. The “digital tools adoption” construct, which represents the dimension technology, is evaluated using a 15-item scale of digital tools that might have an impact on one or more of the capabilities of SCR (Table 2). The four other dimensions (governance, connectivity, value creation and competences) are measured by evaluating the level of agreement with statements based on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). In order to guarantee better homogeneity in the measurement of the digital maturity variable, we decided to measure it based on the four dimensions detailed above and to separate “technology” (Table 3).

SC resilience. The measurement of this construct was based on Pettit *et al.* (2010, 2013), who measured SCR with 14 first-order constructs: flexibility in sourcing, flexibility in order fulfilment, capacity, efficiency, visibility, adaptability, anticipation, recovery, dispersion, collaboration, organisation, market position, security, and financial strength. Each construct was measured with at least four items. In total, the SCR scale contains 71 items (Table 4). All items are measured by evaluating the level of agreement with statements based on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Construct	Digital tool/ Item code	References	Weight	Loadings
Digital tools adoption KMO = 0.935 Cronbach's alpha = 0.922	TECH_BD	Papadopoulos <i>et al.</i> (2017); Ivanov, Dolgui and Sokolov (2019); Zhang and Zhao (2019)	0.451	0.671
	TECH_AI	Salki <i>et al.</i> (2018)	0.544	0.738
	TECH_ML	Dolgui <i>et al.</i> (2018)	0.524	0.724
	TECH_VR	Ganzarain and Errasti (2016)	0.443	0.666
	TECH_MDW	Salkin <i>et al.</i> (2018)	0.500	0.707
	TECH_ROBOT	Hofmann <i>et al.</i> (2020)	0.500	0.707
	TECH_IoT	Salkin <i>et al.</i> (2018)	0.523	0.723
	TECH_CLOUD	Schumacher <i>et al.</i> (2016); Salkin <i>et al.</i> (2018)	0.538	0.734
	THEC_BLOCKCHAIN	Koonce (2016); Somapa <i>et al.</i> (2018); Min (2019); Dolgui <i>et al.</i> (2020)	0.460	0.678
	THEC_AHTI	Oyekan <i>et al.</i> (2017)	0.556	0.745
	TECH_SMT	Salkin <i>et al.</i> (2018)	0.380	0.616
	TECH_LDT	Ivanov <i>et al.</i> (2014)	0.494	0.703
	TECH_COLLAB	Sheffi and Rice (2005); Schumacher <i>et al.</i> (2016)	0.395	0.628
	TECH_SS	Büyüközkan and Göçer (2018)	0.533	0.730
TECH_SDV	Büyüközkan and Göçer (2018)	0.357	0.598	

Table 2. Operational measurement scale for the construct “digital tools adoption”

First-order construct	Items		Adapted from
Competences	COMP_1	1. SCM team members are equipped with relevant skills for digital transformation.	Schumacher <i>et al.</i> (2016) ; Schuh <i>et al.</i> (2017); Issa <i>et al.</i> (2018); Büyüközkan and Göçer (2018); University of Warwick Maturity Model cited by Akdil <i>et al.</i> (2018); Colli <i>et al.</i> (2019)
	COMP_2	2. SCM team members have a digital mindset.	
	COMP_3	3. My company (MC) can rely on the digital skills of supply chain partners and/or services providers to drive digital initiatives.	
	COMP_4	4. MC can rely on SC partners and/or services providers who have a digital mindset.	
	COMP_5	5. MC provides training for the SCM team members to better lead the digitisation program.	
Governance	GOV_1	1. MC has the right leader to execute on digital supply chain transformation.	Schumacher <i>et al.</i> (2016); Schuh <i>et al.</i> (2017); Büyüközkan and Göçer (2018); Issa <i>et al.</i> (2018); Colli <i>et al.</i> (2019); Hie (2019)
	GOV_2	2. MC has defined appropriate processes for managing digital program.	
	GOV_3	3. MC has defined a planning /agenda for managing the digital program.	
	GOV_4	4. MC has dedicated appropriate intangibles and material resources to the digital SC program.	
	GOV_5	5. MC has an advanced level of understanding of digital SC tools within the organisation (advanced = Comprehensive knowledge of the latest cutting-edge digital SC technologies)	
Value	GOV_1	1. MC has the right leader to execute on digital supply chain transformation.	Adner and Kapoor (2010); Schumacher <i>et al.</i> (2016); Issa <i>et al.</i>

creation	VC_2	2. The data collected through digital tools allow the implementation of the "pay per use business model".	(2018); Colli <i>et al.</i> (2019)
	VC_3	3. The data collected ... allow better management of returns of goods in the SC.	
	VC_4	4. The data collected ... allow better management of customer orders in the SC.	
	VC_5	5. The data collected ... allow better management of the maintenance programs for the assets required to SCM.	
Connectivity	CONNECT_1	1. MC has needed digital tools to guarantee data sharing inside and outside the organisation	Schuh <i>et al.</i> (2017) ; Akdil <i>et al.</i> (2018); Büyüközkan and Göçer (2018); Colli <i>et al.</i> (2019)
	CONNECT_2	2. There is a high level of information systems security.	
	CONNECT_3	3. There is an organisational structure that supports data-driven cesses.	

Table 3. Operational measurement scale for the second-order construct “digital maturity degree”

First-order construct	Definition	Items	
C1. Flexibility in Sourcing	Ability to rapidly change input or the mode of	C1_FLEX_SOUR_1	1.1 Our supplies are used in multiple finished goods.
		C1_FLEX_SOUR_2	1.2 Our finished goods use modular designs.

	receiving input	C1_FLEX_SOUR_3	1.3 Our products can be made from a variety of machines and workers.
		C1_FLEX_SOUR_4	1.4 Our supply contracts can be easily modified to change specifications, quantities, and terms.
		C1_FLEX_SOUR_5	1.5 We have many alternative sources for key inputs.
C2. Flexibility in Order Fulfilment	Ability to change output or the mode of delivering output quickly	C2_FLEX_OF_1	2.1 We can quickly vary outsourced storage, distribution, and other services.
		C2_FLEX_OF_2	2.2 We are able to delay production to be more responsive to demand.
		C2_FLEX_OF_3	2.3 We pool inventory for a wide variety of customers at centralised locations.
		C2_FLEX_OF_4	2.4 We have a sophisticated inventory management system that regularly computes both safety stock and cycle stock at all storage and retail locations.
		C2_FLEX_OF_5	2.5 We can quickly change the routing and mode of transportation for outbound shipments.
		C2_FLEX_OF_6	2.6 We can quickly reallocate orders to alternate suppliers and reallocate jobs between different production units.
C3. Capacity	Availability of assets to enable sustained production levels	C3_ASSET_AVAIL_1	3.1 We have reliable back-up utilities (electricity, water, communications, etc.).
		C3_ASSET_AVAIL_2	3.2 We maintain access to duplicate or redundant facilities and equipment.
		C3_ASSET_AVAIL_3	3.3 We have significant excess capacity of materials, equipment, and labour to quickly boost output if needed.
C4. Efficiency	Ability to produce output with minimum resource requirements	C4_EFFICIENCY_1	4.1 Our labour productivity is very high.
		C4_EFFICIENCY_2	4.2 Our assets are effectively utilised with no limiting bottlenecks.
		C4_EFFICIENCY_3	4.3 We consistently produce high-quality products with little waste.
		C4_EFFICIENCY_4	4.4 We have effective preventative maintenance programs.

		C4_EFFICIENCY_5	4.5 Our equipment is very reliable.
C5. Visibility	Knowledge of the status of operating assets and the environment	C5_VISIBILITY_1	5.1 We have information systems that accurately track all operations.
		C5_VISIBILITY_2	5.2 We have real-time data on the location and status of supplies, finished goods, equipment, and employees.
		C5_VISIBILITY_3	5.3 We have regular interchange of information among suppliers, customers, and other external sources.
		C5_VISIBILITY_4	5.4 We have effective Business Intelligence gathering programs.
C6. Adaptability	Ability to modify operations in response to challenges or opportunities	C6_ADAPT_1	6.1 We can quickly reallocate orders to alternate suppliers and reallocate jobs between different production facilities.
		C6_ADAPT_2	6.2 We use strategic gaming and simulations to design more adaptable processes.
		C6_ADAPT_3	6.3 We excel at seizing advantages from changes in the market.
		C6_ADAPT_4	6.4 We develop innovative technologies to improve operations.
		C6_ADAPT_5	6.5 We continually strive to further reduce lead-times for our products.
		C6_ADAPT_6	6.6 We effectively employ continuous improvement programs.
C7. Anticipation	Ability to discern potential future events or situations	C7_ANTICIP_1	7.1 We effectively use demand forecasting methods.
		C7_ANTICIP_2	7.2 We have a formal risk identification and prioritisation process.
		C7_ANTICIP_3	7.3 We closely monitor deviations to normal operations, including near misses.
		C7_ANTICIP_4	7.4 We quickly recognise early warning signals of possible disruptions.
		C7_ANTICIP_5	7.5 We have detailed contingency plans and regularly conduct preparedness exercises and readiness inspections.
		C7_ANTICIP_6	7.6 We recognise new business opportunities and take immediate steps to

			capitalise on them.
C8. Recovery	Ability to return to normal operational state rapidly	C8_RECOV_1	8.1 We can quickly organise a formal response team of key personnel, both on-site and at the corporate level.
		C8_RECOV_2	8.2 We have an effective strategy for communications in a variety of extraordinary situations.
		C8_RECOV_3	8.3 We are very successful at dealing with crises, including addressing public relations issues.
		C8_RECOV_4	8.4 We take immediate action to mitigate the effects of disruptions, despite the short-term costs.
C9. Dispersion	Broad distribution or decentralisation of assets	C9_DISP_1	9.1 Our key inputs are sourced from a decentralised network of suppliers.
		C9_DISP_2	9.2 Our production facilities are distributed at various locations.
		C9_DISP_3	9.3 Our senior leaders are based at a variety of different locations.
		C9_DISP_4	9.4 Our organisation empowers on-site experts to make key decisions, regardless of level of authority.
		C9_DISP_5	9.5 Our products are sold to customers in a variety of geographic locations.
C10. Collaboration	Ability to work effectively with other entities for mutual benefit	C10_COLLAB_1	10.1 We effectively employ collaborative demand forecasting techniques using shared data.
		C10_COLLAB_2	10.2 Our data flow transparently between supply chain members, with full access by all firms to facilitate collaborative decision making.
		C10_COLLAB_3	10.3 Our customers are willing to delay orders when our production capacity is hampered.
		C10_COLLAB_4	10.4 We have proactive product life-cycle management programs that strive to reduce both costs and risks.
		C10_COLLAB_5	10.5 Our firm invests in facilities and

			equipment at suppliers' plants and is prepared to share risks with both suppliers and customers.
C11. Organisation	Human resource structures, policies, skills and culture	C11_ORG_1	11.1 We encourage creative problem-solving.
		C11_ORG_2	11.2 We enforce individual accountability for performance.
		C11_ORG_3	11.3 We train employees in a wide variety of skills.
		C11_ORG_4	11.4 We are capable of filling leadership voids quickly.
		C11_ORG_5	11.5 We are a learning organisation, regularly using feed-back and benchmarking tools.
		C11_ORG_6	11.6 We have a culture of caring for employees.
C12. Market Position	Position status of a company or its products in specific markets	C12_Market_POS_1	12.1 Our brands have excellent customer recognition and a strong reputation for quality.
		C12_Market_POS_2	12.2 Our customers are very loyal to our products.
		C12_Market_POS_3	12.3 Our products command a significant share of the market.
		C12_Market_POS_4	12.4 Our customers can clearly differentiate our products from competitors' products.
		C12_Market_POS_5	12.5 Our firm has strong, long-term relationships directly with each of our customers.
		C12_Market_POS_6	12.6 Representatives of our firm communicate effectively with our customers.
C13. Security	Defence against deliberate intrusion or attack	C13_SECURITY_1	13.1 We employ layered defences and do not depend on a single type of security measure.
		C13_SECURITY_2	13.2 We use stringent restrictions for access to facilities and equipment.
		C13_SECURITY_3	13.3 We have active security awareness

			programs that involve all personnel.
		C13_SECURITY_4	13.4 We effectively collaborate with government agencies to improve security.
		C13_SECURITY_5	13.5 We have a high level of information systems security.
		C13_SECURITY_6	13.6 We use a variety of personnel security programs such as awareness briefings, travel restrictions, and threat assessments.
C14. Financial Strength	Capacity to absorb cashflow fluctuations	C14_FINANCE_1	14.1 We have significant financial reserves to cover most potential needs.
		C14_FINANCE_2	14.2 Our portfolio of businesses is very diverse.
		C14_FINANCE_3	14.3 We have significant insurance coverage for facilities, equipment, goods, and personnel.
		C14_FINANCE_4	14.4 We sell our products at a relatively high margin.

Table 4. Operational measurement scale for the second-order construct “SCR”

3.2. Moderating effects

Gray and Mabey (2005) show that the size of a company influences the decision-making processes and the strategic choices the organisation may adopt. Organisational size can be measured in terms of the number of employees, turnover or even market share. From a resilience point of view, most large firms have specialised teams working on day-to-day issues regarding risk and SC challenges. However, smaller firms could be exposed to the same challenges and difficulties but experience more constraints, such as in their ability to access certain resources, especially financial and intangible (human resources, lack of knowledge, etc.) (Bhagwat and Sharma, 2007). To test if the size of the company has any influence on our model, a factor that

potentially exerts a key moderating effect is the turnover of the firm, since the financial aspect is important to consider in technology adoption and ensuring better SCR capacity.

3.3. Data analysis and measurement model

The measurement model was designed as a composite factor model that follows a reflective approach (Van Riel *et al.*, 2017). In a reflective model, the block of manifest variables (items) related to a latent variable (construct) is assumed to measure a unique underlying concept (Vinzi *et al.*, 2010).

To test the research model, we used the ordinary least squares (OLS) regression model approach. The reason for selecting OLS is that the research model represents relationships between multiple variables that are supposed to be linear. OLS also allows us to investigate the relationships between multiple independent constructs and the dependent construct at the same time (Stouthuysen *et al.*, 2012). Moreover, OLS allows analysis of the moderating effects in a single research model. For the estimation of our structural model, we used the OLS regression option for path coefficients implemented in the PLSPM module of the XLSTAT software (Vinzi *et al.*, 2010).

3.4. Sampling method and data collection

We carried out a quantitative study to measure a new phenomenon in SCM: to measure the potential impacts of SC digitalisation on SCR. This quantitative study was based on an online

survey and employed a questionnaire placed on a website, i.e., a web survey (Google Forms). The survey was conducted from 30th November 2019 until 7th January 2020.

A validity process for the questionnaire seemed particularly important in order to benefit from the changes or improvements recommended. Ten people were selected, either for their academic qualities or for their professional experience: eight are academic researchers in SCM and two are senior SC managers.

The target sampling frame of this study was that the respondent participates actively in the management of an SC without any restriction with regard to industry. Each person was contacted by email explaining the aim of the study and the link to our survey. In total, 2,320 surveys were sent to SC managers in different firms, 349 of whom responded. After eliminating several surveys because of recurrent values and inconsistent or incomplete responses, the sample contained 300 observations. The response rate is 12.93%; according to Dillman (2000), a range from 6% to 16% is considered acceptable.

Our sample mainly contains respondents with major responsibilities in SCM and considerable experience in their respective positions. 54% of respondents come from very large manufacturing companies (annual turnover of more than €500 million). Descriptive information and sample statistics are included in Table 5.

<u>Respondent title</u>	<u>Industry role</u>
SC Manager	116 Manufacturing activities 190

Director of SCM	68	Wholesaler and retailer	45
Purchasing and Procurement Manager	30	Other service activities	16
VP SCM	25	Health and social action activities	9
Director of Operations	13	Production and distribution of electricity, gas, steam and air conditioning	8
SC Project Manager	13	Agriculture, forestry and fisheries	6
Logistics Manager	12	Logistics and transport	6
Buyer	9	Construction	6
Logistician	7	Professional, scientific and technical activities	5
VP Operations	4	Accommodation and catering activities	4
Senior Project Manager	3	Extractive activities	3
		Arts, entertainment and recreation	2
		<u>Respondents' experience (years)</u>	<u>Company turnover (EUR)</u>
0-3	48	Between 0 and less than 250 million	112
05-8	39	Between 250 and less than 500 million	26
9-15	71	Between 500 million and more	162
	Total sample	300	

Table 5. The Sample description

3.5. Response and common method bias

Potential biases were considered during the survey and in the analysis. To achieve a high response rate and avoid non-response bias, personalised emails can be sent with the assurance of sharing the results (Frohlich, 2002). We assessed non-response bias using the procedure proposed by Rogelberg and Stanton (2007). The first 25% of respondents to reply were compared with the last 25%, to detect if any difference existed between their responses. A *t*-test comparison between these two groups regarding two descriptive variables – the number of employees and the company turnover – indicated no significant difference in the responses of early and late participants ($p < 0.05$). These results indicate that common method bias is of no concern.

4. Analyses and results

We used a theory-driven approach as a benchmark. The theoretical framework was initially evaluated through exploratory factor analysis (EFA) with varimax rotation (Hair *et al.*, 2017) and confirmatory factor analysis (CFA) in OLS to assess the consistency between the scale items (Stouthuysen *et al.*, 2012).

4.1. Validity of the constructs

Content validity: The framework includes two hierarchical constructs involving more than one dimension: the DMD degree scale contains 18 items with 4 variables (Table 3) and the SCR scale contains 71 items organised into 14 variables (Table 4). The DTA construct includes 15 items (15 tools) and a single variable (Table 2).

We used the EFA method as it allowed us to identify the underlying dimensions that explain the results regarding the unidimensionality of the variables. This analysis is recommended in the case of exploratory research, i.e., in the absence of theoretical knowledge of the relationships between the measurement indicators of the constructs. This step allowed us to eliminate three variables from the SCR scale (C2. Flexibility in Order Fulfilment, C3. Capacity, and C11. Organisation). We eliminated 39 items during this phase.

The aim of CFA approach is to check whether the items are consistent and share sufficient variance. In order to verify sampling adequacy, we used the Kaiser-Meyer-Olkin (KMO) test, the value of which must be greater than 0.50 to be acceptable (Tables 4, 6 and 7).

Convergent validity: This is defined as the extent to which blocks of items strongly agree in their representation of the underlying construct they were created to measure (Chin, 2010). We tested the validity of the latent variables and their items in our study and the results are shown in Tables 4, 6 and 7. These tables show the weighting factors of the items. The role of factor weighting is to explain the contribution of an item to its construct. Thus, the objective is to show the degree of importance of each item and to establish if the weights are significant by having a value greater than 0.5.

Table 7 allows us to confirm that all the latent variables that make up the DMD scale are constructs that have significant convergent validities with factor weightings greater than 0.5. However, the DTA and SCR constructs contain some weight factors with non-significant values. If we estimate that dropping these items will have an impact on the meaning of the variable we are investigating, we can keep them and investigate the loadings estimates. We can thus

safeguard the construct content validity. As shown in Tables 4 and 6, the loading estimates of all items are greater than 0.5 (Hair *et al.*, 2017).

Construct reliability: Cronbach's alpha is an indicator that qualifies how well a set of indicators measures the unidimensionality of a construct (Chin, 2010). The Cronbach's alphas of the items that make up the DMD, DTA and SCR scales are between 0.6 and 0.8. This confirms the internal consistency of the scale.

Dillon-Goldstein's rho is an indicator that evaluates the composite reliability of latent variables (Wertz *et al.*, 1974). Dillon-Goldstein's rho is above the 0.7 threshold for all the variables of the model (Tables 6 and 7), which confirms the homogeneity of the constructs. Since reliability deals with the internal reliability of a measurement (evaluating the common variance of items), a reliability of 0.7 states that the item shares 50% variance when measuring the construct.

Convergent validity: This is the extent to which the indicators belonging to one latent variable actually measure the same construct (Chin, 2010). We used average variance extracted (AVE) to demonstrate convergent validity of the construct. This indicates how much of the indicators' variance can be explained by the latent variable. In our model, all AVE values are greater than 0.5 (Table 6 and Table 7), indicating the convergent validity of our variables.

Discriminant validity: Evaluating discriminant validity refers to the extent to which factors are different and uncorrelated statistically (Chin, 2010). To check the evidence of this difference, the square root of each construct's AVE should have a greater value than the correlations with other

latent constructs. Our results (Tables 4, 6 and 7) show that all constructs in the model are different (square root < AVE) (Table 8).

Nomological validity: In reflective hierarchical constructs, the path coefficient of each first-order variable represents its contribution to the second-order variable (Wetzels *et al.*, 2009). Our results show that the second-order variable (DMD) is well reflected in its four first-order variables (competences, governance, value creation, and connectivity) with significant path coefficient values between 0.6 and 0.9. The governance construct is the most representative ($\beta=0.899$) (Table 7). The reflection of the other second-order construct (SCR) in its eleven first-order variables is supported with an intensity of path coefficients that remains homogeneous for all constructs of the scale except for the flexibility of sourcing construct, which represents a low one ($\beta=0.247$) (Table 6).

	Within-scale factor analysis - SCR scale					Validation of the SCR scale		
	D-G rho = 0.941							
Construct	KMO	Cronbach's alpha	Items	Weight	Loadings	Path coefficient	t-value	AVE
C1. Flexibility in Sourcing	0.620	0.600	C1_FLEX_SOUR_1	0.445	0.667	0.247	4.405	0.544
			C1_FLEX_SOUR_2	0.783	0.885			
			C1_FLEX_SOUR_3	0.403	0.635			
C4. Efficiency	0.665	0.757	C4_EFFICIENCY_3	0.549	0.741	0.651	14.792	0.674
			C4_EFFICIENCY_4	0.743	0.862			

			C4_EFFICIENCY_5	0.733	0.856			
C5. Visibility	0.677	0.795	C5_VISIBILITY_1	0.779	0.882	0.664	15.331	0.752
			C5_VISIBILITY_2	0.721	0.849			
			C5_VISIBILITY_3	0.634	0.796			
C6. Adaptability	0.500	0.671	C6_ADAPT_2	0.751	0.866	0.618	13.572	0.711
			C6_ADAPT_3	0.755	0.869			
C7. Anticipation	0.710	0.818	C7_ANTICIP_3	0.428	0.853	0.767	20.664	0.733
			C7_ANTICIP_4	0.452	0.876			
			C7_ANTICIP_5	0.415	0.840			
C8. Recovery	0.818	0.893	C8_RECOV_1	0.398	0.822	0.768	20.682	0.757
			C8_RECOV_2	0.466	0.889			
			C8_RECOV_3	0.473	0.896			
			C8_RECOV_4	0.449	0.873			
C9. Dispersion	0.500	0.680	C9_DISP_2	0.734	0.857	0.513	10.308	0.757
			C9_DISP_3	0.782	0.884			
C10. Collaboration	0.666	0.728	C10_COLLAB_1	0.729	0.854	0.689	16.409	0.646
			C10_COLLAB_2	0.563	0.751			
			C10_COLLAB_4	0.648	0.805			
C12. Market	0.786	0.824	C12_Market_POS_3	0.670	0.819	0.726	18.207	0.653

Position			C12_Market_POS_4	0.587	0.766			
			C12_Market_POS_5	0.678	0.823			
			C12_Market_POS_6	0.679	0.824			
C13. Security	0.867	0.897	C13_SECURITY_2	0.592	0.770	0.797	22.769	0.710
			C13_SECURITY_3	0.796	0.892			
			C13_SECURITY_4	0.750	0.866			
			C13_SECURITY_5	0.659	0.812			
			C13_SECURITY_6	0.756	0.869			
C14. Financial Strength	0.764	0.771	C14_FINANCE_1	0.716	0.846	0.685	16.225	0.594
			C14_FINANCE_2	0.578	0.760			
			C14_FINANCE_3	0.675	0.821			
			C14_FINANCE_4	0.411	0.641			

Table 6. SCR scale

	Within-scale factor analysis - DMD scale					Validation of the DMD scale		
	D-G rho = 0.932							
Construct	KMO	Cronbach's alpha	Items	Weight	Loadings	Path coefficient	t-value	AVE
Competences	0.683	0.819	COMP_1	0.709	0.842	0.840	26.748	0.649
			COMP_2	0.637	0.798			

			COMP_3	0.647	0.805			
			COMP4	0.601	0.775			
Governance	0.849	0.9.14	GOV_2	0.812	0.901	0.899	35.396	0.795
			GOV_3	0.823	0.907			
			GOV_4	0.819	0.905			
			GOV_5	0.728	0.853			
Value creation	0.792	0.853	VC_2	0.559	0.748	0.848	27.656	0.695
			VC_3	0.740	0.860			
			VC_4	0.740	0.860			
			VC_5	0.741	0.861			
Connectivity	0.500	0.665	CONNECT_2	0.733	0.856	0.643	14.508	0.749
			CONNECT_3	0.765	0.875			

Table 7. DMD scale

	Competences	Governance	Value creation	Connectivity	digital_tools – adoption	Efficiency	Adaptability	Anticipation	Recovery	Dispersion	Collaboration	Market_position	Security	Flexibility_sourcing	Finance	Visibility
Competences	1.000															
Governance	0.426	1.000														
Value creation	0.377	0.433	1.000													
Connectivity	0.201	0.254	0.182	1.000												
digital_tools_adoption	0.290	0.412	0.276	0.270	1.000											
Efficiency	0.057	0.110	0.087	0.093	0.138	1.000										
Adaptability	0.131	0.192	0.262	0.091	0.219	0.140	1.000									
Anticipation	0.199	0.236	0.247	0.242	0.280	0.272	0.221	1.000								
Recovery	0.159	0.232	0.197	0.203	0.185	0.149	0.196	0.336	1.000							
Dispersion	0.041	0.114	0.026	0.122	0.139	0.058	0.062	0.079	0.134	1.000						
Collaboration	0.197	0.263	0.282	0.179	0.254	0.154	0.281	0.276	0.262	0.114	1.000					
Market_position	0.080	0.152	0.080	0.184	0.092	0.219	0.137	0.172	0.232	0.109	0.133	1.000				
Security	0.136	0.212	0.123	0.387	0.253	0.171	0.123	0.316	0.256	0.204	0.197	0.292	1.000			
Flexibility_sourcing	0.000	0.005	0.007	0.012	0.011	0.036	0.026	0.011	0.022	0.019	0.030	0.035	0.021	1.000		
Finance	0.100	0.161	0.100	0.207	0.135	0.163	0.088	0.140	0.191	0.159	0.106	0.343	0.291	0.013	1.000	
Visibility	0.134	0.184	0.250	0.212	0.195	0.176	0.235	0.306	0.195	0.024	0.233	0.137	0.177	0.011	0.126	1.000
Moyenne Communalités (AVE)	0.649	0.795	0.695	0.749	0.480	0.675	0.753	0.733	0.758	0.758	0.647	0.654	0.711	0.544	0.595	0.711

Table 8. Square root < AVE

4.2. Evaluation of the structural model

The structural model exists to evaluate the relationships between hypothetical constructs. The coefficient of determination R^2 is used to evaluate the goodness of fit (GoF) in regression analysis (Tenenhaus *et al.*, 2005). In this study, we are using the OLS regression model where R^2 value gives the share of variance explained in a dependent construct (Benitez *et al.*, 2020).

Table 8 shows that the structural model explains nearly 47% of the DMD variable ($R^2=0.468$). Table 9 shows that the structural model explains almost 42% ($R^2=0.423$) of the SCR scale. These two values are very interesting for the phenomenon being investigated, particularly with regard to the exploratory character of this research. Indeed, the R^2 value can be very low when a phenomenon is not very widely explored (Sharma *et al.*, 2019). We also note that the contribution of digital maturity degree to SCR R^2 is greater than for digital tools adoption (66.81% and 33.19%, respectively).

The contribution of DMD to DTA is confirmed with considerable intensity ($\beta=0.679$). It also appears that DMD has a significant impact on SCR ($\beta=0.494$) but the intensity remains at a medium level. The impact of DTA on SCR is real but less important ($\beta=0.274$). This leads us to conclude that the contribution of DTA to SCR is quite low.

These results point to DMD contributing to the SCR of firms and facilitating their DTA. To be statistically significant, the path coefficient estimate should be different from zero at a 5% significance level when its p -value is < 0.05 . As shown in Tables 9 and 10, the path coefficient estimates for the hypothesised relationships are significant at the 5% significance level.

The t -value result relating to the assumptions linked to the impact of DMD and DTA is significant (>1.96) (Table 9) and once again confirms the validity of our assumptions.

	Path coefficient	t -value	p -value	Hypothesis testing result
(H1) DMD -> DTA	0.679	15.981	0.00	H1 supported
R^2 (Bootstrap) = 0.468				

Table 9. Structural coefficient and contribution to R^2 of the DTA construct

Note: *** $p < 0.001$

	Path coefficient	t-value	p-value	Contribution R ² (%)	Hypothesis testing result
(H2) DMD -> SCR	0.494	8.860	0.00	66.81	H2 supported
(H3) DTA -> SCR	0.274	4.910	0.00	33.19	H3 supported
R ² (Bootstrap) = 0.423					

Table 10. Structural coefficient and contribution to R² of the SCR construct
Note: ***p < 0.001

4.3. Quality of fit of the global model

The absolute GoF of the model (0.511) is very close to the bootstrap estimate (0.510), which confirms the stability of the model. The relative GoFs for the internal and external models (respectively 0.997 and 0.727) are high, which reflects, on the one hand, the good quality of the links between the measurement variables and the latent variables and, on the other, the good quality of the structural relationships.

4.4. Multi-group analysis

The multi-group analysis (MGA) approach allows researchers to determine whether some parameters could have an impact on the measurement model or if the structural model remains invariant irrespective of the groups or sub-samples. To analyse the moderating effect of the “size of the company” variable on the relationship between the variables in the framework, we conducted MGA.

For the MGA, the responses were divided into three groups, depending on the turnover of the company (group 1 = €500 million and above; group 2 = between €250 million and less than €500 million; and group 3 = less than €250 million) (Table 5). Test analyses were done for each of these groups in order to estimate their path coefficients. To detect any moderating effect, the differences between the path coefficients of the groups were analysed. Thus, to determine the significance of the differences between the estimated parameters for each of the groups, we conducted a permutation test (Chin and Dibbern, 2010).

The MGA was interpreted in two steps. We first evaluated the path coefficient of the structural model for each sub-sample, followed by a global test of invariance of some of the parameters, such as structural paths that are constrained to be stable across the groups (Chin and Dibbern, 2010).

As Table 11 shows, with regard to the path coefficient of the model for each sub-sample (G1, G2 and G3), the first results concern G1 and G2 and indicate that there is no significant effect of the moderating test compared with the total sample, even if the path coefficients were to vary slightly. Some significant effects appear with G3. Namely, *H3* (DTA \Rightarrow SCR) is not supported, since the path coefficient is close to zero ($\beta=0.059$). This could be explained by (1) financial resources and (2) the operational need for digital tools. First, DSC tools are expensive and the smaller firms may not be able to afford them. Second, the low number of tools adopted and the low adoption level of those tools by small firms. Even if the larger SC entities find it useful to adopt DSC tools because their need for internal and external collaboration is strong, the smaller companies do not face the same issues and may not need the same level of adoption of DSC tools. Another result concerns *H2* (DMD \Rightarrow SCR) and how different it would be if G3 were compared with G1 and G2. *H2* is supported for all groups, but with different intensity. We note that G3 has the highest path compared to the other groups (G1 $\beta=0.461$; G2 $\beta=0.379$; G3 $\beta=0.571$). We can, therefore, state that G3 may be relatively more advanced in terms of DMD than SC DTA, which would explain SCR only being positively and significantly impacted by DMD. Taking into account that *H1* (DMD \Rightarrow DTA) is validated for G3 with a very high path coefficient ($\beta=0.873$), this suggests that those in G3 are well prepared from the point of view of competences, governance, value creation and connectivity in order to guarantee the right adoption of the few SC digital tools they choose.

The second step was to evaluate the invariance using permutation tests. The permutation test showed a significant difference with several *p*-values of < 0.05 . This reinforces the interpretations of the results above. For instance, it appears that G1 vs. G3 is significantly different regarding *H2* (DMD \Rightarrow DTA) (*p*-value=0.04) and *H3* (DTA \Rightarrow SCR) (*p*-value=0.02). We also note concerning *H2* (DMD \Rightarrow SCR) that there are no significant differences throughout the three different groups. This makes it difficult to interpret the result concerning the significant difference (*p*-value=0.04) between G2 vs. G3 regarding *H1* (DMD \Rightarrow DTA), since sub-sample G2 is based on only 26 responses which is quite low to generalise this result.

Therefore, we can state that the “turnover of the company” variable has a moderating impact on the G2 and G3 samples.

MGA: G1 vs G2

	Path coef. G1	Path coef. G2	Diff.	p-value	Sig.
(H1) DMD -> DTA	0.722	0.762	0.040	0.713	No
(H2) DMD -> SCR	0.461	0.379	0.082	0.693	No
(H3) DTA -> SCR	0.330	0.356	0.027	0.921	No

MGA: G1 vs G3

	Path coef. G1	Path coef. G3	Diff.	p-value	Sig.
(H1) DMD -> DTA	0.772	0.562	0.159	0.040	Yes
(H2) DMD -> SCR	0.461	0.572	0.111	0.406	No
(H3) DTA -> SCR	0.330	0.059	0.271	0.020	Yes

MGA : G2 vs G3

	Path coef. G2	Path coef. G3	Diff.	p-value	Sig.
(H1) DMD -> DTA	0.762	0.562	0.200	0.040	Yes
(H2) DMD -> SCR	0.379	0.572	0.193	0.228	No
(H3) DTA -> SCR	0.356	0.059	0.298	0.079	No

Table 11. Results of the structural models and permutation tests

5. Results discussion

The results of this study enabled us to validate all three hypotheses previously presented. While some earlier studies highlighted the potential impact of the use of certain DSC tools on SC risk mitigation (Baryannis *et al.*, 2019), SC traceability and transparency (Somapa *et al.*, 2018; Junge, 2019), SC visibility and information sharing (Koonce, 2016; Kache and Seuring, 2017; Lezoche *et al.*, 2020), the efficiency of SC processes (Junge, 2019; Zhang and Zhao, 2019) and even strategic decision making in the SC (Bienhaus and Haddud, 2018; Lezoche *et al.*, 2020), none has ever statistically confirmed the relationship between SC digitalisation and SCR.

Our findings indicate that ‘SC digitalisation’ is based on two concepts: the adoption of DSC tools and the degree of digital maturity (Colli *et al.*, 2019). Previous studies have tended to focus on DSC tools, ignoring the degree of the digital maturity variable. However, our findings show the importance of the digital maturity variable: not only does it significantly influence the adoption of DSC tools, but it also positively influences SCR capabilities. In addition, when discussing the impact of SC digitalisation on SCR, it appears that recent studies have focused on one SC digital tool at a time (e.g., Papadopoulos *et al.*, 2017; Dubey *et al.*, 2019; Ivanov and Dolgui, 2019a; Zhang and Zhao, 2019). In practice, many companies may introduce several DSC tools simultaneously, with different levels of adoption for each. 15 DSC tools and their adoption levels were considered at the same time. The findings show that, overall, the level of adoption of the different DSC tools has a positive impact on the SCR capabilities to a moderate degree.

The size of the company is a commonly used variable for determining whether results are valid, regardless of differences in the financial status between companies. When it comes to investments such as DSC tools, the turnover of the company can be expected to influence this type of strategic choice (Gray and Mabey, 2005; Bhagwat and Sharma, 2007). Indeed, our results show that the degree to which digital maturity facilitates the adoption of digital tools in the SC is significantly different between companies with the highest turnover (G1) compared with the lowest (G3). More precisely, the positive impact of the digital maturity degree on the adoption of digital tools in the SC is significantly stronger for G1 than for G3 companies. In the same vein, the results show that there is a significant difference between G1 and G3 with regard to the positive impact of the adoption of digital tools on SCR: if the strength of the impact of digital tools adoption on SCR is much less important than that of digital maturity degree for G1 (highest turnover) companies, it is important to point out that the hypothesis is not supported for G3 (lowest turnover) companies. Other than the link between digital maturity degree and SCR, where all groups show a strong positive impact, it appears that companies with the lowest turnover show a weaker contribution of digital maturity degree to SC digital tools adoption and in the contribution of those tools to SCR. This may be explained by the low capacity for investing in SC digital tools for those companies.

6. Conclusion

6.1. Theoretical implications

First, this study synthesises the existing literature to develop and apply a research model for examining the relationship between SCR and ‘SC digitalisation’. We proposed evaluating SC digitalisation based on two concepts: DSC tools adoption and digital maturity degree. Therefore, a higher-order variable was generated to measure the digital maturity degree of the firm. Second, this study is the first to assess statistically the impact of the degree of digital maturity and the adoption of several DSC tools at the same time on SCR. This contributes to theory since other studies have examined digital tools separately, as if companies do not use several digital tools at the same time with different adoption levels. The predominance of the degree of digital maturity as a positive contribution to SCR compared with the weaker (but significant) contribution of the adoption of DSC tools to SCR helps researchers grasp the key importance of the degree of digital maturity when examining this topic. Third, since all the hypotheses are supported, this confirms that SC digitalisation has a positive impact on SCR; previous studies were either qualitative or focused on a single DSC tool, restricting their ability to draw formal conclusions regarding the impact of SC digitalisation on SCR. Here, the impact is clear, quantified and confirmed on a large scale (300 valid surveys concerning 15 DSC tools at the same). Fourth, the study used Pettit *et al.*’s (2010, 2013) measurement scale, which includes 71 items spread over 14 variables. This is the most complete, and complex, SCR measurement scale that exists in the literature and is thus not often mobilised. The data collection and analysis enabled us to improve and simplify this complex scale by analysing Cronbach’s alphas and removing three variables and several other items. This study is one of the few to contribute to theory by studying the link between SC digitalisation and its resilience for companies of different sizes. Our MGA results show that, based on size, the link between digital maturity degree and SCR is supported in large, medium and small companies to different levels of intensity. This model could also be used in future research to explain this difference by testing the effect of other segmentation variables, such as ‘company sector’.

6.2. Managerial implications

The findings are based on 300 valid surveys collected from qualified and highly qualified SCM professionals. This means that they are well grounded in the reality of businesses and their SCs, bringing clearer insights to the decisions, actions and practices of SC managers in relation to the research question. The results should encourage SC managers to consider continuing to digitalise their SCs (thus improving digital maturity degree and the level of adoption of digital tools) in order to obtain greater SCR in the current volatile and uncertain business environment. SC managers need to be aware that adopting digital tools in an SC is

not enough in itself to improve SCR capabilities. The findings clearly show that there is a strong need to develop digital maturity, which will, of course, help to enhance the adoption of DSC tools but has an even stronger positive impact on SCR capabilities than the digital tools themselves. Improving the digital maturity degree implies, for instance, formalising processes, engaging all hierarchical levels in digital projects, improving data architectures and information sharing, and even training employees towards a digital mindset. All these elements can be linked to SCR capabilities, such as organisation, visibility, collaboration, and security. Thus, by focusing on and investing in digital maturity degree elements, any company, even one with a low turnover, could significantly improve its SCR. Today, many companies might launch SC digitalisation projects that encompass the adoption of new DSC tools without taking into account how to develop their digital maturity degree.

Finally, this research allows SC managers to prioritise their digitalisation projects and to be aware of the importance of the four variables that make up digital maturity. The engagement and support of the management team for the adoption of new digital tools are essential.

6.3. Limitations and future research directions

One limitation pertains to the measurement of the second-order construct “digital maturity degree”, since this has never been measured. In further studies, researchers are encouraged to investigate this construct by exploring other potential variables. Another limitation is that the study does not identify exactly which tool(s) contribute the most to SCR capabilities. Future research could identify the more specific contributions of each digital tool to overall SCR capabilities, or even to each of the SCR variables. A third limitation is linked to the size of G2. Having more responses from middle-range companies would reinforce the MGA and contribute to the conceptual model generalisation. Furthermore, the study does not assess whether the companies in our sample have a low or advanced degree of digital maturity, a low or advanced level of digital tool adoption, or low or high SCR. This was not our aim, but future research could investigate these points.

There are other potential opportunities for future research. As the development of digital tools is a recent phenomenon, many professional reports have highlighted the difficulty of companies and their SCs in adopting these tools. It would be interesting to assess the challenges to the adoption of digital tools for SCM. Another research avenue, aligned with the MGA results, would be to study more precisely the case of small companies. It would be

useful for them to better understand how to allocate their scarce resources (their financial ones in particular) between the several aspects of digital maturity degree and between existing SC digital tools in order to identify the optimum investment to enhance SCR.

To conclude, there are extensive research perspectives on the topic of SC digitalisation and SCR. This study encourages researchers to go further in detailing its various aspects and to contribute to empirical verification of the comprehensive measurement scales for DMD, SCR and DTA.

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