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Being digital and flexible to navigate the storm: How digital transformation enhances supply chain flexibility in turbulent environments

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ABSTRACT

The growing environmental business uncertainties have forced companies to focus on developing more flexible supply chains. Digital transformation has been considered a key means to achieving such flexibility, but the literature lacks empirical evidence about how digital technologies effectively contribute to it. Thus, this study aims to analyze how Smart Supply Chain (i.e., a supply chain enabled by digital transformation) contributes to supply chain flexibility and operational performance in environments surrounded by customer and supplier uncertainty. We adopt the organizational information-processing theory to explain the fit between information needs to reduce these uncertainties through more supply chain flexibility (sourcing, delivery, and manufacturing) and information capabilities provided by three main dimensions of the Smart Supply Chain (digital transformation strategy, digital base technologies, and digital front-end technologies). We relate these information-processing fit between Smart Supply Chain and flexibility with the boundary conditions of environmental uncertainty and operational performance improvements. Such relationships are analyzed through moderation and mediation regression tests based on 379 manufacturing companies surveyed. Our findings show that Smart Supply Chain has a statistical association with operational performance through the sequential mediating role of the three supply chain flexibility dimensions. We also found that environments with high customer uncertainty increase the use of base technologies (IoT, cloud, big data, AI, and blockchain) to reach delivery flexibility and support manufacturing flexibility. When companies face high supplier uncertainty, they use front-end technologies (i.e., robotics, 3D printing, simulation, and augmented reality) to increase sourcing flexibility. We show new advances in supply chain flexibility through digital transformation.

1. Introduction

For several decades, global value chains focused on building stable operations alongside the supply chains based on long-term inter-organizational relationships and cost efficiency through countries' specialization (Berger, 2005). However, this scenario has dramatically changed recently due to several market uncertainties provoked by situations like international commercial trade conflicts, the COVID-19 pandemic, or regional wars (El Baz and Ruel, 2020). The growing proliferation of emerging technologies has also created technological uncertainties (Frank et al., 2022). Therefore, increasing operational flexibility has become a key priority for companies to deal with uncertain conditions in this new global scenario (Sreedevi and Saranga, 2017; Enrique et al., 2022). This flexibility is recognized as the *ability of companies to react to changing environments by adapting necessary processes quickly and with minimum use of resources* (Pérez Pérez et al., 2016; Schneeweiss and Schneider, 1999). Flexibility is not only limited to the company boundaries; it is a multidimensional concept that comprises the whole operations from internal production to external supply chain activities (Sethi and Sethi, 1990; Kumar et al., 2006). Achieving such flexibility is

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extremely difficult because the supply chain is a complex system configurated by intra-organizational and inter-organizational relationships that take time to react and adapt to changing situations (Seebacher and Winkler, 2015). Therefore, the literature has been concerned with this topic for decades, especially when different contextual challenges demanded supply chain adaptation to new realities.

Along its 250 vol, the International Journal of Production Economics (IJPE) has made important contributions to this field as one of the main journals studying supply chain flexibility. Different studies from this journal have contributed to understanding several antecedents of internal and external flexibility sources (e.g., Tang and Tomlin, 2008; Blome et al., 2014; Seebacher and Winkler, 2015). Other ones have been focused on the conditions and risks of implementing flexibility (e.g., Seebacher and Winkler, 2015; Kesen et al., 2010; Sreedevi and Saranga 2017) and the benefits obtained when supply chain flexibility is achieved (e.g., Shekarian et al., 2020; Wagner et al., 2018; Gosling et al., 2010; Francas et al., 2009; Tang and Tomlin, 2008). Also, the IJPE literature has presented important literature reviews on this topic, such as Yu et al. (2015) and Kamalahmadi and Parast (2016), showing how vast this topic has been for researchers in the whole operations management community. IJPE has also released special issues like the one from Chang and Lin (2010) that covered new opportunities in this field.

With the advent of the 4th Industrial Revolution (Industry 4.0) and the digital transformation of companies, new opportunities have been envisioned to increase supply chain flexibility, deserving more research to contribute to this vast literature (Dolgui et al., 2020). In this sense, there are new perspectives and potential avenues of research for supply chain flexibility. Considering this new context, some scholars have proposed that companies can develop Smart Supply Chains (Supply Chain 4.0), i.e., a supply chain enabled by digital transformation to improve information flows and operations activities (Frank et al., 2019a, b; Meindl et al., 2021). The literature has highlighted digital technologies like the Internet of Things (IoT) and Artificial Intelligence (AI) that can help to integrate different tiers of the supply chain through real-time data flow (Büyüközkan and Göçer, 2018; Liu et al., 2022). Such technologies can also help to automate and anticipate decision-making (Sharma et al., 2022), and they enable hardware applications like 3D printing for quick provision of spare parts (Delic and Eyers, 2020; Chan et al., 2018) and advanced robotics for transportation and distribution (Meindl et al., 2021). These are only examples provided by the literature about how a Smart Supply Chain can use emerging technologies to increase flexibility in operations. However, most studies that focus on the Smart Supply Chain and operational flexibility do not consider the several dimensions that represent a Smart Supply Chain (Lerman et al., 2022; Meindl et al., 2021). Since Smart Supply Chain comprises both strategic and technological aspects of the digital transformation (Nasiri et al., 2020), more evidence is still necessary about an integrative and holistic perspective of its contribution to increasing the required flexibility in the supply chain.

Furthermore, although the literature has defended the relevance of digital technologies implementation and more flexibility in the supply chain activities (e.g., Hartley and Sawaya, 2019), there is a lack of empirical evidence of what happens with the firm's operational performance when these two perspectives are combined. Prior studies have considered how information technologies contribute to supply chain integration and flexibility (e.g., Swafford et al., 2008; Jin et al., 2014; Han et al., 2017). However, when digital tools such as IoT, big data, AI, or blockchain are considered, the literature is still incipient about their contribution to supply chain flexibility and their combination to increase operational performance. This is important because prior results have also shown that, in some cases, when information systems in Industry 4.0 are integrated, they can become less flexible to adapt to different situations (Tabim et al., 2021). Although the literature has demonstrated that Smart Supply chains can positively affect performance (Liu et al., 2022; Lerman et al., 2022), supply chain flexibility can also help performance under uncertainties (Merschmann and Thonemann, 2011). In this vein, little is known about the combination of both Smart Supply Chain and flexibility to increase performance. Thus, what happens when these different elements are combined, especially in turbulent contexts of high uncertainty? Can smart supply chains support supply chain flexibility and increase operational performance when companies face uncertain environments?

In this paper, we aim to contribute to the IJPE literature in the context of its 250 vol by expanding the supply chain flexibility theory developed in this journal over the last decades. In this sense, our objective is to explore the role of Digital Transformation in supply chain operations – what we call Smart Supply Chain – to support supply chain flexibility when facing uncertainty in upstream and downstream relationships. We also aim to analyze how combining Smart Supply Chain and flexibility contributes to operational performance. To address the proposed questions, we explore the organizational information process theory (OIPT). This theory affirms that firms facing uncertain environments will require to process more information which can be supported by the development of information processing capacity (Fan et al., 2017; Srinivasan and Swink, 2018; Wong et al., 2020). We argue that Smart Supply Chain is a form of information-processing capacity that can help overcome such uncertainties and increase supply chain flexibility and operational performance. We test these relationships through a quantitative survey with 379 companies which was analyzed through regression and bootstrapping techniques. Our results show how the three dimensions of Smart Supply Chain, namely digital transformation strategy, base, and front-end digital technologies, are associated with three types of supply chain flexibility, i.e., sourcing, manufacturing, and delivery flexibility. We show full and partial mediating effects of these three supply chain dimensions between Smart Supply Chain and operational performance, enlightening the mechanisms through which companies increase performance when dealing with market and technological uncertainties as boundary conditions. Our results contribute to the debate on digital transformation in supply chains, showing how Smart Supply Chain can be effective for the uncertain contexts in which more flexibility is required.

2. Theoretical background

2.1. Supply chain flexibility: conceptualization and research antecedents

Flexibility has been one of the main concerns of the operations management literature for several decades (Sánchez and Pérez, 2005; Stevenson and Spring 2007). Seminal papers proposed different dimensions of flexibility (Duclos et al., 2003; Kumar et al., 2006) and forms of configurations of a flexible supply chain (Garavelli, 2003; Kumar et al., 2006). We summarized such studies in a review in Appendix A, in which the main perspectives and dimensions are considered.

According to the studies presented in Appendix A, flexibility is usually seen as an adaptive strategy that allows companies to develop an adaptive capacity to changing circumstances or instability caused by the environment (Gupta and Goyal, 1989; Sethi and Sethi, 1990; Koste and Malhotra, 1999). This capability is related to reconfiguring manufacturing resources and processes with a minimum wasted time, effort, cost, or performance (Upton, 1994). Moreover, Gerwin (1993) presented two different approaches for flexible manufacturing: (i) adaptive approach that fits with the traditional term presented above and (ii) proactive approach, whose objective, in contrast with the adaptative, is the capability to adapt the manufacturing resources and process to explore new opportunities and change the market (Gerwin, 1993). Furthermore, several authors proposed hierarchical models to explain flexibility (Slack, 1987, 2005; Sethi and Sethi, 1990; Koste and Malhotra, 1999). The hierarchical perspective asserts that flexibility is made up of layers, organized hierarchically from the most basic individual resource and shop floor levels to the highest levels of flexibility, such as plant flexibility, and each level is precedent and necessary to achieve the highest levels of flexibility.

The literature also extended the flexibility concept from internal manufacturing to a supply chain perspective (Appendix A). Supply chain flexibility is the ability of companies to react to changing environments by adapting necessary supply chain processes quickly and with minimum use of resources (Pérez Pérez et al., 2016; Schneeweiss and Schneider, 1999). Several authors proposed dimensions of supply chain flexibility (Appendix A). We adopt for our study the three most considered dimensions: sourcing flexibility – also known as supply flexibility, delivery or logistic flexibility, and manufacturing flexibility (Kumar et al., 2006; Fantazy et al., 2009; Malhotra and Mackelprang, 2012). Further, we follow several authors' strategic views of supply chain flexibility (Kumar et al., 2006; Gosling et al., 2010; Malhotra and Mackelprang, 2012). According to this view, supply chain flexibility covers internal and external dimensions. The internal dimension considers the manufacturing flexibility, i.e., the company's ability to respond to environmental uncertainty by adjusting the operational process to deliver the requested volume and mix of products and introduce and modify products (Kumar et al., 2006; Liao, 2020). On the other hand, the external dimension considers sourcing and delivery flexibility (Vickery et al., 1999; Malhotra and Mackelprang, 2012). The external dimension refers to a company's ability to respond to environmental uncertainty by configuring the supply chain and adjusting the flow of materials and information through sourcing flexibility and delivery flexibility (Stevenson and Spring 2007; Fantazy et al., 2009). Sourcing flexibility considers maintaining a flexible supply base through efficient supplier relationship management by developing collaborative approaches with key suppliers and making joint decisions (Liao, 2020; Sreedevi and Saranga, 2017). Delivery flexibility, in turn, is related to developing a flexible delivery strategy, adopting different kinds of transportation modes, and the capacity to change the warehouse layout and material and product handling (Liao, 2020; Maqueira et al., 2020).

We summarize these different perspectives of supply chain flexibility collected in Appendix A in Table 1. As shown in this table, we also highlight the adopted view for our present study, i.e., supply chain flexibility, which is deployed into internal and external flexibility as explained above.

Table 1
Summary of the different flexibility perspectives.

Strategic Dimensions	Hierarchical Dimensions	Flexibility Type
Internal Flexibility	Individual Resource Level	Machine Flexibility Material Handling Flexibility Labor Flexibility
	Shop Floor Level	Operation/Sequency Flexibility Routing Flexibility
External Flexibility/Result Flexibility	Plant Level	Process/Mix Flexibility Product Flexibility Volume Flexibility Expansion/Capacity Flexibility
	Functional Level	Marketing Flexibility R&D Flexibility System Flexibility Organizational Flexibility Manufacturing Flexibility
	Strategic Level	**Strategic Flexibility**
Supply Chain Flexibility (adopted perspective for the present study)	Internal flexibility	Manufacturing Flexibility
	External flexibility	Sourcing Flexibility Delivery Flexibility

2.2. Opportunities for supply chain flexibility in the digital transformation era

Two research streams of supply chain flexibility deserve more careful attention regarding our research problem. The first one is that previous studies have already acknowledged the role of supply chain flexibility under uncertainty, demonstrating its importance as a boundary condition (Das and Abdel-Malek, 2003; Merschmann and Thonemann, 2011; Jafari et al., 2022). This has been addressed not only by the IJPE community but also in studies published in other field journals (e.g., Manders et al., 2017; Rojo et al., 2017). Such studies recognized that supply chain flexibility is highly required when the business environment becomes more turbulent and companies face uncertain conditions. However, this is especially important to be considered even more now with the new post-pandemic scenario, where the turbulence of supply chains increased and resulted in high uncertainties for global operations (Lerman et al., 2022). In such a context, the IJPE community has opportunities to provide answers to the need for new configurations of supply chain management.

On the other hand, prior literature has addressed the role of integrating information technologies in the supply chain to support more flexible supply chains (e.g., Swafford et al. (2008); Jin et al. (2014); Han et al. (2017). In general, such studies argue that integrating information technologies from the supply chain partners will be important for the supply chain to anticipate disruptions and become more agile in adapting the supply chain to changing scenarios. Therefore, why should we consider the contribution of digital transformation (Smart Supply Chain) to supply chain flexibility when information technologies have already been addressed in this field? One answer is that digital technologies should not be treated simply as information technologies. While information technologies consider the background for digital transformation, as they enable the computerization of information processing, providing software and hardware, and information exchange between sources and recipients, digital transformation goes a step forward (Schuh et al., 2020). Digital transformation comprises at least four base technologies: IoT, Big Data, Cloud Computing, and AI (Meindl et al., 2021; Frank et al., 2019a,b). In the case of supply chains (Smart Supply Chain), it is also extended to adopting blockchain technologies (Esmaeilian et al., 2020; Agi and Jha, 2022). Such technologies bring a different perspective into the supply chain field because they enable a real-time information flow and the massive amount of data that can be processed to increase prediction capacity (Büyüközkan and Göçer, 2018). For instance, Agrawal et al. (2018) provide an example of Amazon, which improves prediction capacity based on Big Data and AI in the supply chain to change in the future from a business model based on buying-then-shipping to shipping-then-buying. As argued by the authors, this was not possible with information technologies integration, but now it becomes more feasible with Big Data and AI mechanisms. Such situations are examples of digital transformation becoming a new factor in enhancing supply chain flexibility.

Furthermore, digital transformation in the supply chain (Smart Supply Chain) is represented by new front-end technologies like collaborative robots, 3D printing, or augmented and virtual reality, which can also be useful in supply chains (Meindl et al., 2021). Such technologies are enhanced by base technologies like IoT, cloud, or AI and can become a competitive factor in achieving flexibility. Therefore, this new context of the Fourth Industrial Revolution (Industry 4.0) creates new conditions for studying supply chain flexibility, as Enrique et al. (2022) suggested. IJPE community has many opportunities to analyze which and how different digital-enabled technologies from Industry 4.0 can contribute to increasing supply chain flexibility in this context.

2.3. Organizational information-processing theory (OIPT)

Smart Supply Chain is enabled by the base technologies that promote digital transformation (IoT, Cloud Computing, Big Data, AI, and Blockchain) (Meindl et al., 2021). Even when such technologies can be present in front-end applications (Frank et al., 2019a,b), the main background of them is that they enhance the information processing capacity of firms through new forms and velocity of analysis that for innovation of the supply chain activities (Yu et al., 2021). In this sense, Dalenogare et al. (2022) analyzed supply chain integration in the digital transformation context. They showed that digital technologies enable companies to share real-time data from different sources and types. As argued by them, the data-integration nature in the digital transformation of the supply chain can be treated as an information-processing phenomenon based on the Organizational Information-Processing Theory (OIPT) perspective (Galbraith, 1974). The information-processing perspective differs from other usual lenses as the resource-based view, dynamic capabilities, or cumulative capabilities, which focus on what the actors own in terms of resources, or from the evolutionary perspective, which focuses on the nature of changes in the firm's relationships and organization. Instead, it focuses on the fit between information capabilities and needs by considering what is necessary to achieve such a fit. This means that OIPT considers that companies have information-processing needs to perform their activities. Such needs should be attended to through the information-processing capability. The organizational information-processing fit that a company should meet when information needs and capability are matched will help increase organizational performance (Premkumar et al., 2005). The usefulness of this theory for digital transformation has been evidenced by its adoption in prior studies in this field (e.g., Dalenogare et al., 2022; Rong et al., 2021; Akhtar et al., 2018).

According to Premkumar et al. (2005), information processing is needed to reduce contextual uncertainties that companies face, and technologies can provide the information-processing capability to support such needs. Therefore, we follow this theory as it represents our aim to investigate Smart Supply Chain and supply chain flexibility under uncertainty. First, Smart Supply Chain should provide the information-processing capability, as it comprises digital strategies and technologies that create the firm's conditions to process a high amount of information and data through decision-making processes (e.g., the anticipation of demands, pricing definition, etc.) and operational activities (e.g., a collaborative robot can process data from the environment to react and respond as required) (Frank et al., 2019a,b; Meindl et al., 2021). Second, achieving operational flexibility under turbulent conditions will depend on how the company processes the information needed to make the right decisions (Blome et al., 2014; Swafford et al., 2008). Recent studies have also considered this view about the organizational information-processing fit between digital technologies and flexibility through the OIPT. For instance, Yu et al. (2021) analyzed big data analytics' role in creating information-processing capability and attending operational flexibility in hospitals, while Srinivasan and Swink (2015, 2018) associated supply chain integration and visibility with planning comprehensiveness and analytic capabilities under organizational flexibility. Such studies provide a robust background to support the adoption of this view in our empirical investigation.

3. Hypotheses development

We use the OIPT theory to propose the conceptual research model (Fig. 1). We investigate the effects of Smart Supply Chain on supply chain flexibility as a form of *organizational information-processing fit* between the *information-processing capacity* and *the information-processing need* to achieve supply chain flexibility. We also argue that supply chain flexibility enhances operational performance (H2), mediating between Smart Supply Chain and operational performance (H2). This hypothesis is divided into two sub-hypotheses, H2a and H2b since we argue that source and delivery flexibility are antecedents of manufacturing flexibility. Finally, we propose that supply chain uncertainties act as a moderator in both relationships between Smart Supply Chain and flexibility (H3) and between flexibility and operational performance (H4). The model is proposed using the OIPT theory to explain the relationship between digital transformation, supply chain flexibility, and uncertainties. First, following Dalenogare et al. (2022) study that used OIPT, we consider Smart Supply Chain as a form to represent the information-processing capability. On the other hand, supply chain flexibility represents the need for information processing, assuming that more integrated information from the supply chain will enhance such flexibility. Finally, the supply chain uncertainties are considered information-boundary conditions that create tensions for the information-processing fit.

Next, we detail the proposed hypotheses represented in Fig. 1 that connect Smart Supply Chain, uncertainties, and operational performance with these three forms of supply chain flexibility.

3.1. *Smart supply chain enabling flexible supply chain in the context of environmental uncertainty*

Smart Supply Chain can be defined through two main dimensions,

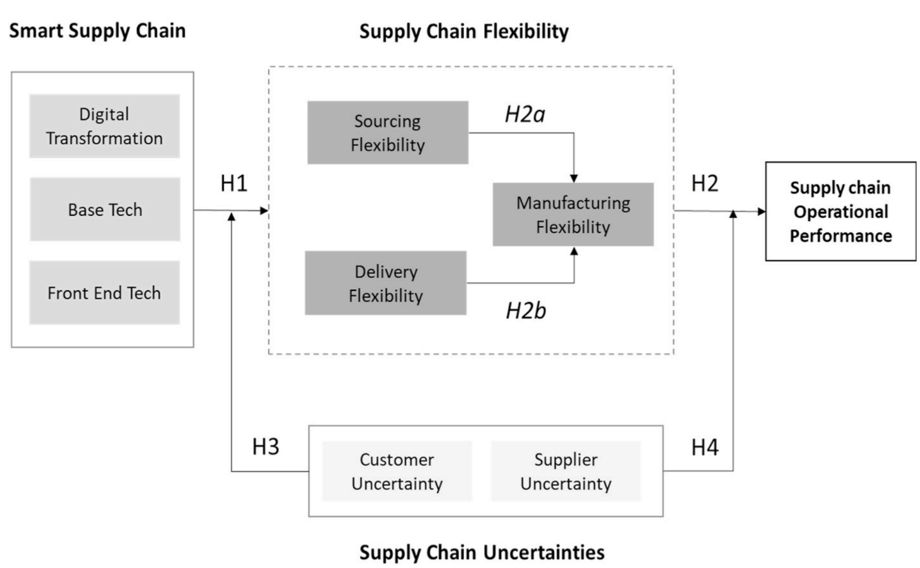

Fig. 1. Conceptual research model.

the strategic perspective of the supply chain digital integration and the technology perspective of digital solutions for supply chain operations (Meindl et al., 2021). Moreover, the technology perspective can be divided into base and front-end technologies, which Frank et al. (2019a, b) proposed for Industry 4.0 technologies. Base technologies are cross-cutting digital technologies focused on real-time data integration across the supply chain and digital solutions run by IoT, big data, cloud computing, and AI (Manavalan and Jayakrishna, 2019; Shao et al., 2021). Besides, blockchain technologies are also a key base technology in supply chain operations (Esmaeilian et al., 2020; Agi and Jha, 2022). On the other hand, front-end technologies comprise hardware technologies run by digital base technologies that aim to provide solutions to the supply chain operations, like 3D printing (Delic and Eyers, 2020), robotics (Realyvásquez- Vargas et al., 2019), simulation tools and augmented and virtual reality tools (Rejeb et al., 2021; Dornelles et al., 2022). We argue that these three dimensions (digital transformation strategy, base technologies, and front-end technologies) contribute to increasing supply chain flexibility.

Regarding the digital transformation strategy, this dimension considers all the organizational efforts that the company makes to facilitate the implementation of digital technologies (Nasiri et al., 2020). This dimension also considers the openness that companies must integrate data with external partners of the supply chain and how companies integrate supply partners to become more digitalized (Benitez et al., 2022). Consequently, this dimension is a keystone to becoming more flexible in supply chain operations since the digital transformation strategy will define how companies aim to develop their flexibility through digital solutions (Holmström et al., 2019; Enrique et al., 2022). For instance, the supply chain will need more integrated data in centralized cloud solutions to become more flexible. This will be only feasible if companies are more open to sharing and integrating strategic information of their operations instead of behaving opportunistically with access to information from other partners (Son et al., 2021). Without a strategic orientation toward digital transformation, companies tend to be technology 'fashionistas' but not leaders that provide an agile organization to the changing environment (Westerman et al., 2014).

From the technology perspective, base technologies allow the capture, analysis, and dissemination of large amounts of data to develop a smart supply chain (Manavalan and Jayakrishna, 2019; Shao et al., 2021). When supported by AI tools, such technologies can make better predictions and anticipate supply chain demands (Oh and Jeong, 2019; Toorajipour et al., 2021). They also facilitate the synchronization of internal operations based on more proactive production planning and control processes (Bueno et al., 2020) and better visualization of the different layers of the supply chain (Wang et al., 2016). Moreover, real-time visibility of the supply chain is one of the starting points of a flexible supply chain that can adapt quickly to different changes. It is only possible when the various supply chain partners are integrated through IoT solutions run on cloud systems (Dalenogare et al., 2018; Dos Santos et al., 2020). Thus, base technologies should also be an antecedent of supply chain flexibility.

Finally, the front-end technologies are responsible for executing operational activities of the supply chain management based on the use of collected and analyzed data by base technologies. For instance, computer simulation can improve supply chain flexibility by simulating if forecasting could improve product routes and change production volume (Terzi and Cavalieri, 2004). Furthermore, employees using Augmented Reality could also change warehouse space by guiding employees in more efficient ways to organize and structure the storage (Rejeb et al., 2021; Dornelles et al., 2022). The collaborative robots also improve flexibility given by the direct participation of employees in the most complex work and control phases and by eliminating the structural and technological limitations of automatic and fixed systems (Realyvásquez- Vargas et al., 2019). As shown qualitatively by Enrique et al. (2022), these are essential tools to increase the internal operational flexibility of Industry 4.0-oriented companies. As argued by these authors, these tools tend to be more flexible when the systems need to reconfigure routes and types of products to be produced. Some preliminary studies have also shown the usefulness of these tools alongside the supply chain. For instance, Delic and Eyers (2020) showed the benefit of 3D printing of flexible spare parts repositioned alongside the supply chain. Meindl et al. (2021) have also argued that simulation and virtual tools could be useful for supply workers to reschedule and readapt quicker for their distribution or internal logistics activities. These are some examples that indicate that front-end digital technologies should support the supply chain flexibility of companies.

Based on our arguments regarding the above three dimensions of the Smart Supply Chain, we argue that they should support the whole supply chain flexibility, as stated in the following hypotheses.

H1. Smart Supply Chain (i.e., digital transformation, base digital technologies, and front-end digital technologies) is positively associated with higher supply chain flexibility (source, manufacturing, and delivery flexibility).

3.2. Smart and flexible supply chain to increase operational performance in the context of environmental uncertainty

Several authors have widely recognized the impact of the Smart Supply Chain on operational performance in the digital transformation field (e.g., Büchi et al., 2020; Chauhan et al., 2021). For example, IoT and Big Data analytic tools allow the collection and analysis of data about supply chain operations and product performance, which can improve logistics operations and manufacturing practices (Heppelmann and Porter, 2014; Büchi et al., 2020). Also, new digital technologies enable a closer approach to the customer and, consequently, the development of more customized solutions (Benitez et al., 2022). Thus, adopting Smart Supply Chain tools should help companies improve their response to market demands, elevating the supply chain operational performance.

However, as Enrique et al. (2022) argued, digital technologies may have little contribution when they are not oriented before to support the structure of the company. These authors show that Industry 4.0 technologies can increase organizational flexibility, resulting in higher firm performance. Such results were evidenced by Enrique et al. (2022) in internal manufacturing activities, which we extend to the external supply chain operations. A company can meet customer demands for product delivery better if the products can be flexibly manufactured or assembled and if the incoming materials are also flexibly supplied (Zhang et al., 2002; Maqueira et al., 2020). Thus, the smart supply chain could potentialize the supply chain flexibility to improve operational performance. For example, companies can use machine learning to deepen their understanding of their operations and predict future customer behavior, improving delivery time and reducing logistics costs (Toorajipour et al., 2021). At the same time, they also need to coordinate between suppliers and distributors to ensure material and product flow according to the machine learning predictions. In this sense, front-end technologies such as robots are recognized for guaranteeing great machine flexibility that allows the production of a large variety of products in the same production line to respond to customer demand (Zhong et al., 2017; Alcácer and Cruz-machado, 2019). However, the impact of robots is limited because the process and product need to be designed in a flexible way to facilitate the manufacturing of several products (Enrique et al., 2022; Dalenogare et al., 2018). In that way, companies will improve their operational performance efficiently because adopting digital technologies will impact supply chain flexibility and operational performance. Therefore, manufacturing companies will be taking better advantage of the use of technologies, enhancing their use through flexibility and achieving their desired operational performance goals.

H2. Supply Chain Flexibility mediates the relationship between Smart Supply Chain and operational performance.

However, the literature also argues that sourcing and delivery flexibility are necessary for manufacturing flexibility (Duclos et al., 2003; Malhotra and Mackelprang, 2012; Liao, 2020). For instance, in lean production, flexible management of the relationship with suppliers and quick adaptation to customer demands are essential elements to increase the agility and response of the internal production system (Marodin et al., 2017). This means that upstream and downstream supply chain behaviors are antecedents of how manufacturing will be configured. This is especially important in the Industry 4.0 context, where data collected from products and the suppliers' activities will help to organize the manufacturing production and planning based on integrated data from these external sources (Frank et al., 2019b; Bueno et al., 2020). Therefore, we subdivide hypothesis H2 on the mediating role of supply chain flexibility between Smart Supply Chain and operational performance as follows:

H2a. Sourcing flexibility is an antecedent of manufacturing flexibility in the mediating role of supply chain flexibility between Smart Supply Chain and operational performance.

H2b. Delivery flexibility is an antecedent of manufacturing flexibility in the mediating role of supply chain flexibility between Smart Supply Chain and operational performance.

3.3. Supply chain uncertainties as boundary conditions between smart supply chain and flexibility

Turbulent business environments create uncertainties in the companies' structure that require a response, reinforcing companies' decisions on technology investment or triggering some new implementations (Frank et al., 2022). The literature has shown that turbulent environments interact with digital transformation by reinforcing digital technologies' relevance to achieving organizational goals (Chen and Tian, 2022; Li, 2022). We use the OIPT to argue that this is because under uncertain conditions, in which companies have more information-processing needs to be able to make the right decisions. They will focus on increasing information-processing capability to fit such needs, which can be achieved through digital technologies like Smart Supply Chain (Yu et al., 2021; Srinivasan and Swink, 2018). Supply chain uncertainties are mainly rooted in two direct sources: upstream uncertainties provoked by supplier disruptions and changes and downstream uncertainties caused by the customers' rapid demand changes (Merschmann and Thonemann, 2011). Although there might be other sources of uncertainty (e.g., Aldrighetti et al., 2021), they are the two most often present and analyzed due to their direct effects on companies and because they represent the most important external effects on companies (Frank et al., 2022). Also, from an Industry 4.0 perspective, these are the two sources of information that need to be integrated to achieve horizontal integration of the supply chain (Benitez et al., 2022). Thus, we propose the following hypotheses H3:

H3. Supply Chain uncertainties positively moderate the relationship between Smart Supply Chain and supply chain flexibility.

At the same time, the literature has also demonstrated that environmental uncertainty acts as a moderator between supply chain flexibility and firm performance (Merschmann and Thonenmann, 2011). Supply chain flexibility is more pursued when companies face turbulent environments and need to adapt quickly to changing organizational contexts to keep competitiveness (Candace et al., 2011; Shekarian et al., 2020). A good practical example of this was during the pandemic of COVID19 when global manufacturers started to change their focus toward more flexible factories that could quickly change their production configuration in order to reset any disruption in the supply chain (El Baz and Ruel, 2020; Belhadi et al., 2021). Following the OIPT view, achieving higher flexibility because of the increase of information-processing capability through its antecedent (i.e., Smart Supply Chain, as hypothesized in H1) will help to fit the information-processing need to be able to reconfigure the organizational processes quickly in uncertain environments (i.e., flexibility required, as hypothesized in H2 and H3), which should help to obtain better organizational performance (Premkumar et al., 2005). Therefore, flexibility will increase when supply chain uncertainties are present, and Smart Supply Chain supports such flexibility. Thus, we propose the following hypothesis:

H4. Supply Chain uncertainties positively moderate the relationship between supply chain flexibility and operational performance.

4. Research method

4.1. Sampling

Our research was carried out through a cross-industry survey with experts in the supply chain and operations management fields. The target respondents were top executives, directors, and managers, especially from large manufacturing firms operating in Brazil (location of the survey) with mass production models on their shop floors. This was necessary since firms that develop or aim to develop flexible systems are usually large firms with a vast product portfolio and a volatile market demand (market-push trajectory) (Castellaci et al., 2008). To validate our questionnaire, we sent a preliminary version to executives from the supply chain and operations management field and obtained 27 feedbacks regarding our survey. Then, our questionnaire was sent to our target population three times via email through the SurveyMonkey platform from the beginning of October till the end of November 2021. We sent the questionnaire to 4532 enterprises who already invested in some digital transformation technologies and strategies for operations, being aligned with the worldwide trends. These companies are enrolled in a list of companies with industrial supply chain activities, represented by a business association.

Moreover, most of these companies have their supply chain operations in all national territories and abroad. We obtained a total of 399 answers, with a total of 379 useful answers to our analysis (one respondent per company). Although we only investigated Brazilian supply chains, this was not an arbitrary choice. Most of our samples are large companies that have foreign activities impacting their supply chain operations. Because our survey was designed for the supply chain and operations management field, we asked about the enterprise's supply tier, which was represented by 67.81% in tier 1, 23.75% in tier 2, and 8.44% in tier 3. As expected, most of the respondents were from large companies representing 83.91% of our sample population. To measure this, we followed the IBGE's (2015) classification, which defines 500 or more employees as a large company. The overall respondent profile was essentially composed of directors (42.48%), managers (34.04%), and coordinators or supervisors (15.56%). Table 2 shows our population composition and further details described in this section.

4.2. Survey instrumentation

The survey instrumentation was based on pre-formatted constructs from the literature on flexibility, digital transformation, supply chain, and operations management. To analyze and build the constructs, we used five-point Likert scale questions. According to Babakus and Mangold (1992), a five-point Likert scale is used to increase response rate and quality while reduce respondents' "frustration level". This means that it helps capture the variance among respondents and, simultaneously, avoids complex scales that can reduce the response rate.

For this study, we utilized five blocks of questions: (i) sample composition, (ii) digital transformation, (iii) flexibility, (iv) supply chain uncertainty, and (v) supply chain performance. Our utilized items are presented in Appendix B, highlighting our main statistical results regarding item grouping. For Smart Supply Chain, we utilized three constructs, namely [FRONT-END], [DT_STRATEGY], and [BASE]. These

Table 2
Sample composition.

Description	(%)	Category	Description	(%)
Automotive	19.79%	Company size	Small and medium companies	16.09%
Non-durable consumer goods	19.79%		Large companies	83.91%
Durable consumer goods	10.29%	Supply chain's tier	Tier 1	67.81%
Electronics	6.33%		Tier 2	23.75%
Construction	6.33%		Tier 3	8.44%
Chemicals and Petrochemicals	6.33%	Respondent's profile	Director	42.48%
Agribusiness	6.07%		Manager	34.04%
Energy	4.49%		Coordinator or Supervisor	15.56%
Mining	3.43%		President/Vice/CEO	5.28%
Steel Industry	3.43%		Owner/Partner owner	2.64%
Capital goods	3.17%			
Pharmaceutical	2.37%			
Paper and Cellulose	1.58%			
Digital industry	1.06%			
Agriculture production	1.06%			
Transport	0.53%			
Others	3.96%			

constructs were retrieved from previous studies by Frank et al. (2019a, b), Nasiri et al. (2020), and Meindl et al. (2021) about digital transformation in manufacturing. The first, known as [DT_STRATEGY], we retrieved from Nasiri et al. (2020) study and formed a four-item scale construct that comprises the strategical aspects and goals regarding digital transformation implementation in supply chains. This construct considers aspects like digitizing the whole supply chain, data collection from different sources, creating a stronger communication network between different sectors, and improving customer interface through digitization (Nasiri et al., 2020). We adopted a composite measure for the constructs related to Industry 4.0 technologies. In other words, because of the different nature and purpose of Industry 4.0 technologies (e.g., IoT connected systems, while AI gives a decentralized decision to flexible systems), our approach was a formative construct (i.e., the sum of indexes) rather than a reflexive construct normally deployed by techniques like Confirmatory Factor Analysis (CFA).

For front-end technologies [FRONT-END], we considered a four-scale formative scale, including simulation, augmented reality, 3D printing, and robotics. According to Frank et al. (2019a,b) these technologies are considered front-end technologies in Industry 4.0 because they enable the four 'smart' dimensions (Meindl et al., 2021), which are concerned with operational and market needs. Therefore, they have an end-application purpose for the companies to enable Smart Supply Chain. For base technologies [BASE], a five-item formative scale composed of the Internet of Things, Cloud Computing, Big Data, Artificial Intelligence, and Blockchain was formed. Four of these technologies (IoT, cloud, big data, and AI) are considered base technologies in Industry 4.0 because they are necessary to allow companies' digital transformation process (Frank et al., 2019a,b). Moreover, blockchain is also considered a base technology in supply chain management literature (Frederico et al., 2019; Queiroz and Wamba, 2019; Meindl et al., 2021) since it is a keystone for secure transactions and relationships alongside supply chain ties.

For supply chain flexibility, we considered three major types of flexibility used in literature: sourcing flexibility [SOUR_FLEX], delivery flexibility [DEL_FLEX], and manufacturing flexibility [MAN_FLEX]. Thus, SOUR_FLEX is a four-item scale composed of features such as quick new supplier identification, ease to add or remove suppliers, openness and ease to make contractual adjustments with suppliers, and mutual decision with main suppliers about product/project/process design modifications. DEL_FLEX is a four-item scale construct that considers the ease of adding or removing carriers or distributors, the ease of changing warehouse space and load capacity, the ease of changing the merchandise delivery schedule, and the existence of a defined and flexible delivery strategy. Finally, manufacturing flexibility refers to the organization's ability to manage production resources and uncertainty to meet various customer requests (Rojo et al., 2017; Sreedevi and Saranga, 2017; Maqueira et al., 2020). MAN_FLEX has five-item scales which correspond to the ability to operate with various production volumes and different service levels, the efficiency in changing production volumes and/or services, the ability to produce various combinations of products, the capability to develop new products and/or services every year, and the ability to change the mix of products and/or services efficiently.

In the case of supply chain uncertainty, we used two constructs: supplier uncertainty [SUPPLIER_UN] and customer uncertainty [CUSTOM_UN], mostly used in supply chain literature to measure supply chain relationships uncertainty (Zhou et al., 2019; Jaworski and Kohli, 1993; Merschmann and Thonemann, 2011; Sreedevi and Saranga, 2017; Qi et al., 2011). For SUPPLY_UN we measured this construct by including a three-item scale of uncertainties related to materials and components prices bought by the company, dependence on suppliers' materials for production, and frequent supplier material delays handling. For CUSTOM_UN we also measured this construct with a three-item scale by considering uncertainties related to customers' preferences change, frequent product and service demands from new customers, and new customers with different needs than the current customers. Finally, for performance, we measured two constructs, one for our original model (Operational Performance) and another for our robustness check (Financial Performance). OPER_PERF was measured with a three-item scale, including improvement in the last two years in delivery reliability over customer orders, lead time, and order time reduction (Merschmann and Thonemann, 2011; Yu et al., 2018; Maqueira et al., 2020). While FINAN_PERF (Amoako-Gympah et al., 2020; Asare et al., 2013; Flynn et al., 2010; Jayaraman et al., 2013; Saeed et al., 2019; Yu, 2015) was measured with a three-item scale construct: sales grown, profit on sales increase, and market share grown in the last two years.

Finally, regarding our control variables, we controlled the firm size and supply chain tiers since they can affect how firms make their processes more flexible and digital (Thomé et al., 2014; Gligor, 2018; Delic and Eyers, 2020). We used one dummy for size [large = 1; 0 = small or medium] and two dummies for three levels of supply chain tiers (tier 1 – B2C; tier 2 – B2B of finalized goods and solutions; tier 3 – B2B of raw-material and basic components).

4.3. Construct definition and variable handling

To build our constructs, we used a confirmatory factor analysis (CFA) approach to ascertain the unidimensionality of our metrics. Overall, our constructs showed the goodness of fit since our reference values for the Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha fell in the acceptable values (Hair et al., 2018), as shown in our Appendix B. Regarding our factor loadings reference values, all items showed a good or high factor value, which explains their aggregation in the referred construct. Moreover, as previously explained, for technology constructs (BASE and FRONT-END), we adopted a formative approach by summing the scales from the respondents. This was necessary since the technologies are, in essence, different. However, we reported some indexes like Alpha's Cronbach and factor loadings to evidence their consistency. Lastly, we measured the final and complete model, including all constructs, and our model showed a good fit (RMSEA = 0.060; CFI = 0.884; $\Delta\chi2$: 1231.27).

As recommended by Hair et al. (2018), we also checked discriminant validity by using a series of two-factor model estimations among the constructs. Since our model has seven independent constructs, we performed a factorial (k-1) approach, totalizing 21 tests for discriminant validity. As Cable and DeRue (2002) recommended, we performed pairwise comparisons between CFA models for each construct, looking for their respective goodness of fit. In the first step, the correlation between the two constructs was restricted to a unit. In the second step, the model restriction was freed, and we calculated the goodness of fit for the original constructs. In this test, all the results showed discriminant validity ($\Delta\chi 2 > 3.84$, p-value $p < .01$), evidencing our constructs are measured with theoretically different concepts (Bagozzi et al., 1991). As a final test, we assessed the normality of our data by examining the skewness and kurtosis values. The results suggest that our variables for the general model are normally distributed since all values fall between the thresholds of ± 2.58 ($\alpha = 0.01$) (Hair et al., 2018). We also analyzed the means, standard deviations, and correlations for our constructs and control variables incorporated in the model. Appendix C summarizes all descriptive statistics, as well as normality and correlations.

4.4. Response bias and common method variance

Because bias can be a potential issue in survey design, we employed a series of procedures and statistical medicines to attenuate it, as recommended by Podsakoff et al. (2012). Firstly, because our survey is composed of single respondents, common method variance (CMV) can be a potential concern. As an initial procedure, we pre-validated the questionnaire with 27 executives from the supply chain and operations management field to better clarify our utilized instruments. For procedural remedies, we assessed the respondents' reliability by introducing two pairs of positively worded and reverse-worded items. These questions were used only as a test for correlated topics and were not central to the model. In addition, to avoid order bias, also known as order-effects bias, which can bias the survey responses through "priming" and the desire people have to give internally consistent answers (Suresh, 2011), we adopted a block randomization procedure in the instrumentation of the survey. This procedure was performed to avoid primacy bias, which happens when respondents remember how they responded to the first questions and try to respond to the following questions consistently (Krosnick and Alwin, 1987). For the magnitude of CMW, we employed Harman's single factor test, in which a single factor loads on all measured items from our model. This test suggests that if the total variance extracted by one factor exceeds 50%, common method bias is likely present in the study (Podsakoff et al., 2012). The single factor explained 25.51% of the total variance, indicating CMV is not a concern in our study. However, since other authors (Williams et al., 2010; Simmering et al., 2015) recommend other approaches to measure CMV, especially for single respondents, we also performed the marker variable technique.

The marker variable technique considers adding a variable to the survey, which is expected to be theoretically unrelated to the substantive variables measured in the model (Lindell and Whitney, 2001). We used "use of human resources from external partners to develop digital transformation in the supply chain" as a marker since our model was oriented to the internal development of digital transformation and not outsourcing. When added to our models, the marker variable did not perform a significant change in the models (i.e., most of the sigma from F-change were above the threshold of 0.1, or the model did not suffer a significant influence from the addition of this variable). This item was added to all estimations necessary for hypothesis testing, and the results were compared with the outputs without markers. The results remained stable with the addition of a marker variable, meaning there were no significant changes in the models. Hence, we concluded that response bias should not be a concern in this dataset.

4.5. Data analysis

We performed a set of hierarchical OLS regression models for data analysis to test our hypotheses. To this end, we first standardized all independent variables using a mean-centering Z-score. Overall, we tested four OLS models, where the first stage of each hierarchical regression was a model only with the control variables. Depending on the model, the hierarchical set from the following stages was different. For instance, for DEL_FLEX and SOUR_FLEX, the second stage included digital transformation constructs (DT_STRATEGY, FRONT-END, BASE), while the third stage was constructed the fourth stage included the moderation effects from uncertainty. For MAN_FLEX, the second stage included digital transformation constructs, and the third stage included DEL_FLEX and SOUR_FLEX constructs. Finally, for OPER_PERF, the second stage included the inclusion of flexibility constructs, the third stage included uncertainty constructs, and the fourth was the moderation effect of uncertainty constructs. We performed the PROCESS macro from Hayes (2017) for the mediation effect. To assess mediation effects, we calculated the indirect effects of the relationships as suggested by Preacher and Hayes (2008). PROCESS analysis allows for a bootstrapping procedure to examine the conditional indirect effects, a more effective procedure than Sobel's z test to test for mediation effects (Zhao et al., 2010). We set up 5000 bootstrap samples, as Preacher and Hayes (2008) suggested. Our final model contains three control variables (size, tier1, and tier2), eight independent variables (FRONT-END, DT_STRATEGY, BASE, DEL_FLEX, SOUR_FLEX, MAN_FLEX, CUSTOM_UN, and SUPPLIER_UN) which some (flexibility) are considered dependent in some models, and one dependent variable (OPER_PERF).

Furthermore, to start our regression models, some assumptions like linearity, homoscedasticity, normality, multicollinearity, and power design must be checked (Cohen, 1992; Hair et al., 2018). We analyzed collinearity by plotting the partial regressions for the independent variables, while homoscedasticity was visually examined in plots of standardized residuals against a predicted value. All these requirements were met in our dataset for regression analysis. Normality, we also checked, as previously explained, by assessing the skewness and kurtosis parameters. For multicollinearity, we checked the variance inflation factor (VIF) to ensure that our regression estimates are not unstable and have high standard errors. Our results indicate a low VIF (<3.5) for all variables, far below the threshold of 10 (Hair et al., 2018). Finally, for power design, we used g-power analysis with a reference value of 0.80 and an effect size of 0.15, as suggested by Cohen (1992), to verify the feasibility of using an OLS approach with the proposed sample size ($n = 379$). We tested all models (DEL_FLEX, SOUR_FLEX, MAN_FLEX, and OPER_PERF) using the main variables as predictors to check for the minimum sample size to perform the regression. The minimum necessary to achieve a statistical power significance level was the threshold of 109 observations. Since our sample is far from the minimum necessary, this analysis suggests we have a large sample size to proceed with the OLS statistical analyses.

5. Results

Our results report four independent models in a hierarchical structure for each model. We also present a different structure for our mediation analysis, following Hayes's (2017) approach, which suggests calculating the indirect effects as a posthoc analysis. For the OLS procedure, we present Table 3, which highlights our main results from regression analysis. As shown in Table 3, all final stage models (i.e., Models 3 or 4) were significant at $p < .001$. As a result, for the final step of each model we had: SOUR_FLEX ($F = 4.815$, $p = .000$), DEL_FLEX ($F = 5.584$, $p = .000$), MAN_FLEX ($F = 24.510$, $p = .000$), and OPER_PERF ($F = 4.886$, $p = .000$). Unstandardized coefficients are reported in Table 3 since all scales were standardized with Z-scores because they represent a standardized effect (Goldsby et al., 2013).

Regarding our H1 (Smart Supply Chain on Supply Chain Flexibility),

Table 3
Results of the regression analysis.[a]

	SOUR_FLEX				DEL_FLEX				MAN_FLEX			OPER_PERF			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 4
Firm size	.082	.014	.000	−.025	−.119	−.172	−.156	−.198* (p = .098)	.055	−.005	.069	−.329** (p = .013)	−.333*** (p = .007)	−.316** (p = .011)	−.340*** (p = .007)
Tier1	−.175	−.341** (p = .024)	−.327** (p = .031)	−.291* (p = .056)	−.151	−.368** (p = .019)	−.382** (p = .015)	−.362** (p = .023)	.085	−.115	.069	−.177	−.168	−.209	−.197
Tier2	.299* (p = .084)	−.324** (p = .050)	−.284* (p = .089)	−.235	−.339* (p = .064)	−.423** (p = .014)	−.465*** (p = .008)	−.437** (p = .013)	.001	−.058	.149	−.374* (p = .051)	−.315* (p = .085)	−.394** (p = .033)	−.384** (p = .039)
DT_STRATEGY		.204*** (p = .000)	.211*** (p = .000)	.194*** (p = .001)		.277*** (p = .000)	.270*** (p = .000)	.264*** (p = .000)		.256*** (p = .000)	.120** (p = .014)				
BASE		.055	.059	.088		−.114	−.120* (p = .098)	−.086		.162*** (p = .007)	.060				
FRONT-END		.075	.083	.032		.223*** (p = .000)	.216*** (p = .001)	.181*** (p = .006)		−.046	.000				
CUSTOM_UN			−.066	−.068			.071	.056						.127** (p = .010)	.118** (p = .019)
SUPPLIER_UN			.017	.016			−.024	−.020						−.032	−.046
SOUR_FLEX											.059		.054	.068	.052
DEL_FLEX											.388*** (p = .000)		.104* (p = .081)	.094	.101* (p = .093)
MAN_FLEX													.199*** (p = .000)	.170*** (p = .003)	.197*** (p = .001)
CUSTOM_UN x DT_STRATEGY				−.055				.010							
CUSTOM_UN x BASE				−.055				−.057							
CUSTOM_UN x FRONT-END				.162*** (p = .009)				.062							
SUPPLIER_UN x DT_STRATEGY				−.025				−.035							
SUPPLIER_UN x BASE				.109				.133* (p = .058)							
SUPPLIER_UN x FRONT-END				−.044				−.029							
CUSTOM_UN x SOUR_FLEX															.004
CUSTOM_UN x DEL_FLEX															.001
CUSTOM_UN x MAN_FLEX															.103* (p = .079)
SUPPLIER_UN x SOUR_FLEX															−.014
SUPPLIER_UN x DEL_FLEX															−.019
SUPPLIER_UN x MAN_FLEX															.027
F-Value	1.275	8.782***	6.868***	4.815***	1.762	11.631***	9.035***	5.584***	0.340	10.346***	24.510***	3.615**	9.225***	7.832***	4.886***
R^2	.010	.124	.129	.156	.014	.158	.163	.177	.003	.143	.346	.028	.13	.145	.158
Adj.R^2	.002	.110	.11	.124	.006	.144	.145	.145	−.005	.129	.332	.020	.115	.126	.126
R Square Change	.010	.114***	.005	.026*	.014	.144***	.005	.013	.003	.124***	.203***	.028**	.101***	.015**	.013

[a] Unstandardized beta coefficients are reported since the main variables were standardized before regression. n = 379. *** <0.01, ** <0.05, * <0.10.

we have statistical support from DT_STRATEGY for all flexibility constructs. However, we did not have statistical support for BASE. FRONT-END was only statistically associated to DEL_FLEX ($B = 0.181$, $p = .006$). For hypotheses H3 (Environmental Uncertainty moderating the relationship between Smart Supply Chain and Supply Chain Flexibility), we only found statistical evidence for CUSTOM_UN x DT_STRATEGY on SOUR_FLEX ($B = .162$, $p = .009$) and SUPPLIER_UN x BASE on DEL_FLEX ($B = 0.133$, $p = .058$). For hypothesis H4 (Environmental Uncertainty moderating the relationship between Supply Chain Flexibility and Operational Performance), we found support for CUSTOM_UN x MAN_FLEX on OPER_PERF ($B = .103$, $p = .079$).

Regarding the mediation analysis proposed in hypothesis H2, we used Hayes' (2017) bootstrapping approach (Table 4). The iterative process allowed us to assess the direct effect of Smart Supply Chain constructs on OPER_PERF. In this case, DT_STRATEGY and BASE have a significant and direct association with OPER_PERF. Moreover, we also tested these effects individually, and FRONT-END also showed a positive association with OPER_PERF ($B = 0.154$, $p = .045$), supporting the full direct effects of Smart Supply Chain on operational performance. We also tested the hypothesis on the mediation role of supply chain flexibility (H2, H2a, H2b) in a sequential procedure in which Smart Supply Chain constructs were considered the direct effects. At the same time, DEL_FLEX and SOUR_FLEX were set as mediators between Smart Supply Chain and MAN_FLEX (H2a, H2b), and, finally, all the supply chain flexibility constructs mediating between Smart Supply Chain and OPER_PERF (H2). These results are summarized in Table 4. The results support a full mediation effect of DEL_FLEX and SOUR_FLEX between FRONT-END and MAN_FLEX and then with OPER_FLEX, and partial mediation when we tested the similar paths for DT_STRATEGY and BASE. Therefore, our findings support hypothesis H2 regarding the mediating role of supply chain flexibility (Fig. 1) and the intermediate role of sourcing and delivery flexibility as antecedents of manufacturing flexibility (H2a, H2b).

After our results, we also assessed the statistical power of our models by analyzing our regression models through Cohen's f2 estimation (Cohen et al., 2003, p.95). By calculating the population effect size from all four final models in the last stage of our OLS hierarchical procedure, we obtained a statistical power of ≈ 0.95 at $\alpha = 0.01$ for all models. Therefore, this suggests our results are in accordance with the minimum statistical power necessary for regression models (Cohen et al., 2003).

5.1. Robustness checks

We performed a series of robustness checks to ensure our results previously presented are stable and consistent. We explored how the results of our regressions analyses might vary using three distinct approaches: (i) inclusion of a new construct; (ii) individual analysis from predictors; and (iii) inclusion of a competing model. For the first (i) approach, we included a new construct, namely "own digital resources" [OWN_DIG_RES]. We assume that when a company focuses on resources to enable digital transformation, these resources do not directly impact flexibility. Basically, we argue this construct is an antecedent to enable digital transformation, which can support a supply chain's flexibility. Therefore, there is no direct association to these types of resources on flexibility constructs. To this end, we measured [OWN_DIG_RES] with CFA approach (RMSEA = 0.051; CFI = 0.994; AVE = 0.55; Cronbach = 0.85; CR = 0.98) in a five-item scale construct composed by: necessary information to develop digital transformation in the supply chain (0.79); sufficient human resources to develop the digital transformation in the supply chain (0.63); the necessary technological resources to develop the digital transformation in the supply chain (0.89); the necessary financial resources to develop the digital transformation in the supply chain (0.72); and the organizational culture necessary to develop digital transformation in the supply chain (0.65). Our assumption was confirmed when we added this construct in models where [DEL_FLEX; SOUR_FLEX; and MAN_FLEX] were the dependent variables, showing that [OWN_DIG_RES] was not statistically significant in all models. For the second approach (ii), we analyzed the individual effect of each construct in our models, and overall, we found consistency with our main findings presented in Table 3. In addition, we also confirmed [FRONT-END] has a significant and positive effect on [OPER_PERF], which validate our H3, as previously discussed when we presented mediation results. Finally, for approach (iii), we utilized a financial performance construct (see Appendix B) as a competing model. Our assumption is that this performance metric will not suffer a direct and positive effect from these relationships were since all constructs in our model have the primary goal to improve operational aspects of the supply chain and not corporate performance aspects. As expected, this competing model was not supported, while our main model showed robust results reported above. In addition, the R^2 from the competing model showed a low value (i.e., below 0.100), and we did not find similar results to our main model [OPER_PERF]. Therefore, these procedures suggest our models are not overfitted, and we have consistency in our analysis.

6. Discussions

We summarized our results and their connections with the OIPT in Fig. 2. This framework shows that the digital transformation strategy is at the top of the structure because it directly affects all supply chain flexibility dimensions. When associated with operational performance, it is also partially mediated by supply chain flexibility dimensions. Therefore, the results indicate that the digital transformation strategy provides the complete organizational view to implement digital transformation and supports increased flexibility. From the OIPT perspective, this represents the requirement of creating a strategic alignment for organizational information-processing fit (Galbraith, 1974), as represented in Fig. 2. In other words, companies need to develop a digital transformation strategy that supports all the supply chain flexibility structure dimensions to create an information-processing capability that fits the information processing needs (Premkumar et al., 2005). Our results showed that this is the basic requirement for Smart Supply Chain in turbulent environments to achieve higher flexibility and operational performance.

Table 4
Indirect effects (bootstrapping outcome).

Interactions	Direct effect				Indirect effect			Total Effect				Conclusion
	Effect	95% confidence interval		Sig.	Effect	95% confidence interval		Effect	95% confidence interval		Sig.	
		LLCI	ULCI			LLCI	ULCI		LLCI	ULCI		
DT_STRATEGY-SOUR_FLEX-MAN_FLEX-OPER_PERF	.1946	.0977	.2914	.0001	.0162	.0056	.0313	.2761	.1855	.3666	.000	**Partial**
DT_STRATEGY-DEL_FLEX -MAN_FLEX -OPER_FLEX	.1877	.0920	.2835	.0001	.0243	.0041	.0488	.2761	.1855	.3666	.000	**Partial**
FRONT-END-SOUR_FLEX-MAN_FLEX- OPER_PERF	.0753	−.0198	.1705	.1204	.0160	.0064	.0291	.1586	.0652	.2520	.000	**Complete**
FRONT-END-DEL_FLEX-MANF_FLEX -OPER_PERF	.0685	−.0264	.1634	.1565	.0261	.0079	.0483	.1586	.0652	.2520	.000	**Complete**
BASE-SOUR_FLEX-MAN_FLEX_OPER_PERF	.1634	.0689	.258	.0007	.0176	.0067	.0332	.2367	.145	.3284	.000	**Partial**
BASE-DEL_FLEX-MAN_FLEX -OPER_PERF	.1625	.0698	.2552	.0006	.0199	.0045	.0407	.2367	.145	.3284	.000	**Partial**

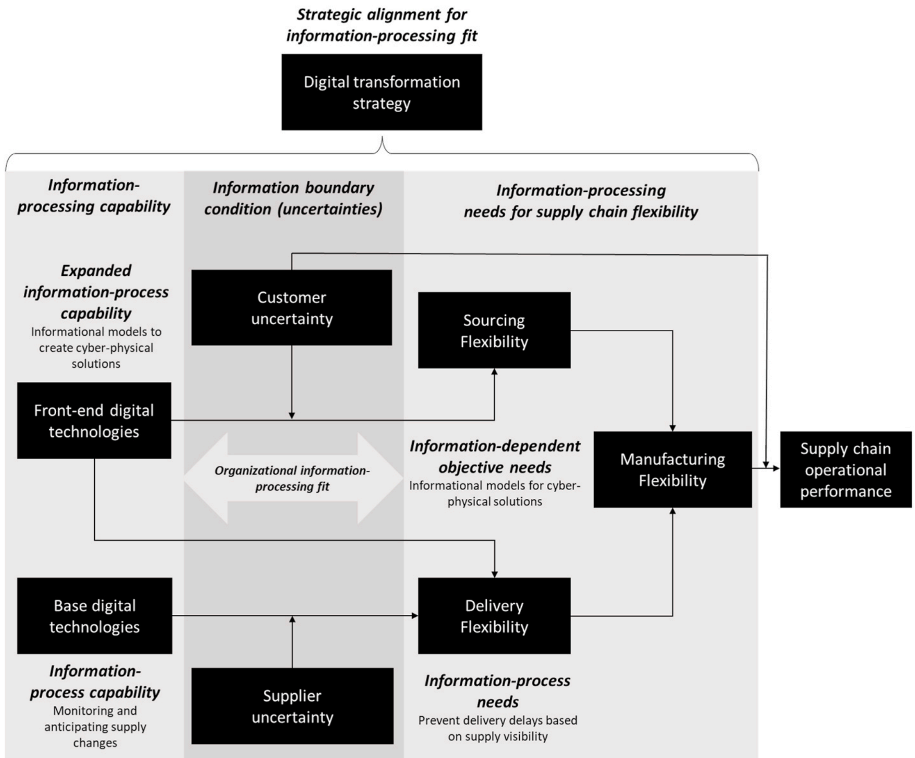

Fig. 2. Framework representing the findings and their relationship with OIPT.

Considering sourcing flexibility, one could be surprised with a first look at the results, where base digital technologies did not show significant associations with it. In contrast, front-end technologies did when moderated by customer uncertainty. We expected technologies like IoT, Big Data, or Cloud Computing to provide more flexibility (Frank et al., 2019a,b). However, by investigating the elements of sourcing flexibility, it is important to notice that they consider the ability of the company to easily switch the source of supply (Jin et al., 2014; Rojo et al., 2017; Sreedevi and Saranga, 2017). IoT-based solutions require an end-to-end horizontal integration between the focal company and the suppliers (Wang et al., 2016). The results could suggest that such solutions will not enhance flexibility (or maybe be even negative, as suggested by the negative sign in the interaction with customer uncertainty reported in Table 3, although without statistical significance). On the other hand, front-end digital technologies consider tools that can be helpful to easily select new sources of supply, especially when the company cannot stabilize the sources of supply due to the high market dynamism (moderating effect of customer uncertainty). For instance, simulation tools can help analyze which new source of supply can respond faster to each demand (Terzi and Cavalieri, 2004; Vieira et al., 2019). Augmented reality and robotics can help automate the reception and quality control of the new type of raw material supplied (Dornelles et al., 2022), and 3D printing can reduce the dependence on the supply of some very specific components required by the company (Delic and Eyers, 2020; Hohn and Durach, 2021).

From the OIPT point of view of sourcing flexibility, such front-end technologies are supported by information-processing capability because they need a large amount of data and interconnectivity to operate these solutions (e.g., pieces are manufactured in 3D printers based on AI models of generative design that analyze and create the best solution for broken components). However, they go beyond providing information and a real solution, either by a digital image like in augmented reality and simulation or printed components. We call this expanded information-processing capability intended to create cyber-physical solutions (i.e., virtual models or physical elements) that fit what we call an information-dependent objective need (in this case, the need to switch quickly from one source of supply to another). The expanded information-processing capability occurs under customer uncertainty, an information boundary condition about the market behavior due to rapid changes in product and customer demands. We represent these concepts from OIPT in our framework in Fig. 2.

Second, we found that delivery is more flexible when companies collect and analyze more data in the context of suppliers' uncertainty (i.e., moderating the role of supplier uncertainty between base technologies and delivery flexibility). Supplier uncertainty represents the risk of increasing input prices, suffering supply delays, or even supply disruption (Sreedevi and Saranga, 2017). From the OIPT perspective, supplier uncertainty also represents an information boundary condition because the lack of information about supplier behavior creates an uncertain condition that moderates this relationship (Zhu et al., 2018). This affects the capacity of planning the delivery and ensures that customers will receive their products as agreed with the company, independently of the problems the company can suffer in the supply chain. Therefore, the results suggest that companies enhance their information-processing capability by adopting digital technologies like IoT, Cloud, Big Data, Blockchain, and AI, which are oriented to increase the real-time data collection and processing in order to improve the decision-making process based on useful and updated information (Zhu et al., 2018). Such technologies can help to predict risks and problems with the supply and, based on this, anticipate deliveries, or reschedule such deliveries before disruptions may happen (Srinivasan and Swink, 2015). Therefore, this allows for creating an organizational information-processing fit between the information needed to adapt the delivery system quickly and the information-processing capability represented by the base technologies operating as monitoring and prediction systems of the supply behavior under an information boundary condition.

At the same time, front-end digital technologies are directly associated with delivery flexibility but did not show statistical significance in moderation with uncertainties. In this sense, our results evidence the usefulness of such tools to support delivery flexibility, as hypothesized, but independently on facing or not uncertainties. Front-end technologies like augmented reality, collaborative robots, simulation, and 3D printing applications are increasing the downstream of supply chain management (Delic and Eyers, 2020; Meindl et al., 2021). They are a form of increasing flexibility, like in the case of train spare parts, printed in 3D printers to quickly respond to maintenance demands near the customer (Delic and Eyers, 2020; Chan et al., 2018). This significantly increases the service level offered to the customer in the delivery system and represented an expanded information-processing capability to fit information-dependent objective needs, as explained above.

Finally, our results showed that the information-processing fit between Smart Supply Chain and supply chain flexibility could generally act as a reaction to uncertain conditions and help improve supply chain operational performance. This is achieved when manufacturing flexibility is in the structure's core, as shown in Fig. 2. This is in line with previous findings from Enrique et al. (2022). The authors showed that Industry 4.0 technologies could be organized to support manufacturing flexibility as the central dimension of the industrial digital transformation. They showed that digital technologies and manufacturing flexibility depend on several companies' internal and external factors. Thus, in this present study, we show that such external and internal conditions are essentially those related to the information-processing requirements achieved through Smart Supply Chain and supply chain flexibility. Therefore, this present study provides a zoom-out of the external structure that connects digital transformation with manufacturing flexibility to increase operational performance. Complementarily, Enrique et al. (2022) detailed the manufacturing flexibility conditions. Thus, both studies provide complementary findings that expand the view of Industry 4.0 and flexibility in operations management.

7. Conclusions

Our results contribute to the theory by showing the connections between Smart Supply Chain and Supply Chain Flexibility and how they are important to better deal with uncertainty based on the OIPT. We also contribute to advancing OIPT from the supply chain perspective since we showed a general mediation effect of supply chain flexibility between Smart Supply Chain and operational performance. This could lead companies to rethink how they would organize the adoption of digital base and front-end technologies based on their digital strategy and how they would change their supply chain operations to become more flexible, mainly focusing on supply flexibility, distribution flexibility, and sourcing flexibility. For this transition from supply chain flexibility using digital technologies, the company needs to analyze the uncertainties of both consumers and suppliers. Therefore, the OIPT argues that information processing can reduce uncertainty. Our study demonstrates that smart supply chains and supply chain flexibility can support companies to fit such information-processing needs with new information-processing capabilities.

Against a current and growing context of high uncertainties, our results and discussions provide a foundation for the future implementation of digital transformation by proposing the consolidation of Smart and Flexible Supply Chains. As a key contribution, we show how combining these two concepts can provide more capability for companies to deal with rapidly changing environments. Also, by applying this OIPT to Smart Supply Chain, we provide a new view of the supply chain flexibility literature, especially in the context of the 250th volume of IJPE. Our study presented a historical perspective on the studies developed over the last decades and the new frontier in this subject when considering new turbulent conditions and digital transformation opportunities.

7.1. Practical implications

We provide the following recommendations to supply chain practitioners based on our findings. First, managers need to set a digital transformation strategy that will drive the implementation of Smart Supply Chain technologies to achieve supply chain flexibility. Such strategy should be focused on the required fit between these technologies and specific types of supply chain flexibility (i.e., sourcing, delivery, or manufacturing). Front-end technologies can be used in both sourcing and delivery, while base digital technologies are proven to be useful for delivery flexibility when supplier uncertainty is a threat. Second, managers should structure sourcing and deliver flexibility to support manufacturing flexibility and not the contrary. Our study showed that these two external dimensions are antecedents of manufacturing flexibility and mediate the contribution of digital technologies. Third, practitioners should take care of manufacturing flexibility as the core of the supply chain flexibility to increase operational performance. As argued in the Industry 4.0 literature (Frank et al., 2019a,b; Dalenogare et al., 2018), manufacturing should be the core of an Industry 4.0-oriented structure, while the external support of digital technologies will help the manufacturing to achieve its goal of producing according to the market requirements and demands. Finally, practitioners can find a set of technologies from Industry 4.0 that they can use to support supply chain activities.

7.2. Limitations and future research

Regarding our methodological procedures, two key limitations are the single respondent survey and the opinion-based aspect, which could lead to potential bias. Following Ketokivi (2019), we show some procedures to avoid such issues. However, as discussed by the author, those aspects are limitations present in primary data survey research. Concerning the dimensions considered, recent studies have shown that manufacturing flexibility in the Industry 4.0 context can be deployed in several dimensions and can be supported by different manufacturing digital technologies (Enrique et al., 2022). We did not include such a level of detail. Rather, we remained in the macro-structure of the supply chain. Therefore, future studies should advance in the connection between these micro-elements that were assumed as a black box in our study. Moreover, the recent literature has argued that Industry 4.0 and digital transformation should be considered as a socio-technical system for its implementation (Marcon et al., 2022). This is an important limitation of our study because we only focused on a technological and organizational perspective, while the social elements that involve supply chain workers have not been considered in this study. Therefore, future studies need to advance our research to the field of social elements by analyzing how smart workers can support flexibility as they do in manufacturing (Dornelles et al., 2022). As demonstrated by Meindl et al. (2021) in an analysis of more than 5000 studies from the ten years of Industry 4.0, the integration of studies between social and workers elements with Smart Supply Chain is one of the greatest gaps in the nowadays literature on digital transformation and Industry 4.0 in the operations management field. Thus, future opportunities can arise from integrating our findings with this social perspective of supply chains (Chen et al., 2017). In our study, we decided to look at external uncertainties (customers and suppliers). With this analysis, it is possible to have a wide perspective of both demand and supply views, involving upstream and downstream actors. In addition, as consumers and suppliers are at opposite ends of the supply chain, it is possible to ensure a more comprehensive view of the supply chain, understanding different uncertainties that can affect supply chain flexibility supported by Smart Supply Chain. However, some authors (Mason-Jones and Towill, 1998;

Christopher, 2004) expose that there are more than two uncertainties considered in our work. They propose four main causes of uncertainties: manufacturing/process, control, supply-side, and demand-side. Therefore, future studies could include internal uncertainties in their analysis, such as manufacturing and control uncertainties, rather than only external uncertainties. Finally, the role of sustainability in supply chain management should also be considered because the current turbulent environments and uncertain scenarios have raised more concern about how digital transformation and supply chains can also contribute to sustainable operations (Liu et al., 2019). Our study did not include such an element, but future studies can integrate our findings with this subject and provide advances in this direction.

Data availability

The data that has been used is confidential.

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Appendix A. Overview of the different flexibility concepts in the literature

Level of study	Author	Flexibility Concept
Manufacturing Level	Slack (1987), Slack (2005)	The study proposes a hierarchical model of flexibility, which includes four levels: (i) The production resources themselves (Labor Flexibility, Technology Flexibility, Infrastructure Flexibility); (ii) The tasks which the production function needs to manage (Product flexibility, Mix flexibility, Volume flexibility, Delivery flexibility), (iii) The overall performance of the production function; and (iv) The competitive performance of the whole company
	Gupta and Goyal (1989)	The study considers flexibility as the ability of a manufacturing system to cope with changing circumstances or instability caused by the environment. Flexibility types: Machine Flexibility, Process Flexibility, Product Flexibility, Routing Flexibility, Volume Flexibility, Process Sequence Flexibility and Production Flexibility
	Sethi and Sethi (1990)	The study proposes a hierarchical model of flexibility, that includes three levels: (i) Component or basic flexibilities, (ii) System Flexibilities and (iii) Aggregate Flexibilities
	Gerwin (1993)	The study proposes a model that looks at flexibility as an adaptive strategy in the face of uncertainties, if not they bring a proactive approach as well (Mix Flexibility, Changeover Flexibility, Modification Flexibility, Volume, Rerouting, Material, Flexibility, Responsiveness)
	Suarez et al. (1996)	The study understands flexibility as a Low order Flexibility type and First order Flexibility Type. The low order flexibility is related to the internal flexibility capabilities that companies developed to reach the First order Flexibility Type or Result Flexibility.
	Koste and Malhotra (1999)	The study proposes a hierarchical model which includes four levels: (i) Individual Resource Level, (ii) Shop Floor Level, (iii) Plant Level, (iv) Functional Level, (v) Strategic Level.
	Gerwin (1993)	The study proposes a hierarchical model that includes flexibility at following levels: (i) the individual machine or manufacturing system level, (ii) the manufacturing function such as forming, cutting, or assembling, (iii) the manufacturing process for a single product or group of related ones, (iv) the factory, (v) and the company's entire factory system
Supply Chain level	Vickery et al. (1999)	The study proposes considers that Supply chain flexibility cover those flexibilities that directly impact a firm's customers (i.e., flexibilities that add value in the customer's eyes) and are the shared responsibility of two or more functions along the supply chain, whether internal (e.g., marketing, manufacturing) or external (e.g., suppliers, channel members) to the firm.
	Kumar et al. (2006)	The study considers supply chain flexibility as the ability of supply chain partners to restructure their operations, align their strategies, and share the responsibility to respond rapidly to customers' demand at each link of the chain, to produce a variety of products in the quantities, costs, and qualities that customers expect, while still maintaining high performance. The proposed the follow flexibility Types: Product, Sourcing, Delivery, New Product, Responsiveness
	Kamel Aissa Fantazy Vinod Kumar Uma Kumar et al. (2006)	The study considers that the supply chain flexibility concept includes five dimensions: (i) new product flexibility, (ii) sourcing flexibility, (iii) product flexibility, (iv) delivery flexibility and (v) information systems flexibility.
	Gosling et al. (2010)	The study considers that Supply chain flexibility is rationalized as comprising two key concepts: vendor flexibility and sourcing flexibility. The combination of these two flexibilities impacts the flexibility of new product flexibility, volume flexibility, mix flexibility, delivery flexibility and access flexibility.
	Stevenson and Spring (2009)	The study considers that the Supply Chain flexibility concept incorporates both within-firm and between-firm flexibility. Operations System Flexibility, Market Flexibility, Logistic Flexibility, Supply Flexibility, Organizational Flexibility, Information System Flexibility
	Malhotra and Mackelprang (2012)	The study considers Supply chain flexibility as a system or network of interrelated external flexibilities (inbound and outbound) and internal manufacturing flexibilities, which taken together support the focal firm's performance outcomes from a customer-oriented perspective
	Sreedevi and Saranga (2017)	The study deploys supply chain flexibility according to three dimensions: (i) supply flexibility, (ii) manufacturing flexibility, and (iii) distribution/logistics flexibility.
	Rojo et al. (2017)	The study considers that the supply chain flexibility concept includes four dimensions: (i) Sourcing, (ii) Operating System, (iii) Distribution and (iv) Information System
	Liao et al. (2019)	The study considers flexibility as the firms' ability to configure and manage the supply chain through collaboration with supply chain partners in responding to a rapidly changing environment in an effective and efficient manner. Types of supply chain flexibility: Volume, Mix, Delivery, Supply Network, Logistic, Spanning.

Appendix B. Questionnaire

Questionnaire items to assess Digital Transformation Strategy (DT_STRATEGY) (Adapted from Nasiri et al., 2020). *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. RMSEA = 0.049; CFI = 0.998; AVE = 0.63; Cronbach = 0.87; CR = 0.87. Factor loadings are shown in parentheses.*

a. We aim to digitalize everything possible in the supply chain (0.84).
b. We aim to collect large amounts of data from different sources in the supply chain (0.83).
c. We aim to create a stronger communication network between different sectors of the supply chain with digital technologies (0.85).
d. We aim to improve the interface with customers with digitization efficiently (0.63).

Questionnaire items to assess Front-End Technologies (FRONT-END) (Adapted from Frank et al., 2019a,b). *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. We only reported Cronbach of this construct because we performed a formative approach. Cronbach = 0.80. Factor loadings are shown in parentheses.*

a. We use robotics in our company processes and in the supply chain (0.69).
b. We use computer simulation in supply chain processes (0.66).
c. We use augmented reality in supply chain processes (0.73).
d. We use 3D printing in supply chain processes (0.76).

Questionnaire items to assess Base Technologies (BASE) (Adapted from Frank et al., 2019a,b; Narayanamurthy and Tortorella, 2021). *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. We only reported Cronbach of this construct because we performed a formative approach. Cronbach = 0.90. Factor loadings are shown in parentheses.*

a. We use Internet of Things in our supply chain processes (0.81).
b. We use Cloud Computing in our supply chain processes (0.75).
c. We use Big Data Analytics in our company processes and in the supply chain (0.84).
d. We use Artificial Intelligence in supply chain processes (0.81).
e. We use Blockchain in the supply chain processes (0.78).

Questionnaire items to assess Sourcing flexibility (SOUR_FLEX) (Adapted from Jin et al., 2014; Rojo et al., 2017; Sreedevi and Saranga, 2017; Maqueira et al., 2020). *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. RMSEA = 0.085; CFI = 0.977; AVE = 0.36; Cronbach = 0.69; CR = 0.69. Factor loadings are shown in parentheses.*

a. Our company can quickly identify a new supplier when needed (0.60).
b. Our company can easily add and remove suppliers when needed (0.70).
c. Our company is able to make contractual adjustments in the relationship with suppliers with ease (0.63).
d. Our company makes decisions together with the main suppliers (in relation to design/product modifications, project/process modifications, etc (0.46).

Questionnaire items to assess Delivery Flexibility (DEL_FLEX) (Adapted from Jin et al., 2014; Rojo et al., 2017; Sreedevi and Saranga, 2017; Maqueira et al., 2020). *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. RMSEA = 0.050; CFI = 0.994; AVE = 0.42; Cronbach = 0.74; CR = 0.74. Factor loadings are shown in parentheses.*

a. Our company can easily add or remove carriers or distributors (0.57).
b. Our company can easily change warehouse space and/or load capacity (0.68).
c. Our company is able to change merchandise delivery schedules with ease (0.67).
d. Our company has a defined and flexible delivery strategy (0.67).

Questionnaire items to assess Manufacturing Flexibility (MAN_FLEX) (Adapted from Jin et al., 2014; Rojo et al., 2017; Sreedevi and Saranga, 2017; Maqueira et al., 2020). *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. RMSEA = 0.073; CFI = 0.989; AVE = 0.52; Cronbach = 0.83; CR = 0.84. Factor loadings are shown in parentheses.*

a Our company is able to operate with various production volumes and/or with different service levels (0.75).
b Our company can change production volumes and/or services efficiently (0.79).
c Our company is able to produce various combinations of products (0.60).
d Our company manages to develop new products and/or services every year (0.66).
e Our company has the ability to change the mix of products and/or services efficiently (0.79).

Questionnaire items to assess Supply Chain Uncertainty (including customer uncertainty and supplier uncertainty) *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. RMSEA = 0.084; CFI = 0.970; AVE = 0.59; Cronbach = 0.80; CR = 0.85. Factor loadings are shown in parentheses.*

Customer Uncertainty [CUSTOM_UN] (Adapted from Zhou et al., 2019; Jaworski and Kohli, 1993; Merschmann and Thonemann, 2011; Sreedevi and Saranga, 2017; Qi et al., 2011).

a. Our customers' preferences change frequently (0.87).
b. Our company frequently receives demand for products and services from new customers (0.54).

c. Our company's new customers have different needs than current customers (0.62).

Supplier Uncertainty [SUPPLIER_UN] (Adapted from Zhou et al., 2019; Jaworski and Kohli, 1993; Merschmann and Thonemann, 2011; Sreedevi and Saranga, 2017; Qi et al., 2011).

a. The price of raw materials and components that our company buys changes frequently (0.65).
b. Our company is highly dependent on suppliers to acquire the materials needed for production (0.62).
c. Our company must deal with supplier delays in material deliveries frequently (0.52).

Questionnaire items to assess Performance (including operational performance and financial performance) *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. RMSEA = 0.047; CFI = 0.991; AVE = 0.54; Cronbach = 0.65; CR = 0.87. Factor loadings are shown in parentheses.*

Operational Performance [OPER_PERF] (adapted from Merschmann and Thonemann, 2011; Yu et al., 2018; Maqueira et al., 2020).

a. Our company has improved the delivery reliability of customer orders over the past two years (0.81).
b. Our company has improved the lead time for delivering customer orders over the past two years (0.87).
c. Our company has reduced customer order time over the past two years (0.83).

Financial Performance [FINAN_PERF] (adapted from Amoako-Gympah et al., 2020; Asare et al., 2013; Flynn et al., 2010; Jayaraman et al., 2013; Saeed et al., 2019; Yu, 2015).

a. Our company's sales have grown in the last two years (0.70).
b. Profit on sales has increased in the last two years (0.51).
c. Market share has grown over the past two years (0.65).

Questionnaire items for control variables.

a. Please inform the size of your company in the number of employees (based in IBGE - Instituto Brasileiro de Geografia e Estatística, 2015)
b. Please inform the position of your company in the supply chain (two dummies):
   Tier 1 - Supplier of products/services to the final consumer;
   Tier 2 - Provider of products or solutions to other companies;
   Tier 3 - Suppliers of Raw Materials and Basic Inputs to other companies.

Appendix C. Bivariate correlation matrix

	SOUR_FLEX	DEL_FLEX	MAN_FLEX	DT_STRATEGY	BASE	FRONT-END	CUSTOM_UN	SUPPLIER_UN	OPER_PERF	Size	Tier1	Tier2
SOUR_FLEX	1											
DEL_FLEX	.496[a]	1										
MAN_FLEX	.354[a]	.553[a]	1									
DT_STRATEGY	.316[a]	.336[a]	.347[a]	1								
BASE	.279[a]	.242[a]	.272[a]	.648[a]	1							
FRONT-END	.236[a]	.285[a]	.286[a]	.469[a]	.724[a]	1						
CUSTOM_UN	−.012	.133[a]	.256[a]	.155[a]	.171[a]	.222[a]	1					
SUPPLIER_UN	−.017	−.004	.116*	−.056	−.046	.073	.273[a]	1				
OPER_PERF	.192[a]	.273[a]	.293[a]	.295[a]	.253[a]	.169[a]	.172[a]	.018	1			
Firm size	.040	−.046	.024	.062	.128*	.073	−.054	.022	−.125*	1		
Tier1	.025	.052	.046	.225[a]	.208[a]	.153[a]	−.043	.039	.048	.006	1	
Tier2	−.073	−.097	−.038	−.183[a]	−.177[a]	−.075	.134[a]	−.015	−.095	−.026	−.810[a]	1
Mean	3.501	3.321	3.830	3.697	13.192	8.926	3.554	3.901	.161	.839	.678	.237
S.D.	.84	.89	.848	.924	5.953	4.363	.917	.762	.368	.368	.468	.426
Skewness	−.448	−.333	−.86	−.612	.231	.808	−.415	−1.018	1.853	−1.853	−.765	1239
Kurtosis	−.28	−.585	.4	−.18	−1204	−.252	−.487	1.441	1.440	1.440	−1.422	−.468

[a] Correlation is significant at the 0.01 level (2-tailed).

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