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RESEARCH ARTICLE

Contribution of big data analytics to risks and disruptions mitigation and agility performance

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Abstract

The main objective of this study is to understand the mechanisms by which supply chain data analytics (SCDA) capabilities impact supply chain agility performance (SCAP) directly or through the mediation of other capabilities, particularly supply chain risk mitigation (SCRMI), supply chain robustness (SCROB), and supply chain resilience (SCRES). The study is based on survey data collected from 203 foreign companies in global value chains located in Morocco's industrial acceleration zones, whose legal status is assimilated to foreign territory. Respondents were mainly senior and middle managers with experience in general management and operations and supply chain management. Validity and reliability analyses as well as hypothesis testing were performed through structural equation modeling (SEM) using SPSS Amos. The results showed that SCDA capabilities strengthen the capabilities of SCRMI, SCROB, and SCRES and indirectly improve SCAP through partial and exclusive mediation of SCRES capability. The results of this study revealed the importance of developing SCDA capabilities for strengthening risks and disruptions mitigation capabilities and improving SCAP. Also, optimizing the return on investment in SCDA capabilities should incorporate dedicated risks and disruptions mitigation tools and alerts to facilitate supply chain managers' decision making in this area.

Keywords

data analytics; risks; disruptions; mitigation; robustness; resilience; agility.

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1. Introduction

Today's supply chains are long and complex, making them unpredictably vulnerable to risks and disruptions (Scheibe & Blackhurst, 2019). The effects of disruptions can be transmitted to other regions and supply chain actors (Ivanov et al., 2014). Consequently, disruptive risks represent a new challenge for supply chain managers (Ivanov & Dolgui, 2019). To this end, it is essential to develop supply chain data analytics (SCDA) capabilities to improve those of supply chain risk mitigation (SCRMI), supply chain robustness (SCROB) and supply chain resilience (SCRES) and, ultimately, to directly and indirectly improve supply chain agility performance (SCAP).

However, supply chain managers can only effectively control and manage risks, including disruptive ones, if supply chain visibility is improved and real-time information is available (Bag et al., 2020). As such, supply chain partners can take advantage of technologies dedicated to data analytics, to prevent disruptive risks and monitor their propagation (Kamble & Gunasekaran, 2020).

In view of the above, data analytics is one of the opportunities offered by the technological environment, which could be seized to generate business value for companies (Chen et al., 2012). Supply chain partners invest in data analytics to reduce costs and uncertainties and improve their decision-making capability (Kache & Seuring, 2017), all with a view to gaining competitive advantage (Wamba et al., 2017).

In addition, data analytics involves the extraction, diagnosis, integration and transformation of supply chain data into valuable information and meaningful models for decision-makers (Tiwari et al., 2018). Data analytics can boost partners' agility performance (Wang et al., 2016), while providing insights and predictive models that can improve risks and disruptions mitigation capabilities in the supply chain (Shamout, 2021). Also, accurate and timely data combined with data analytics can generate or reconfigure risk mitigation, resilience and robustness capabilities.

The literature on the potential impact of data analytics capabilities on performance seems to have grown in recent years. According to researchers, the effects of data analytics capabilities on performance are indirect and therefore mediated by other organizational capabilities (Mikalef et al., 2020). To this end, it seems important to conduct further empirical researches on the mechanisms by which data analytics capabilities contribute to improving agility performance (Mikalef et al., 2020).

In response to calls for further research in the field of operations and supply chain management, this study is one of the first to explore the mechanisms by which data analytics and risk mitigation capabilities interact and contribute to improved agility performance, in the presence of risks and disruptions generated by changes and uncertainties in the business environment.

In light of the above, the main objective of this study is to understand the mechanisms by which data analytics capabilities impact agility performance, either directly or through the mediation of other capabilities, specifically those of risk mitigation, robustness and resilience. Indeed, this study aims to fill this gap by answering the following research questions (RQs):

- RQ1. What are the effects of supply chain data analytics capabilities on strengthening risk management capabilities, particularly risk mitigation, robustness and resilience?
- Q2. How do these data analytics, risk mitigation, robustness and resilience capabilities interact to improve supply chain agility performance?

This paper responds to a specific call by describing the direct effects of data analytics capabilities on agility performance, risk mitigation, robustness and resilience, as well as its indirect effects on this agility performance through the mediation of robustness and resilience capabilities. Then, the direct effects of risk mitigation capability on robustness and resilience as well as their effects on agility performance were investigated, using the knowledge-based view as a theoretical basis. This being said, this paper attempts to shed new light on data analytics capabilities and its contribution to improving operational and disruptive risk management capabilities, particularly those of risk mitigation, robustness and resilience, as well as their joint contribution to improving agility performance.

This document is organized into six sections. Following the introduction, section 2 presents the theoretical background. Section 3 presents the hypothesis development. The methodology is described in section 4. The results and their theoretical and managerial implications are presented and discussed in section 5. Future directions and the main limitations of the research are announced in section 6.

2. Theoretical background

2.1. knowledge-based view

The knowledge-based view asserts that companies excel through the effective use of knowledge rather than its exclusive possession. Indeed, the capability of the company or supply chain to capture, process and disseminate knowledge appears to be more important in differentiating itself from the competition (Blome et al., 2014; Wang et al., 2024). To this end, data analytics can enrich the knowledge base and, consequently, improve both non-disruptive and disruptive risk mitigation capabilities to achieve competitive advantage (Dubey et al., 2019; Cooper et al., 2023).

Furthermore, the knowledge-based view holds that improving knowledge flows reduces uncertainty (Bode et al., 2011). In this respect, supply chain partners exchange knowledge as part of effective cooperation in various areas, including risks and disruptions management (Kong et al., 2020). In this respect, data analytics enables the effective use of knowledge related to risk prevention, identification and assessment, which in turn should strengthen risk management capabilities, particularly those of risk mitigation, robustness and resilience. Indeed, the knowledge-based view has been adopted as the theoretical basis for developing and testing the research model.

2.2. Supply chain data analytics

Supply chain data analytics (SCDA) has been identified by the use of descriptive, predictive and prescriptive methodologies in supply chain planning, procurement, manufacturing and delivery operations (Souza, 2014). Consequently, supply chain risk management (SCRM) is one of the areas where data analytics could be highly beneficial (Saleem et al., 2021; Khan et al., 2023).

Many researchers believe that data analytics enables supply chain partners to capture, integrate, deploy and analyze large quantities of big data, which could give them a competitive advantage (Khan et al., 2023). Data analytics capabilities enable more effective perception and analysis of external developments (Dubey et al., 2018). Having the capabilities to collect, analyze, and synthesize data will enable partners to develop effective and correct plans and policies, which are critical to assigning supply chain a competitive advantage in a dynamic and uncertain business environment (Wamba et al., 2017; Khan et al., 2023). In addition, data analytics involves the use of past and present data analysis tools for predictive modeling that can improve agility performance (Shamout, 2019). These data analytics tools reduce costs, risks, and improve the speed and accuracy of decisions (Kache & Seuring, 2017). The knowledge-based view postulates that knowledge can enable companies as well as supply chains to achieve long-term competitive advantage. In addition, research has shown that SCDA contributes to improved visibility, resilience and robustness and, ultimately, agility performance (Schoenherr & Speier-Pero, 2015).

2.3. Supply chain risk management

In a bid to improve supply chain network management, develop a competitive advantage and reduce the impact of risks and disruptions due to global events, organizations have sought to develop strategic and operational capabilities, particularly SCDA (Park & Singh, 2023).

Some researchers have attempted to examine how SCDA capabilities enable organizations to better manage risks in their supply chains (Park & Singh, 2023). Park & Singh (2023) argue that organizations can develop their resilience capability by leveraging SCDA, thereby mitigating disruptions in their supply chains and positively impacting business performance. Similarly, SCDA capabilities enhance the risk mitigation capability of supply chain partners, enabling them to specifically identify and respond to non-disruptive risks in a timely manner (Park & Singh, 2023). In addition, the development of SCDA capabilities leads to an improvement in the company's capability to perceive changes in the internal and external environment that could potentially create a disruptive event in its supply chain network (Wamba et al., 2020). Similarly, Modgil et al (2021) have argued that SCDA enhances the sensing and sense-making capabilities within an organization. Indeed, once potential points of concern appear in the company's supply chain network, SCDA creates and transmits knowledge that enables the company to develop risk mitigation, robustness and resilience capabilities (Park & Singh, 2023). Furthermore, Spieske and Birkel (2021) examined how SCDA enables companies to develop risk management capabilities. Furthermore, Vieira et al. (2020) have argued that big data supported by analytics tools can be used effectively to predict all potential risks, including those that disrupt the supply chain and, subsequently, enhance the risk mitigation, robustness and resilience of the entire supply chain (Vieira et al., 2020; Park & Singh, 2023). To this end, this work uses the knowledge-based view to understand how SCDA capabilities could enable organizations to generate or reconfigure other capabilities dedicated to risk mitigation, robustness and resilience, and to predict risks and disruptions before they occur in the supply chain.

3. Hypothesis development

Figure 1 presents our research model.

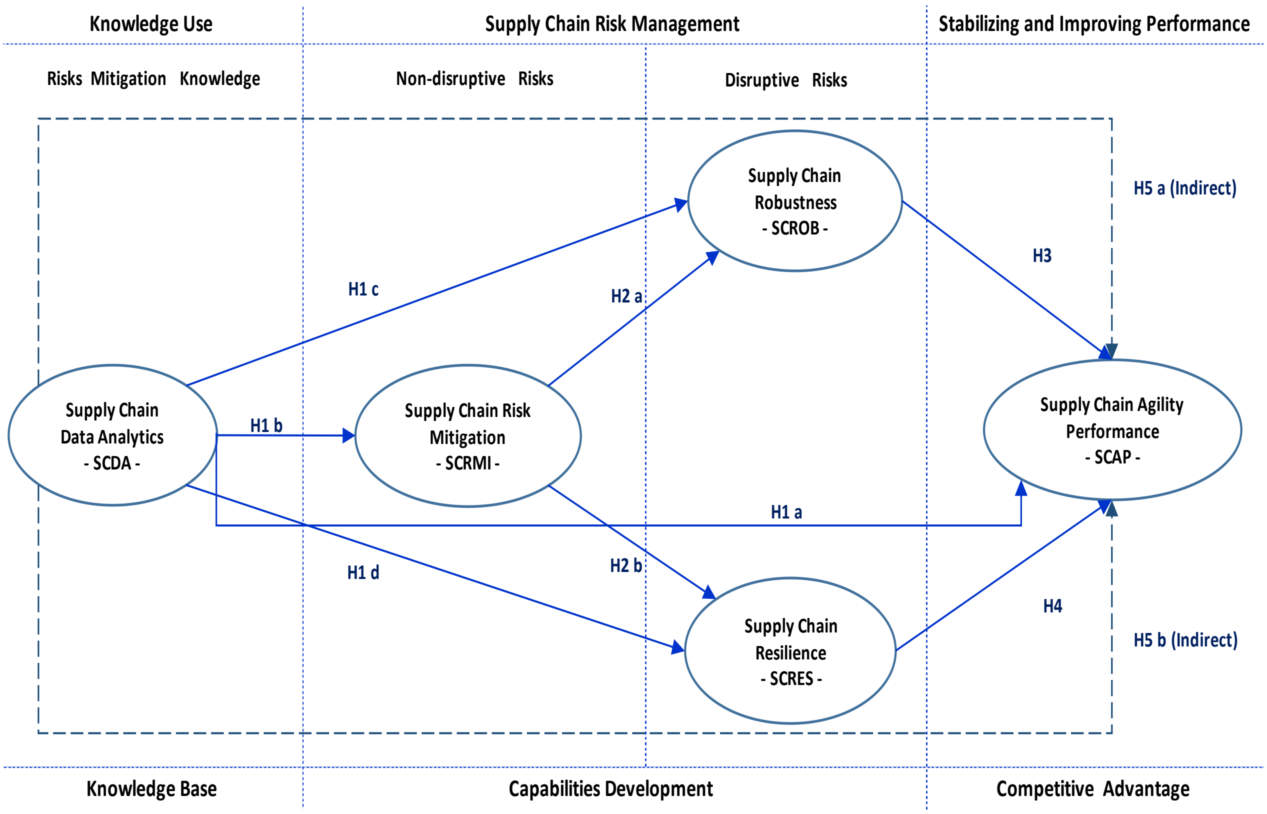

Fig. 1. Research Model

3.1. Direct effects of the SCDA

SCDA and SCAP

One of the main objectives of SCDA is the collection of actionable and new information that can be used to improve operational performance and gain competitive advantage (Khan et al., 2023). In this respect, some authors have distinguished between high-performing and low-performing companies on the basis of SCDA capabilities development (Wamba et al., 2017). Although SCDA capabilities have been recognized as a key competitive factor, their impact on agility performance remains poorly understood in times of disruptions (Khan et al., 2023; Ma & Chang, 2024, Al Mamun et al., 2025).

Therefore, it is hypothesized that: *H1a. SCDA has a positive impact on SCAP.*

SCDA and SCMI

According to Gualandris & Kalchschmidt (2015), companies have been trying to develop strategic and operational capabilities aimed at controlling supply chain risks caused by global events and, consequently, gaining competitive advantage. Recently, companies have relied on the development of SCDA capabilities to strengthen the knowledge base for achieving this competitive advantage (Park & Singh, 2023). Thus, Park & Singh (2023) have shown that SCDA enhances the risk mitigation capability of organizations through early identification and response to risks in the supply chain. Similarly, Modgil et al (2021) have argued that SCDA capabilities enhance sensing and decision-making capabilities within an organization, thereby strengthening SCRMI capability. In addition, SCDA capabilities enable supply chain partners to perform effective environmental analysis and integrate the identification of potential risks and disruptions (Talwar et al., 2021). Therefore, in a disruptive and highly volatile situation, SCDA is intimately linked to SCRMI.

Therefore, it is hypothesized that: *H1b. SCDA has a positive impact on SCRMI.*

SCDA and SCROB

Robustness refers to the capability to withstand various shocks, human errors and variability in the business environment (Wieland & Wallenburg, 2012). This robustness capability plays an important role in times of disruptions because well-equipped, risk-aware supply chains can mitigate or eliminate their occurrence (Kwak et al., 2018). In other words, a robust supply chain is able to withstand, cope with and control disruptions. Robustness capability can save a company time in identifying and implementing the control mechanisms needed to mitigate or, where appropriate, eliminate risks (Kwak et al., 2018). As such, it is important to note that risks identification and mitigation is contingent on the a priori development of SCDA capabilities (Shamout, 2019; Alvarenga et al., 2023).

Therefore, it is hypothesized that: *H1c. SCDA has a positive impact on SCROB.*

SCDA and SCRES

Resilience capability refers to how supply chain partners control disruptions in order to mitigate their impact (Dennehy et al., 2021). Previous studies have highlighted the importance of developing data analytics capabilities for their positive effect on organizational performance (Waller & Fawcett, 2013). However, the literature has not sufficiently examined the role of SCDA capabilities in creating or reconfiguring resilience capability (Dennehy et al., 2021 Recently, Dubey et al. (2021) have argued that SCDA has a direct and positive effect on supply chain resilience. To this end, investment in developing SCDA capabilities leads to improved visibility and, consequently, resilience (Barhmi et al., 2024; Jiang et al., 2025).

Therefore, it is hypothesized that: *H1d. SCDA has a positive impact on SCRES.*

3.2. Direct effects of the SCMI

<u>SCMI and SCROB</u>

Robustness capability plays an important role in mitigating uncontrollable disruptions through the a priori development of SCRMI capability (Kwak et al., 2018). Indeed, robust supply chains are able to withstand, cope with and control disruptions by gaining time to identify and implement the necessary adaptation mechanisms to mitigate disruptions induced by unavoidable risks (Kwak et al., 2018; Shamout, 2019). In view of the above, a robust supply chain remains effective for all future situations (Klibi et al., 2010), preserving the same situation before and after changes without responding to them.

Therefore, it is hypothesized that: *H2a. SCRMI has a positive impact on SCROB.*

<u>SCMI and SCRES</u>

Highly resilient supply chains have a priori a risk mitigation capability enhanced by data analytics. Indeed, resilience enables continuity during severe disruptions caused by uncontrollable events, including Covid-19 and the Russian-Ukrainian war (Yang et al., 2021). Similarly, Jüttner & Maklan (2011) assert that there is an already recognized relationship between resilience and risk mitigation. In addition, Heckmann et al. (2015) have created a theoretical framework for risk mitigation in which supply chain risks are considered a primary state concept, while the resulting disruptions are seen as effects requiring, among other things, resilience capability for their mitigation. Indeed, resilience can be seen as an outcome of the concept of risk mitigation (Pereira et al., 2014). Consequently, the creation or reconfiguration of resilience capability must build on the knowledge already created through data analytics and risk mitigation (Ribeiro & Barbosa-Povoa, 2018; Rashid et al., 2024).

Therefore, it is hypothesized that: *H2b. SCRMI has a positive impact on SCRES.*

3.3. Direct effect of the SCROB and SCRES

<u>SCROB and SCAP</u>

Developing robustness capability as a proactive rather than reactive strategic investment (Wieland & Wallenburg, 2012) enables performance stabilization during volatile phases. Furthermore, a robust supply chain will not experience significant performance degradation in the event of disruptions (Mackay et al., 2020). However, developing robustness capability requires additional financial investment (Wieland & Wallenburg, 2012) induced by the incorporation of redundancies, including multiple suppliers and unused generation or transmission capacity resources. Indeed, robustness is the capability to proactively manage disruptions in the supply chain, thereby stabilizing and improving the agility performance of its partners (Wieland & Wallenburg, 2012). To this end, a robust supply chain is designed to maintain performance at its level during disruptions caused by unavoidable risks. This research argues that SCROB can absorb any SCAP degradation caused by disruptions (Mackay et al., 2020; Liu et al., 2024).

Therefore, it is hypothesized that: *H3. SCROB has a positive impact on SCAP.*

<u>SCRES and SCAP</u>

Resilience has been considered by this research as a capability to ensure supply chain recovery (Munoz & Dunbar, 2015). Furthermore, resilience should be combined with risk mitigation capability (Wieland & Wallenburg, 2013) to cope with disruptive risks constituting a failure of this mitigation capability. Disruptive risks have a serious impact on the entire supply chain, causing disruption to informational, physical and financial flows, and disrupting regular operations (Bahrami & Shokouhyar, 2022). The negative impact of disruptions in the supply chain could be avoided thanks to its resilience capability to return to a favorable performance level within a desirable timeframe after the impact of an incident (Wieland & Wallenburg, 2013). Indeed, this research supports a favorable association between resilience capability and agility performance (Chowdhury & Quaddus, 2017; Altay et al., 2018; Liu & Lee, 2018; Liu et al., 2024).

Therefore, it is hypothesized that: *H4. SCRES has a positive impact on SCAP.*

3.4. Mediating effects of SCROB and SCRES

SCDA, SCROB and SCAP

Data analytics capabilities can boost companies' operational performance (Wang et al., 2016) by providing information and predictive models, which can improve robustness capability dedicated to mitigating disruptive supply chain risks (Shamout, 2021). In addition, accurate and timely data combined with data analytics can generate or reconfigure robustness capability.

Therefore, it is hypothesized that: *H5a. SCROB mediates the link between SCDA and SCAP.*

SCDA, SCRES and SCAP

Recent research has asserted that, in general, information technology innovations (DeGroote & Marx, 2013) and, in particular, data analytics capabilities contribute to improved business performance and supply chain agility (Dubey et al., 2019). As such, Dubey et al. (2021) stated that data analytics capabilities enable companies to gain competitive advantage through resilience capability. Similarly, Bahrami & Shokouhyar (2022) demonstrated that data analytics capabilities support the improvement of business agility performance through the enhancement of resilience capability.

Therefore, it is hypothesized that: *H5b. SCRES mediates the link between SCDA and SCAP.*

4. Research methodology

4.1. Data collection

The study used a survey to collect data from foreign companies operating in Morocco. Through a pilot interview, preliminary data were collected from three manufacturing companies located in industrial acceleration zones to ensure that the questions were understandable to each respondent and without any uncertainty or confusion due to the official language of their respective countries.

Next, the Ministry of Industry and Commerce database was exploited to conduct an online survey in 2024 to test the hypotheses. Indeed, the initial sample included informants involved in the general management and supply chain management of foreign manufacturing companies operating in Morocco. After eliminating mailing errors, the sample contained 845 contacts. At the end of the survey period, 203 completed questionnaires had been received by respondents, representing an acceptable response rate of 24% (Fosnacht et al., 2017). This is because the sample size is medium (Kline, 2023) and the number of observations exceeds the free parameters of the model, which is a necessary condition for identifying a structural model (Kline, 2023). Table 1 presents the profiles of the respondents to this survey.

Table 1. Respondents' Profile Summary

Structure of the sample	Frequency	Valid %
Firm size:		
Less than 100 employees;	50	24.6%
101 to 200 employees;	15	7.4%
201 to 300 employees;	45	22.2%
More than 300 employees.	93	45.8%
Manufacturing industry type:		
Automotive industry;	60	29.6%
Aeronautics and aerospace industry;	53	26.1%
Food industry;	38	18.7%

Structure of the sample	Frequency	Valid %
Pharmaceutical industry;	25	12.3%
Electronic and electrical components industry;	15	7.4%
Rubber and plastic products industry.	12	5.9%
Respondent designation:		
Top management;	95	46.8%
Middle management;	83	40.9%
Lower management.	25	12.3%
Respondent experience:		
Less than 3 years;	18	8.9%
3 to 5 years;	32	15.8%
6 to 9 years;	63	31%
More than 9 years.	90	44.3%
Total	**203**	

4.2. Measurement model

The survey instrument used a seven-point Likert scale (1-strongly disagree and 7- Strongly agree). The measurement items for the theoretical constructs in the research model are adapted from prior studies. This approach allows for the development of formative and composite measures in the context of this study. Therefore, the measurement items can affect the construct with which they are affiliated and which they measure. The measurement items used in this study are presented in Appendix A.

The SCDA capabilities were operationalized by five items adapted from Shafiq et al. (2020) and Khan et al. (2023). The SCRMI capability was operationalized by four items adapted from Yang et al. (2021). The SCROB capability was operationalized by four items adapted from Wieland & Wallenburg (2012) and Kwak et al. (2018). SCRES capability was operationalized by four items adapted from Dubey et al. (2021). SCAP was operationalized by four items adapted from Swafford et al. (2008).

4.3. Nonresponse bias and common method bias

For testing nonresponse bias, the answers of the firms that quickly respond to participate in the survey and enterprises that accept late were compared by means of t-test. There were no statistically significant differences between early and late responses.

To examine the potential threat of variance bias in the common method, a one-factor test was recommended (Podsakoff et al., 2024). The relevant factor analysis revealed that neither a single factor emerged, nor was a general factor identified in the unrotated factor structure. Additionally, in this study, to examine common method bias, the correlation relationships between the constructs were investigated. When the correlation between the concepts is less than 0.90, the bias of the common method is accepted, which is the case for this study.

4.4. Data analysis

Confirmatory factor analysis (CFA) using SPSS Amos 25 was done to validate the factor structure of variables under the focus of this study and assess the validity and reliability of the measurement models corresponding to each construct in the research model (Figure 1). CFA is an appropriate tool because the associations between the proposed items and constructs have been specified. In addition, structural equation modeling (SEM) is useful for examining causal relationships and dealing with multiple dependent variables as well as the error terms of all dependent and independent variables in a structural model (Kline, 2023). Similarly, SEM facilitates the examination of the overall causal fit of a holistic model as well as mediation effects.

4.5. Reliability and validity

The measurement model was evaluated on the basis of the reliability of the internal consistency and the convergent validity of measurements associated with the constructs and the discriminant validity. Internal consistency reliability was tested by Cronbach's α(α> 0.777) and composite reliability (CRs > 0.802), the results of which verified acceptable internal consistency. Convergent validity was assured, as all the loadings were similar to or greater than 0.5, with acceptable average variance extracted (AVE) values (AVEs > 0.510), as displayed in Table 2.

Table 2. Reliability and Convergent Validity Results and Fit Indices

Scale/Item	Cronbach Alpha	CR	Item Loadings	AVE	Fit Indices
Supply Chain Data Analytics Capabilities:					
SCDA1			0.832		
SCDA2	0.892	0.906	0.870	0.670	
SCDA3			0.933		
SCDA4			0.931		
SCDA5			0.501		
Supply Chain Risks Management Capability:					
SCRMI1			0.501		
SCRMI2	0.804	0.835	0.643	0.574	
SCRMI3			0.973		
SCRMI4			0.842		x^2/df (chi-square/ degrees of freedom) = 299.508/177 = 1.692 GFI = 0.843 SRMR = 0.0743 RMSEA = 0.068 CFI = 0.945
Supply Chain Robustness Capability:					
SCROB1			0.889		
SCROB2	0.881	0.891	0.742	0.671	
SCROB3			0.819		
SCROB4			0.839		
Supply Chain Resilience Capability:					
SCRES1			0.737		
SCRES2	0.777	0.802	0.535	0.510	
SCRES3			0.831		
SCRES4			0.744		
Supply Chain Agility Performance:					
SCAP1			0.854		
SCAP2	0.892	0.895	0.875	0.681	
SCAP3			0.831		
SCAP4			0.773		

Notes: CR, construct reliability; AVE, average variance extracted; The goodness of fit index, GFI; Standardized root mean square residual, SRMR; Root mean squared error of approximation, RMSEA and Comparative fit index, CFI.

In addition, CFA analysis was done to validate the factor structure of variables under the focus of this study. Kline's recommendations (Kline, 2023) on several statistical parameters were used to evaluate the model's goodness of fit (chi-square/degrees of freedom: χ/df < 3, Tucker–Lewis's index: TLI > 0.90, comparative fit index: CFI > 0.90, root mean square error of approximation: RMSEA < 0.10 and standardized root mean square residual: SRMR < 0.09. The hypothesized five-factor measurement model had a satisfactory fit (x^2/df = 299.508/177 = 1.692, GFI = 0.843, SRMR = 0. 0743, RMSEA = 0.068, CFI = 0.945), as displayed in Table 2.

The discriminant validity was verified if the shared variance between the latent variable and its indicators (AVE) was greater than the variances (squared correlation) of each variable with the other latent variables, as displayed in Table 3.

Table 3. Inter-construct correlation estimates and related AVEs

Constructs	SCRES	SCDA	SCRMI	SCROB	SCAP
SCRES	**0.714**				
SCDA	0.549	**0.819**			
SCRMI	0.631	0.412	**0.757**		
SCROB	0.553	0.798	0.239	**0.819**	
SCAP	0.646	0.633	0.445	0.550	**0.826**

Note: Square roots of the AVE are shown on the diagonal.

5. Results and discussion

5.1. Structural model

This study used the R^2 value to estimate the effect of exogenous constructs. The variance is measured by the R^2 that is described in each of the endogenous constructs. So, it measures the model's explanatory power (Hair et al., 2019). Significant, moderate or weak endogenous latent variable R^2 values are 0.75, 0.50 or 0.25 (Hair et al., 2011). Table 4 shows appropriate R^2 values for all dependent variables in the structural model. The R^2 score for the SCAP was 0.54, demonstrating good support for the research model.

Table 4: Results of the path analysis and hypothesis testing

N°	Path			Estimates	P	Support	R^2
H1a	SCDA	→	SCAP	0.172	ns	No	
H1b	SCDA	→	SCRMI	0.257	***	Yes	0.20
H1c	SCDA	→	SCROB	0.518	***	Yes	0.68
H1d	SCDA	→	SCRES	0.300	***	Yes	
H2a	SCRMI	→	SCROB	- 0.116	ns	No	
H2b	SCRMI	→	SCRES	0.605	***	Yes	0.69
H3	SCROB	→	SCAP	0.238	ns	No	
H4	SCRES	→	SCAP	0.382	***	Yes	0.54

Notes: *** p<0.001 and ns: non-significant (p>0.1).

5.2. Hypotheses testing

This study used bootstrapping with 5,000 samples to determine the appropriateness of the path coefficients. Based on the statistical results obtained, with the exception of hypotheses H1a, H2a, and H3 (SCDA → SCAP, SCRMI → SCROB, and SCROB → SCAP), hypotheses H1b (SCDA → SCRMI), H1c (SCDA → SCROB), H1d (SCDA → SCRES), H2b (SCRMI → SCRES), and H4 (SCRES → SCAP) were supported. The path coefficients were presented in Table 4 and Figure 2.

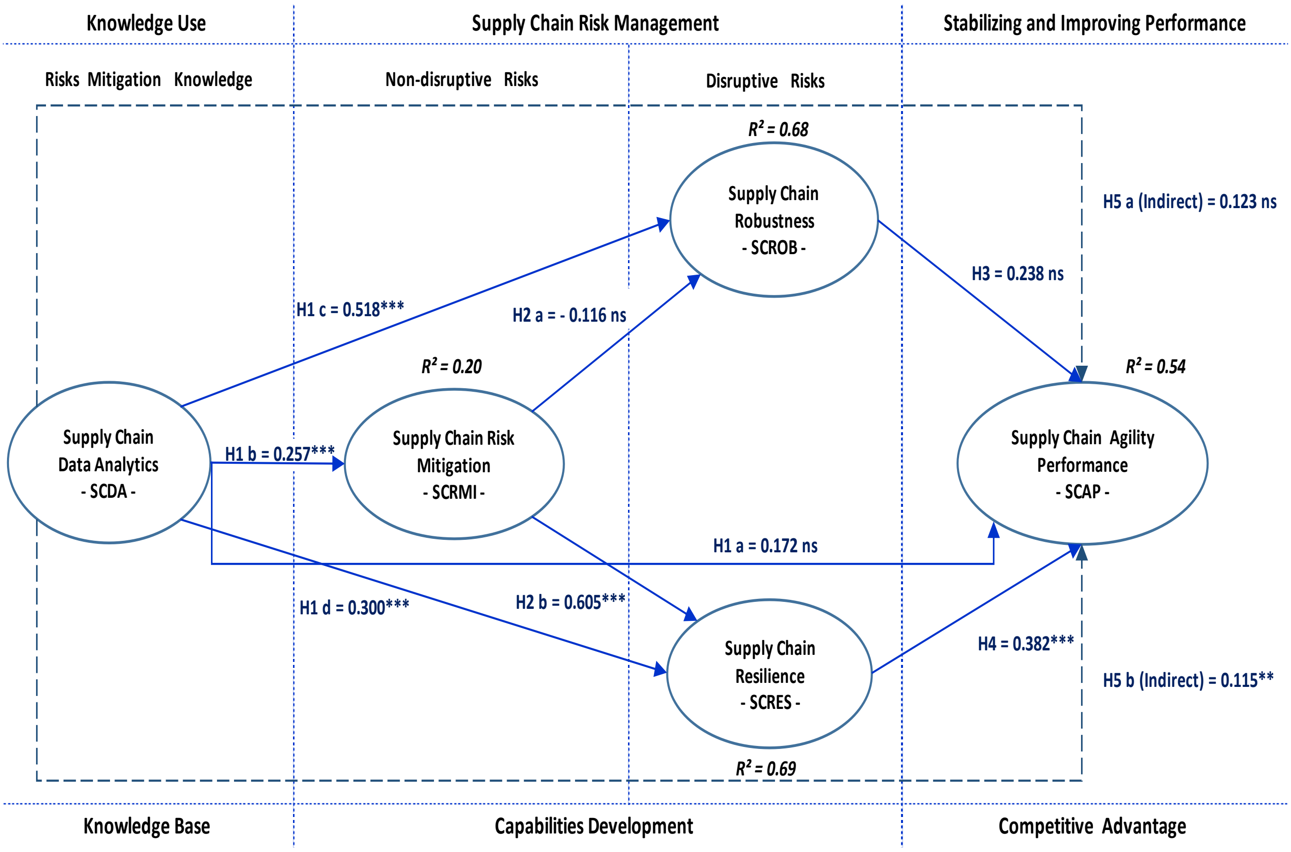

Fig. 2. Research Model Results

5.3. Mediation analysis

This study used the CB-SEM mediation test to assess the magnitude of the mediating effects of SCROB and SCRES capabilities on the relationship between SCDA capabilities and SCPA (Hair et al., 2021). This mediation analysis began by assessing the relevance of indirect effects and then the direct influence of SCDA capabilities on SCPA.

Table 5 summarizes the results of the mediation test using a bootstrapping approach by SPSS Amos 25. The significance of the indirect effects, as shown in Table 5, qualifies the mediation analysis. In addition, this analysis estimated variance accounted for (VAF = indirect effect/direct effect + indirect effect) to test the strength of the mediating effects of SCROB and SCRES.

Table 5. Results of the mediation analysis

Mediated Path	Direct effect with mediator	Indirect effect	VAF	Conclusion	Support
H5a SCDA → SCROB → SCAP	0.415	0.123 ns	0.228	No Mediation	No
H5b SCDA → SCRES → SCAP		0.115**	0.216	Partial Mediation	Yes

Notes: ** p<0.01 and ns: non-significant (p>0.1).

According to Hair et al. (2021), partial mediation is demonstrated when (VAF) exceeds the threshold level of 0.2, and when it exceeds 0.8, full mediation is proposed. The results indicate that SCRES capability partially mediates the association between SCDA capabilities and SCAP, whereas SCROB capability does not mediate this relationship because its indirect effect is insignificant.

5.4. Main findings

By theorizing the phenomenon of SCDA capabilities in the context of manufacturing supply chains, this research work makes important contributions to supply chain management as an emerging discipline (Harland et al., 2006). Because this study focused, among other things, on strengthening capabilities dedicated to risk management through data analytics, it makes an empirical contribution insofar as its results revealed positive effects of SCDA capabilities on risk mitigation (Talwar et al, 2021; Modgil et al., 2021; Park & Singh, 2023), robustness (Wieland & Wallenburg, 2012; Kwak et al., 2018; Shamout, 2019; Alvarenga et al., 2023) and resilience (Waller & Fawcett, 2013; Srinivasan & Swink, 2018; Dennehy et al., 2021).

Furthermore, this study makes a methodological contribution by developing and testing the model in the context of manufacturing supply chains and, therefore, supports calls to go beyond traditional supply chain management (Scholten & Fynes, 2017). That said, this study provides new information on the positive and simultaneous impact of SCDA capabilities on all three risk management capabilities, particularly SCRMI ($\beta = 0.257$, $p < 0.001$), SCROB ($\beta = 0.518$, $p < 0.001$) and SCRES ($\beta = 0.300$, $p < 0.001$), which had not been previously reported.

The main results of this study showed that SCDA capabilities have no direct impact on agility performance. However, their effect is partially mediated by resilience capability (Dubey et al., 2021; Bahrami & Shokouhyar, 2022). In this regard, it is important to point out that, in contrast to previous studies, the results revealed that the effect of SCDA capabilities is not mediated by robustness capability (Wang et al., 2016; Shamout, 2021).

Similarly, SCRMI capability has a positive effect on reactive resilience capability ($\beta = 0.605$, $p < 0.001$), and this is in line with previous studies (Jüttner & Maklan, 2011; Pereira et al., 2014; Heckmann et al., 2015; Ribeiro & Barbosa-Povoa, 2018; Rashid et al., 2024). However, its effect on proactive robustness capability is insignificant, in contrast to previous studies (Klibi et al., 2010; Kwak et al., 2018; Shamout, 2019).

Finally, the results showed that only resilience capability has a positive impact on agility performance ($\beta = 0.382$, $p < 0.001$), in line with previous studies (Chowdhury & Quaddus, 2017; Altay et al., 2018; Liu & Lee, 2018; Liu et al., 2024). However, these results highlighted a non-significant effect of robustness capability on said agility performance, in contrast to previous studies (Wieland & Wallenburg, 2012; Mackay et al., 2020).

5.5. Theoretical and managerial implications

This study sought to understand the mechanisms by which data analytics and risk management capabilities interact to contribute to the stabilization and improvement of agility performance during periods of disruptions in manufacturing supply chains. In addition, data analytics capabilities contribute, through the partial and exclusive mediation of resilience capability, to improved agility performance during periods of supply chain disruptions. This study is one of the first to examine the role of the two capabilities of robustness and resilience in mediating the relationship between data analytics capabilities and agility performance, which should enrich the empirical knowledge of the supply chain management literature.

The results of this study confirm that data analytics capabilities contribute indirectly to improving supply chain performance (Wamba et al., 2020; Khan et al., 2023). As such, this study considers data analytics as knowledge creation and sharing capabilities dedicated to risks and disruptions mitigation, which would facilitate timely and effective decision-making by supply chain managers. Furthermore, the results indicated that only resilience capability serves as a partial mediator between data analytics capabilities and agility performance, providing a valuable framework for investment allocation decisions by supply chain managers. Also, the results of the present study confirm that data analytics capabilities should enable the achievement of competitive advantage in an environment marked by uncertainties and disruptions (Wamba et al., 2017).

Furthermore, the results of this study underlined the vital and exclusive role of resilience capability in maintaining superior supply chain agility in times of risks and disruptions (Christopher & Peck, 2004). That said, managers should be aware that resilience is a prerequisite for success in an unpredictable environment (Gölgeci & Kuivalainen, 2020; Bahrami & Shokouhyar, 2022).

In view of the above, it is important to emphasize that managers must no longer be satisfied with the exclusive use of organizational memory to manage disruptive risks in their respective supply chains, but must resort to the tools and alerts offered by data analytics capabilities to achieve this goal (Singh, N.P. & Singh, S., 2019).

Data analytics reports provide managers with the information and knowledge they need to better understand changes and uncertainties in the environment and, as a result, make more informed and timely decisions in the event of disruptive risks. To this end, the results of this study support the idea that when managers use innovative technologies to improve risk management capabilities, their supply chains would be likely to achieve a higher level of agility performance and, consequently, competitive advantage (Akter et al., 2016; Srinivasan & Swink, 2018).

In a data-driven business environment, investment in big data technology seems a prudent choice for the simple reason that digital transformation is more a strategic than a technological orientation (Rogers, 2016). In this respect, it's important to stress that competitive advantage is a priori determined by the way the technology is exploited, not by the technology itself (Barratt & Oke, 2007).

6. Conclusion

This study was largely motivated by the urgent need to better understand the mechanisms by which data analytics and supply chain management capabilities interact to stabilize and improve agility performance. Although valuable contributions have been made to data analytics, researchers have lagged behind in examining this aspect in manufacturing supply chains. Also, existing studies focus mainly on data analytics as a technology, which has led to limited knowledge of its managerial aspects. To this end, this study uses data analysis and risk management capabilities to advance knowledge on the development of highly agile manufacturing supply chains in times of disruptions. The results showed that resilience is a key capability for building an agile supply chain, unlike robustness capability, whose positive impact on agility performance has not been demonstrated. That said, stakeholders involved in responding to disruptive risks need to take into account the technical and managerial characteristics of data analytics.

Certain limitations can be raised for this study. Firstly, this study did not take into account other dimensions of performance, particularly financial performance, in order to inform supply chain managers about the trade-off between the financial cost of investing in data analytics capabilities and the expected gain in terms of agility performance. Secondly, for reasons of generalizability and simplicity, the data has been consolidated for all companies of different sizes as well as for all manufacturing industries; however, the results could differ depending on company size and industry type. Indeed, the mechanisms by which data analytics capabilities improve risk management capabilities and agility performance deserve to be studied in future, in separate research, for the service sector and the automotive industry, as well as for small and medium-sized enterprises. Thirdly, data analytics capabilities should be explored in relation to artificial intelligence in future research. Finally, the integration of artificial intelligence and other performance dimensions would make the research model more complete for researchers and practitioners alike.

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Appendix A. Construct and survey items

Supply Chain Data Analytics Capabilities (adapted from: Shafiq et al., 2020; Khan et al., 2022):

SCDA1. Collect and analyze the latest unstructured data frequently to improve forecasting and demand planning.

SCDA2. Incorporate analysis of unstructured data into sales and operations planning.

SCDA3. Use advanced statistical techniques to process quantitative (numerical) data from internal and external sources.

SCDA4. Model the entire supply chain (or network) to determine optimal locations for production facilities, distribution centers, cross-docks, etc.

SCDA5. Use simulations to assess non-disruptive and disruptive supply chain risks and/or political, economic or legislative changes.

Supply Chain Risks Management Capability (adapted from: Yang et al., 2021):

SCRMI1. Preventing supply chain risks (e.g. select a more reliable supplier, use clear safety procedures, preventive maintenance).

SCRMI2. Detecting supply chain risks (e.g. internal or supplier monitoring, inspection, tracking).

SCRMI3. Responding to supply chain risks (e.g. backup suppliers, extra capacity, alternative transportation modes).

SCRMI4. Recovering from supply chain risks (e.g. task forces, contingency plans, clear responsibility).

Supply Chain Robustness Capability (adapted from: Wieland and Wallenburg, 2012; Kwak et al., 2018):

SCROB1. Our supply chain and logistics networks can remain effective and sustain even when internal/ external disruptions occur.

SCROB2. Our supply chain and logistics networks can avoid or minimize risks occurrence by anticipating and preparing for them.

SCROB3. Our supply chain and logistics networks can absorb a significant level of negative impacts from recurrent risks.

SCROB4. Our supply chain and logistics networks can have sufficient time to consider most effective reactions.

Supply Chain Resilience Capability (adapted from: Dubey et al., 2021):

SCRES1. Our organization can easily restore material flow.

SCRES2. Our organization would not take long to recover normal operating performance.

SCRES3. The supply chain would quickly recover to its original state.

SCRES4. Our organization can quickly deal with disruptions.

Supply Chain Agility Performance (adapted from: Swafford et al., 2008):

SCAP1. Speed in reducing manufacturing lead-time during periods of supply chain disruptions.

SCAP2. Speed in reducing development cycle time during periods of supply chain disruptions.

SCAP3. Speed in increasing frequencies of new product introductions during periods of supply chain disruptions.

SCAP4. Speed in adjusting delivery capability during periods of supply chain disruptions.

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