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Digital learning, big data analytics and mechanisms for stabilizing and improving supply chain performance

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Abstract:
This study attempts to shed light on the nature of the contribution of digital learning orientation (DLO), as an intangible resource, to the development of the dynamic capability of supply chain data analytics powered by artificial intelligence (SCDA-AI) as well as to the moderation of its effects on the enhancement of the operational capabilities of supply chain flexibility (SCFL), supply chain resilience (SCRE) and supply chain responsiveness (SCRES) in order to stabilize and improve supply chain performance (SCPER) in times of uncertainties and disruptions. The study was based on survey data collected from 200 foreign companies based in Morocco. Respondents were mainly senior and middle managers with experience in general management and supply chain (SC). Validity and reliability analyses and hypothesis testing were carried out using structural equation modelling (SEM) with SPSS Amos. The results revealed that DLO acts as an antecedent to SCDA-AI without moderating its effects on the three operational capabilities of SCFL, SCRE and SCRES. In addition, this study provides further empirical evidence that dynamic capabilities can produce significant results in terms of stabilizing and improving performance through the generation and/or reconfiguration of operational capabilities in situations of uncertainties and disruptions.

Keywords:
digital learning; supply chain; data analytics; capabilities; disruptions.

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1. Introduction

Given the rapid diffusion of information technology, big data has gained strategic importance and is recognized as one of the most valuable assets for many companies [1], [2], [3]. Big data includes heterogeneous formats and is characterized by its volume, variety, velocity, and veracity [4]. The accumulation of data has led many companies and supply chains (SCs) to develop analytical capabilities to transform this data into useful information that can improve decision making and support the performance of their SCs [5].

Supply Chain Data Analytics (SCDA) powered by artificial intelligence (AI) is one of the opportunities offered by the technological environment, which could be seized to generate unanticipated and unpredictable business value for both SCs and their partner companies [6]. To this end, SC partners are investing in the development of a dynamic capability dedicated to supply chain data analytics powered by artificial intelligence (SCDA-AI) in order to reduce costs and uncertainties, increase the effectiveness and efficiency of decision-making [7] and, ultimately, gain competitive advantage [8]. As such, accurate and timely data coupled with AI-driven data analytics could enhance the operational capabilities of supply chain flexibility (SCFL), supply chain resilience (SCRE), and supply chain responsiveness (SCRES) to respond to changes in customer requirements and needs and to risks and disruptive events in SC [9].

Furthermore, the literature on SCDA-AI capability has tended to focus on the technical dimension of the concept and its effects on SC process improvement. However, some studies have highlighted the importance of other complementary and intangible resources, particularly digital learning orientation (DLO) [10]. Indeed, the literature has largely focused on the direct role of DLO in collaborative development of SCDA-AI and performance improvement [11], [12]. These virtual mechanisms are even more important for the manufacturing sector due to its complexity and sensitivity to changes in customer requirements and disruptive events [12]. However, Marra et al. [13] point out that there is no evidence that digital technology in itself contributes to supply chain performance (SCPER).

This article responds to this call by describing the effects of SCDA-AI on SCFL, SCRE, SCRES and SCPER, as well as the direct and moderating effects of DLO on SCDA-AI's dynamic capability and its relationships with operational capabilities, through the reliance on organizational information processing theory (OIPT) and the dynamic capability view (DCV) as theoretical foundations. This being said, this paper attempts to shed new light on DLO as an antecedent resource to the development of dynamic capability of SCDA-AI and their respective contributions to the enhancement of the operational capabilities of SCFL, SCRE and SCRES, which should stabilize and improve SCPER in situations of uncertainties and disruptions. To this end, the present study attempts to answer the following research questions (RQs):

- RQ1. How does the intangible resource of DLO affect the development of the dynamic capability of SCDA-AI and its effects on the enhancement of the operational capabilities of SCFL, SCRE and SCRES?
- RQ2. How do the operational capabilities of SCFL, SCRE and SCRES influence SCPER in times of uncertainties and disruptions in manufacturing companies' supply chains?

In light of the above, the objectives of this study are to examine (1) the direct and moderating effects of DLO's intangible resource on the development of SCDA-AI's dynamic capability and its relationships with SCFL, SCRE and SCRES; (2) the direct effects of SCDA-AI's dynamic capability on strengthening the operational capabilities of SCFL, SCRE and SCRES; (3) the direct effects of SCFL, SCRE and SCRES capabilities on the stabilization and improvement of SCPER in situations of uncertainties and disruptions in SCs. Using survey data obtained from 200 foreign manufacturing companies based in Morocco, this study employs structural equation modeling (SEM) using SPSS Amos. As such, this study seeks to contribute to the literature by highlighting the importance of developing the dynamic and collective capability of SCDA-AI, as well as the intangible resource of DLO, in terms of dealing with changes in customer requirements and disruptive events and, consequently, their impact on strengthening the operational capabilities of SCFL, SCRE, and SCRES and, ultimately, on SCPER.

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. The main limitations and future directions of the research are announced in section 6.

2. Theoretical background

2.1 Organizational information processing theory (OIPT)

OIPT states that an organization evolves in a system, integrating several internal and external processes characterized by their complexity and uncertainty [14]. The theory provides a solid basis for explaining the organizational behavior of firms through the mechanisms of information processing. Gattiker and Goodhue [15] identified several sources of uncertainty, among them, instability in the SC environment, which requires more flexibility, resilience and responsiveness in the SC [16].

The increase in the volume of data managed by organizations implies an increased reliance on information processing, which requires the involvement of multiple internal and external entities [17]. This volume of data requires greater visibility to ensure effective decision making. According to Wong et al. [18], an organization's or SC's capability to deal with data could be initiated by an orientation of learning and inter-organizational sharing of mutually useful information to enhance the collaborative environment, reduce uncertainties, and mitigate disruptions. Premkumar et al. [19] argue that the lack of a learning and information processing orientation in an uncertain environment generates significant costs for organizations. Recent studies have shown that information processing capability, specifically SCDA-AI, improves performance and enhances a firm's competitive advantage [20].

2.2 Dynamic capability view (DCV)

DCV is a theoretical paradigm to better understand how firms develop competitive capabilities by adopting new technologies, including SCDA-AI [21]. In this regard, dynamic capabilities (DCs) also refer to an organization's ability to respond in a rapidly changing environment [22].

An important aspect of DCs is the presence of tools that can promote integrative learning mechanisms of endogenous knowledge. This helps promote DCs, which allows a firm to develop a competitive advantage [23]. DCs are strategically important for firms operating in a rapidly changing environment, where they need to react and adapt in a timely manner to a changing business environment [24]. In line with DCV, SCDA-AI, as a dynamic capability, modifies a company's resource base, operational routines and skills, particularly those relating to flexibility, resilience and responsiveness [25]. DCs have also been associated with tacit organizational elements, such as orientations, routines, processes, knowledge, and managerial knowledge [26]. According to DCV, the presence of a digital learning orientation, as an intangible resource, and SCDA-AI, as a dynamic capability, enables companies to anticipate, mitigate, and respond to changing customer demands and potentially disruptive events and ultimately gain competitive advantage through continuous reconfiguration of operational capabilities.

2.3 Digital learning orientation (DLO)

In the context of contemporary digital transformation, several studies have highlighted the relevance of digital literacy, digital ethics, and digital learning in building sustainable organizations and SCs [27], [28]. According to Graham [29], a learning orientation leads organizations to collaborate externally and be more cross-functional internally, which facilitates the sharing of useful information [30]. Furthermore, recent studies have shown that digital learning influences, primarily, intellectual openness, cognitive processes and strategies, and useful information-based knowledge [31].

However, despite the growing interest in this area of research, previous studies have exclusively examined the use of digital technologies and their results [32], [33], [34]. However, the present study aims to determine whether DLO would influence the development of the dynamic capability of SCDA-AI, while moderating its effects on SCFL, SCRE and SCRES, which ultimately impact SCPER in situations of uncertainty and disturbance.

2.4 Supply chain data analytics powered by artificial intelligence (SCDA-AI)

SCDA, enhanced by the use of cognitive technologies, in particular AI, helps to improve decisions about the complex processes of SC [35], [36]. In this respect, cognitive technologies enable machines to understand complex situations at high speed, process large amounts of data and interact like humans [37].

Today, it is imperative that companies and their SCs develop analytics capabilities to process the large volumes of data collected in real time in order to convert them into useful information and knowledge for achieving competitive advantage [38]. To this end, the joint use of cognitive technology (AI) and SCDA will enable more effective decision-making [39]. Also, AI technology has opened up many opportunities in supply chain management (SCM), especially process improvement, real-time responses to changing customer requirements, resource optimization, cost rationalization, and effective risk and disruption mitigation [40].

2.5 Supply chain flexibility (SCFL)

Companies are pursuing different strategies to achieve flexibility [41], some of which are investing in the development of SCDA-AI capability in order to achieve supply chain visibility and, consequently, minimize uncertainty by promoting rapid, informed decision-making [42]. It is also clear that manufacturing flexibility is essential to achieve responsiveness [43] and to respond quickly and effectively to internal and external changes [42]. In addition, efforts to enhance FSCL capability should extend beyond internal functional areas [44].

The literature has recognized that the development of SCFL capability is a costly investment, which should be undertaken with caution [45]. Recent studies have suggested that companies should perceive SCFL as a collective capability requiring an integrated effort on the part of SC partners. Indeed, this study perceives SCFL as the coordinated capability of SC partners to adjust, adapt and transform their resources and processes to cope with external dynamism.

2.6 Supply chain resilience (SCRE)

SCRE is an operational capability that allows a disrupted SC to recover and be more powerful than before [46]. Indeed, SCRE enables partner firms in a SC to cope with difficulties and adversities and to discern various opportunities in the business environment [47]. Furthermore, it is an indispensable ingredient of holistic risk management practices [47]. It is considered a long-term continuity element [48], creating a competitive advantage [47]. Indeed, members of an SC are responsible for building resilience in their organization and promoting the resilience of the entire system [47]. Due to the increasing exposure to SC risks, there is an increased focus on the need to improve SCRE capability [49].

2.7 Supply chain responsiveness (SCRES)

SCRES is the ability to respond to immediate or sudden market dynamics [50]. In other words, SCRES is a company's ability to respond effectively and rapidly to changing customer needs and requirements [51]. In this respect, a company's ability to be responsive also depends on its SC partners and their collective efforts [52]. According to Singh [53], the level of SCRES is measured by the speed with which the SC can modify its production within the range of the four types of external flexibility, in particular product, volume, combination and delivery, in order to respond to external stimuli [54]. Indeed, SC must be able to meet challenges pertaining to reducing manufacturing and delivery times, shortening product life cycles, and improving product variety [55]. Thus, responsiveness is considered one of the operational capabilities that enable SCs to gain competitive advantage [56].

3. Hypothesis development

Figure 1 presents our research model.

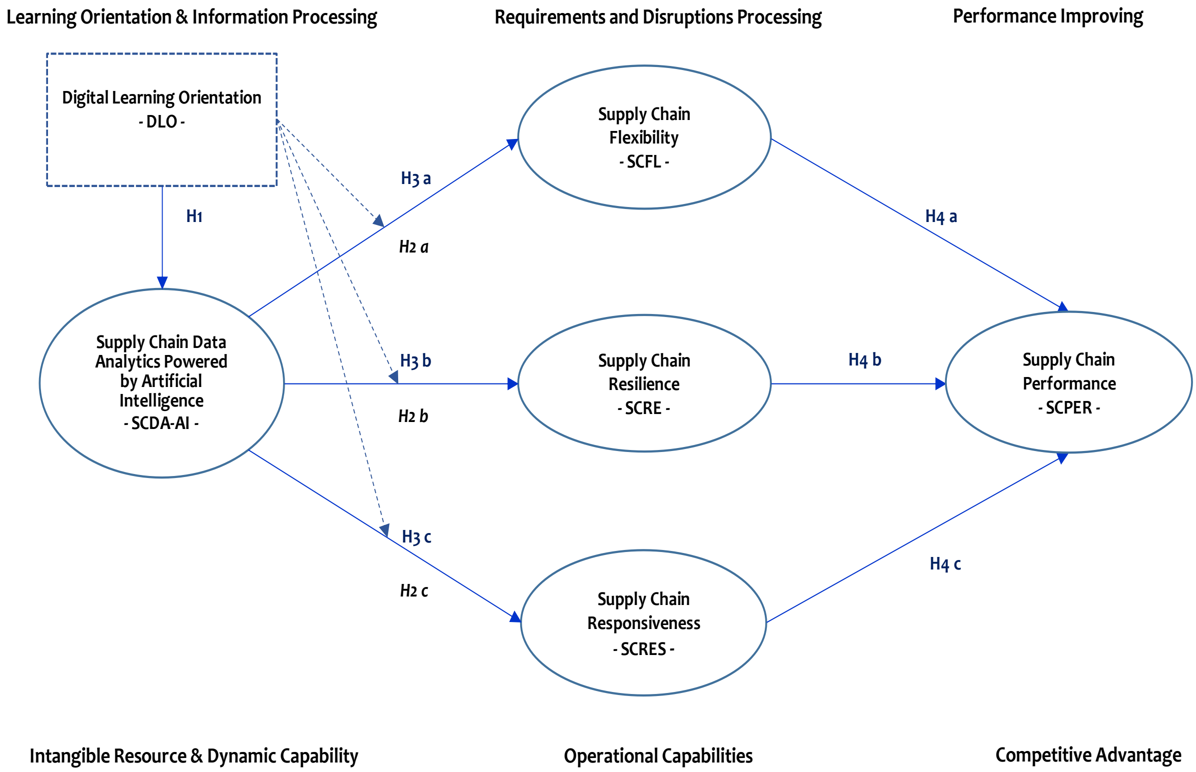

Fig. 1. Research Model

3.1 Direct effect of the DLO

Companies and SCs focused on learning are always looking to improve their processes by adopting effective ways of organizing themselves into cross-company and cross-functional teams [57]. Learning capability is an intangible resource antecedent to any collaborative development of dynamic and/or operational capabilities, enabling the effective and efficient management of changing customer requirements and needs, as well as the mitigation of resulting disruptions [29].

Therefore, it is hypothesized that:

H1. DLO has a positive effect on SCDA-AI.

3.2 Moderating effects of DLO

The focus on learning leads CS partner organizations to collaborate externally and be more cross-functional internally, to facilitate the sharing of useful information and new knowledge [30]. In order to keep learning up to date, information needs to be systematically reassessed and structured, particularly that inherent in customer requirements and needs and potential disruptions, thereby continuously enhancing SCFL, SCRE and SCRES capabilities [57], [3].

Therefore, it is hypothesized that:

H2a. DLO positively moderates the relationship between SCDA-AI and SCFL.

H2b. DLO positively moderates the relationship between SCDA-AI and SCRE.

H2c. DLO positively moderates the relationship between SCDA-AI and SCRES.

3.3 Direct effects of the SCDA-AI

SCDA-AI and SCFL

SCDA-AI can be effectively used to cope with uncertainties in SCs by changing the level of SCFL. Also, SCDA-AI improves SCFL, which results in improved performance [58], [59]. In addition, the development of dynamic capability of SCDA-AI is necessary to meet the SC's needs for flexibility and responsiveness. According to Gawankar et al. [60], SCDA-AI would mitigate decision-making inefficiencies as well as several obstacles to SCFL caused by the bullwhip effect in the SC. Therefore, in a disruptive and highly volatile situation, SCDA-AI is strongly linked to SCFL.

Therefore, it is hypothesized that:

H3a. SCDA-AI has a positive effect on SCFL.

SCDA-AI and SCRE

Previous studies on SCM have highlighted the importance of SCDA-AI for its positive effect on organizational performance [61]. However, the role of SCDA-AI in enhancing SCRE has not been sufficiently examined by the literature. In addition, some studies have shown a positive relationship between SCDA-AI and SCV [17]. Recently, Dubey et al. [62] argued that SCDA-AI has a direct and positive effect on SCRE. To this end, investment in developing SCDA-AI capability leads to improved SCV and, consequently, improved SCRE [63], [64], [65].

Therefore, it is hypothesized that:

H3b. SCDA-AI has a positive effect SCRE.

SCDA-AI and SCRES

In an uncertain and dynamic environment in terms of changing customer requirements and needs, quick action is needed to deal with these changes, which is only possible by developing SCDA-AI, as an environmental information processing capability [66]. SCDA-AI extracts information that can be useful in making decisions about new and non-standard customer requirements. SCRES capability aims to reduce manufacturing flow and transport/distribution time [67]. To this end, SCDA-AI makes it possible to build a responsive SC, facilitating optimized positioning of key resources and actors (suppliers, carriers, distributors), in order to gain a competitive advantage

Therefore, it is hypothesized that:

H3c. SCDA-AI has a positive effect on SCRES.

3.4 Direct effects of the SCFL, SCRE and SCRE

SCFL and SCPER

The SCM literature has recognized that SCFL contributes to the achievement of performance objectives [68]. As such, Chirra et al. [69] have emphasized that SCFL is necessary for companies to improve their SCPER. Other studies have pointed out that SCDA-AI acts as a catalyst for SCFL, which would lead to SCPER improvement. Consequently, Tseng et al. [70] found that SCFL as well as the quality of information created and shared are among the main criteria influencing SCPER.

Therefore, it is hypothesized that:

H4a. SCFL has a positive effect on SCPER.

SCRE and SCPER

This research argues that the SCRE should be supported by the SCDA-AI to mitigate disruptive risks, and this to ensure a stabilization of the SCPER level [71]. The negative impact of disruptions in SC could be avoided by enhancing SCRE capability, enabling a return, within a desirable timeframe, to the favorable performance level after the impact of a disruptive incident [72]. However, other research has demonstrated a favorable association between SCRE and various performance dimensions [47], [73]. Therefore, it is hypothesized that:

H4b. SCRE has a positive effect on SCPER.

SCRES and SCPER

SCRES capability is an essential element for companies to meet changing global market demands and, as a result, withstand global competition [74]. As such, high levels of SCRES enable companies to respond better to customer needs than their competitors. Also, some previous studies have examined the essential role of SCRES in improving company and market performances [51]. Therefore, it is hypothesized that:

H4c. SCRE has a positive effect on SCPER.

4. Research methodology

4.1 Data collection

In this study, the target sample was made up of managers of foreign manufacturing companies located in industrial acceleration zones in Morocco. These managers were targeted because they belong to companies that are partners in global value chains (GVCs), which often face a high degree of uncertainty, adverse conditions and risks of disruption [47]. To this end, the database of the Ministry of Industry and Trade was exploited to carry out an online survey in 2023 to test the hypotheses. The initial sample included informants involved in the general management and SCM. After eliminating mailing errors, the sample included 765 contacts. At the end of the survey period, 200 completed questionnaires were received by the respondents, a response rate of 26.1%. This is, in effect, a medium sample size [75] and a number of observations greater than the free parameters of the model which is a necessary condition for identifying a structural model [75]. 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	25%
101 to 200 employees;	15	7.5%
201 to 300 employees;	45	22.5%
More than 300 employees.	90	45%
Manufacturing industry type:		
Automotive industry;	60	30%
Aeronautics and aerospace industry;	53	26.5%
Food industry;	35	17.5%
Pharmaceutical industry;	25	12.5%
Electronic and electrical components industry;	15	7.5%
Rubber and plastic products industry.	12	6%
Nationality of respondent companies:		
Spanish companies;	50	25%
French companies;	43	21.5%
German companies;	31	15.5%
Portuguese companies;	30	15%
Japanese companies;	26	13%
American companies.	20	10%

Structure of the sample	Frequency	Valid %
Respondent designation:		
Top management;	95	47.5%
Middle management;	83	41.5%
Lower management.	22	11%
Respondent experience:		
Less than 3 years;	18	9%
3 to 5 years;	32	16%
6 to 9 years;	63	31.5%
More than 9 years.	87	43.5%
Total	**200**	

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 Table 2.

The dynamic capability of the SCDA-AI was operationalized by four items adapted from the scale of Srinivasan and Swink [17] and Dubey et al. [20]. The operational capability of SCFL was operationalized by four items adapted from the scale of Rojo et al. [76] and Juan et al. [77]. The operational capability of SCRE was operationalized by four items adapted from the scale of Dubey et al. [62]. The operational capability of SCRES was operationalized by four items adapted from the scale of Qrunfleh and Tarafdar [51] and Williams et al. [42]. The intangible resource of DLO was operationalized by three items adapted from the scale of Iyer et al. [57]. SCPER was operationalized by four items adapted from the scale of Wamba et al. [78] and Gu et al. [79].

Table 2. Measures, reliability, and validity.

Measures	Loadings	Cronbach's α	Composite Reliability (CR)	Average Variance Ext. (AVE)
Supply Chain Data Analytics Powered by Artificial Intelligence (adapted from: Srinivasan & Swink [17]; Dubey et al. [20]):				
SCDA-AI1. Use of advanced analytical techniques (e.g., simulation, optimization, regression) to improve decision-making.	0.831	0.937	0.910	0.719
SCDA-AI2. Use of multiple data sources to improve decision-making.	0.865			
SCDA-AI3. Use of data visualization techniques (e.g., dashboards) to assist decision-maker in understanding complex information.	0.926			
SCDA-AI4. Deployment of dashboard applications/information in communication devices (e.g., smart phones, computers) of the supply chain processes.	0.934			
Supply Chain Flexibility (adapted from: Rojo et al. [76]; Juan et al. [77]):				
SCFL1. Our supply chain can adjust manufacturing facilities, processes and operations.	0.845	0.884	0.838	0.571
SCFL2. Our supply chain can rationalize through information systems the management of transport and distribution.	0.786			
SCFL3. Our supply chain can adjust its delivery lead times.	0.837			
SCFL4. Our supply chain can adjust its size of orders.	0.772			
Supply Chain Resilience (adapted from: Dubey et al. [62]):				
SCRE1. Our supply chain can easily restore the flow of materials.	0.845	0.806	0.859	0.612
SCRE2. Our supply chain would not take long to recover normal operating performance.	0.973			
SCRE3. Our supply chain would quickly recover to its original state.	0.665			
SCRE4. Our supply chain can quickly deal with disruptions.	0.500			

Measures	Loadings	Cronbach's α	Composite Reliability (CR)	Average Variance Ext. (AVE)
Supply Chain Responsiveness (adapted from: Qrunfleh & Tarafdar [51]; Williams et al. [42]):				
SCRES1. Our supply chain is able to handle difficult nonstandard orders.	0.627	0.778	0.827	0.549
SCRES2. Our supply chain is able to produce products characterized by numerous features options, sizes and colors.	0.695			
SCRES3. Our supply chain is able to adjust capacity so as to accelerate or decelerate production in response to changes in customer demand.	0.500			
SCRES4. Our supply chain is able to introduce large numbers of product improvements/variation.	0.792			
Digital Learning Orientation (adapted from: Iyer et al. [57]):				
DLO1. Our supply chain sees digital learning as an investment rather than an expense in the age of big data.	0.775	0.767	0.847	0.649
DLO2. Digital learning capability is essential for improving our supply chain processes in the era of massive data.	0.837			
DLO3. We have specific mechanisms for the digital sharing of useful information and knowledge learned in supply chain processes in the era of big data.	0.571			
Supply Chain Performance (adapted from: Wamba et al. [78]; Gu et al. [79]):				
SCPER1. We were able to save more on operating costs.	0.851	0.891	0.882	0.651
SCPER2. We can achieve a better return on investment.	0.783			
SCPER3. We are able to achieve shorter lead times.	0.776			
SCPER4. We are able to meet customers' diversified product requirements	0.777			
Fit indices: x2/df (chi-square) = 457,430 / 216 = 2.118, standardized root mean square residual (SRMR) = 0.0664, root mean squared error of approximation (RMSEA) = 0.074, Tucker-Lewis's index (TLI) = 0.912, comparative fit index (CFI) = 0.925.				

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 [80]. 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 concepts is less than 0.90, the bias of the common method is accepted [81]. As shown in Table 3, the correlations between concepts in this study are below 0.90.

Table 3. Inter-construct correlation estimates and related AVEs

	SCRE	SCDA-AI	SCFL	SCRES	SCPRE	DLO
SCRE	**0.782**					
SCDA-AI	0.693	**0.848**				
SCFL	0.737	0.707	**0.756**			
SCRES	0.691	0.662	0.704	**0.741**		
SCPER	0.680	0.652	0.694	0.650	**0.807**	
DLO	0.561	0.537	0.572	0.536	0.528	**0.805**

Note: The values on the diagonal (in bold) represent the square root of average variance extracted (AVE) for each factor, while the variables below the diagonal represent the correlations between each pair of factors.

4.4 Data analysis technique

Confirmatory factor analysis (CFA) using SPSS Amos 22 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, 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 [75]. Similarly, SEM facilitates the examination of the overall causal fit of a holistic model as well as moderation effects.

4.5 Reliability and validity

The measurement model was evaluated on the basis of the reliability of the internal consistency and the converging validity of measurements associated with the constructs and the discriminant validity. Internal consistency reliability was tested by Cronbach's α ($\alpha > 0.767$) and composite reliability (CRs > 0.827), 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 > 0.549), 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 [82], as displayed in Table 3.

In addition, CFA analysis was done to validate the factor structure of variables under the focus of this study. Kline's [83] recommendations on several statistical parameters were used to evaluate the model's goodness of fit (chi-squared/degrees of freedom: $\chi 2/df < 3$, 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 six-factor measurement model had a satisfactory fit (x2/df = 457,430 / 216 = 2.118, $p < 0.001$, SRMR = 0.0664, TLI = 0.912, CFI = 0.925, RMSEA = 0.074), as displayed in Table 2.

5. Results and discussion

5.1 Main results

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 three moderation hypotheses H2a (SCDA-AI*DLO → SCFL), H2b (SCDA-AI*DLO → SCRE), and H2c (SCDA-AI*DLO → SCRES), the rest of the research model hypotheses were well supported. The standardized correlation coefficients are presented in Table 4 and Figure 2.

Table 4. Results of the path analysis and hypothesis testing

Causal Path				**Estimate**	**S. E**	**P**	**Support**
H1	DLO	→	SCDA-AI	0.151	0.129	*	Yes
H2a	SCDA-AI*DLO	→	SCFL	-0.176	0.032	ns	No
H2b	SCDA-AI*DLO	→	SCRE	-0.302	0.038	ns	No
H2c	SCDA-AI*DLO	→	SCRES	-0.142	0.041	ns	No
H3a	SCDA-AI	→	SCFL	0,824	0.053	***	Yes
H3b	SCDA-AI	→	SCRE	0.443	0.050	***	Yes
H3c	SCDA-AI	→	SCRES	0.653	0.065	***	Yes
H4a	SCFL	→	SCPER	0.368	0.098	***	Yes
H4b	SCRE	→	SCPER	0.146	0.090	*	Yes
H4c	SCRES	→	SCPER	0.426	0.125	***	Yes

Notes: S.E: Standard error; *** p<0.001; * p<0.1 and ns: non-significant.

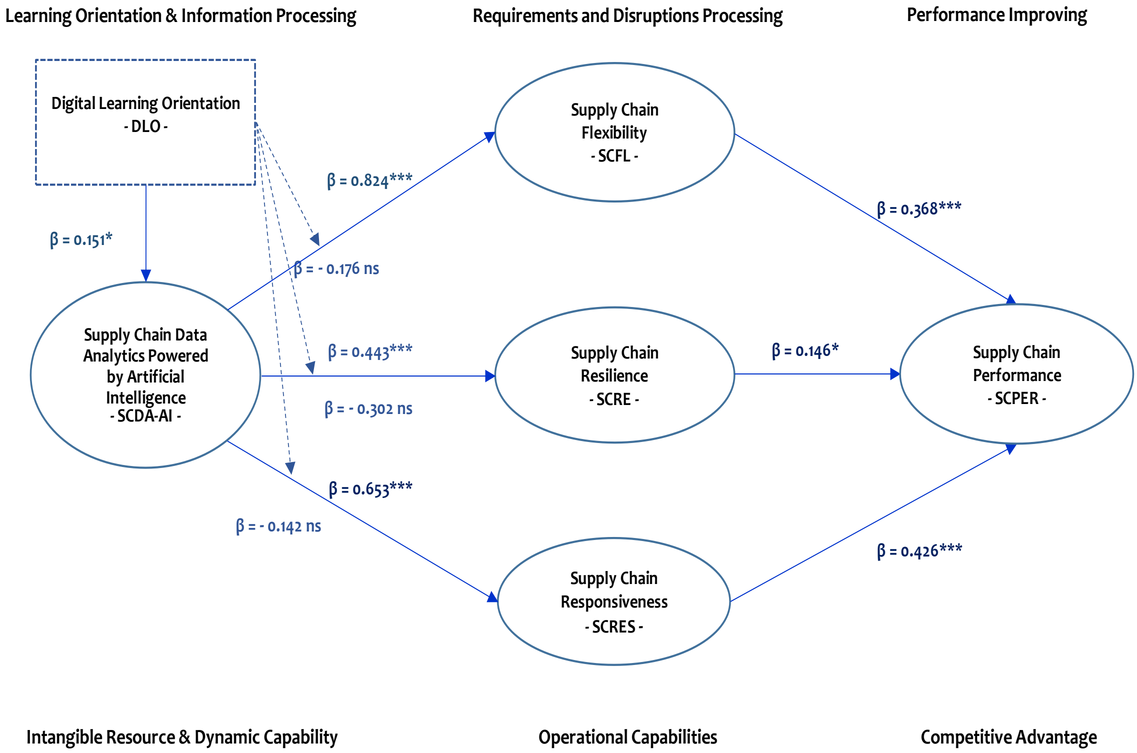

Fig. 2. Final SEM Model.

5.2 *Theoretical implications*

This study used OIPT to understand how the intangible resource of DLO could moderate the direct effects of SCDA-AI on the enhancement of operational capabilities of SCFL, SCRE and SCRES in times of uncertainty and disruption, and address the fact that DVC is inappropriate to explain the antecedents of SCDA-AI development as a dynamic capability. Indeed, the present study is one of the first to test the relationships between an intangible resource (DLO), a dynamic capability (SCDA-AI), three operational capabilities (SCFL, SCRE and SCRES) and SCPER.

Furthermore, the results obtained revealed that DLO acts, in line with the results of the study conducted by Iyer et al [57], as an antecedent to the development of SCDA-AI capability. However, this study did not demonstrate the moderating effect of DLO on the relationships between the dynamic capability of SCDA-AI and the operational capabilities of SCFL, SCRE and SCRES, in contrast to the studies carried out by Iyer et al [57] and Benzidia et al [3].

In addition, this study provided further empirical evidence that the dynamic capability of SCDA-AI can produce excellent results in terms of enhancing operational capabilities, particularly SCFL, SCRE and SCRES, following the example of studies conducted by Fernando et al [58], Edwin Cheng et al [59], Dubey et al [62] and Abdelkafi and Pero [66].

Furthermore, the present study has demonstrated that the three operational capabilities do indeed have direct and positive effects on SCPER, which is comparable to the results announced by the studies carried out by Chirra et al [69], Tseng et al [70], Gölgeci and Kuivalainen [47], Belhadi et al [73] and Qrunfleh and Tarafdar [51].

5.3 *Managerial implications*

The results of this study provide guidance to managers exploiting analytical capabilities to extract information useful for decision-making in the management of complex SC networks. In this regard, SC partners are investing in the implementation of this SCDA-AI collaborative capability, without any assurance of positive results. Indeed, the results obtained suggest that DLO is an antecedent to the development of SCDA-AI, as a higher-order dynamic capability, with positive effects on enhancing the operational capabilities of SCFL, SCRE and SCRES. Consequently, the presence of DLO's intangible resource encourages SC managers to develop SCDA-AI in order to achieve the desired results, in an environment marked by uncertainties in demand and supply and the resulting disruptions.

In addition, the results inspire SC managers and policy-makers alike on the important role that Big Data analytics capability (SCDA) and cognitive technology (AI) jointly play in mitigating uncertainties and disruptions. These findings are explicit and particularly useful for manufacturing sector decision-makers. In addition, they provide guidance to managers engaged in the implementation of SCDA-AI on how this capability enhances operational capabilities, particularly SCFL, SCRE and SCRES, and their contribution to improving SCPER in times of uncertainties and disruptions.

Finally, the results confirm that SC partner companies need to undertake collaborative efforts to develop high-order dynamic capability of SCDA-AI in order to strengthen other operational capabilities dedicated to SCFL, SCRE and SCRES and, ultimately, to mitigate supply and demand uncertainties and related disruptions.

6. Conclusion

Supported by OIPT and DCV, this study examines the interactions between the intangible resource of DLO, the dynamic capability of SCDA-AI and the operational capabilities of SCFL, SCRE and SCRES, as well as their respective contributions to the stabilization and improvement of SCPER. In this respect, the main results show that DLO is indeed an antecedent of SCDA-AI without, however, having a moderating effect on the enhancement of SCFL, SCRE and SCRES capabilities by SCDA-AI.

In addition, SCDA-AI capability has a positive impact on the three operational capabilities of SCFL, SCRE and SCRES, enabling companies and SCs to cope with supply and demand uncertainties and the resulting disruptions. Furthermore, it appears that SCFL and SCRES capabilities have relatively strong positive effects on SCPER compared with SCRE, demonstrating the stabilizing or improving performance role played by each of the three operational capabilities.

Some limitations could be raised for this study. Firstly, this study used cross-sectional data to test the research hypotheses. Indeed, it seems difficult to assess causality between hypothesized relationships using this type of data. Therefore, a longitudinal study is highly recommended to comprehensively address unanswered questions related to causality and common method bias. Secondly, this study tested a research model incorporating six constructs: one intangible resource (DLO), one higher-order dynamic capability (SCDA-AI), three operational capabilities (SCFL, SCRE and SCRES) and a single performance perspective (SCPER). However, other types of resources and capabilities, as well as performance perspectives and dimensions, can be studied to further explain their collective interactions in terms of performance improvement. Thirdly, this study did not take into account other dimensions and perspectives of performance, particularly the financial dimension and the organizational perspective, in order to inform managers of companies and SCs about the trade-off to be made between the financial cost of investing in SCDA-AI capability and the expected gain in terms of performance. Fourthly, for reasons of generalizability and simplicity, data have been consolidated for all manufacturing activities. However, the results may differ according to the type of industry and service companies. Finally, SCDA capability should be explored in relation to AI in future research, making the research model more comprehensive and integrated for researchers and practitioners.

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