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Uncertain Supply Chain Management

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The role of artificial intelligence in supply chain analytics during the pandemic

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A B S T R A C T

Article history:
Received November 1, 2022
Received in revised format
December 10, 2022
Accepted April 5 2023
Available online
April 5 2023

Keywords:
Artificial intelligence
Supply chain analytics
Alliance management
Environmental dynamism
Dynamic capability view

The global supply networks have been disrupted and weak connections exposed to an extent that few people have ever seen in their lifetime due to the COVID-19 epidemic. As a result of the severity of the crisis, every country and industry is feeling the effects, and the massive shifts in demand and supply that have happened throughout the epidemic are easily distinguishable from the effects of previous crises. We looked into the adaptability of alliance management and AI-driven supply chain analytics in the context of an ever-changing external environment. We examined four hypotheses in this area using survey data from the American auto components manufacturing industry. To do the analysis, we used Smart PLS. Alliance management capabilities, mediated by AI-powered supply chain analytics capacity, have been found to increase an organization's operational and financial performance. We also discovered, with environmental dynamics as a moderating factor, that alliance management capability has a substantial impact on AI-powered supply chain analytics capabilities. Based on our findings, we have a deep appreciation for the interplay between dynamic capacities and the relational view of organization. Finally, we pointed up the limitations of our study and offered a number of directions for future investigation that might help address some of the concerns that our results raise.

1. Introduction

Cognitive technologies like artificial intelligence (AI) used in supply chain analytics (SCA) aid in making better judgments about intricate processes in the supply chain (Asmussen & Møller, 2020). Technology with cognitive capabilities can learn and interact like humans, as well as understand complex situations rapidly while processing vast volumes of data (Dwivedi et al., 2021). During a pandemic crisis, interest in AI-powered supply chain analytics (AI-SCA) has soared (Ivanov, 2020). Due to the importance placed on AI-SCA capacity (AI-SCAC), we conducted a theory-driven investigation into its causes and the ways in which it affected performance during the COVID-19 pandemic. AI-SCAC has been heralded as a game-changer in recent years, particularly as a means of coping with the pandemic, with its use rising dramatically across all functional departments of the company at this time of crisis (Sheng, Amankwah-Amoah, Khan, & Wang, 2021). Despite the abundance of theoretical work on AI-SCAC, empirical research is limited.

Since the onset of the COVID-19 pandemic, consumers have been unable to pay for products and services, and businesses have been unable to meet demand for raw materials (Queiroz, Ivanov, Dolgui, & Fosso Wamba, 2020). Day's sales outstanding, accounts payable, and accounts receivable have all been adversely impacted. Most businesses have faced significant challenges with working capital management, many of which have been handled with the use of data analytics.

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doi: 10.5267/j.uscm.2023.4.005

Experts in the field of supply chain management have observed that SCA capacity may fundamentally alter the way businesses are conducted in the future (Schoenherr & Speier-Pero, 2015).

The COVID-19 pandemic has caused widespread disruption to the supply chain, which has resulted in critical resource shortages (Ketchen Jr & Craighead, 2020). Organizations are making substantial efforts to adapt to new norms by leveraging relationships (Crick & Crick, 2020). Successful analytics capability was put to use during the pandemic, and we saw evidence of this in the form of firms with superior alliance management skills (Hanelt, Bohnsack, Marz, & Antunes Marante, 2021). Alliance management capability (AMC) is seen as a source of competitive advantage because of the many benefits that can be gained from working with other businesses. These benefits include increased knowledge sharing and collaboration, access to new technologies and resources, and the promotion of new ideas and products (Schreiner, Kale, & Corsten, 2009). Despite widespread agreement, there is less empirical proof that AMC actually affects SCAs. In light of this, our research is among the first to investigate how AMC affects SCA performance. We further contend that the theory in this field is undeveloped since it lacks a firm foundation in traditional theoretical stances. In light of this, we pose the following as our primary research question: how does AMC affect AISCAC?

Both operational performance (Kar & Dwivedi, 2020) and financial performance can be enhanced by utilizing the insights gleaned from processing massive data sets (Mikalef, Boura, Lekakos, & Krogstie, 2019). However, supply chain managers still face significant obstacles in harnessing AI-SCAC for improved operational and financial performance, despite widespread excitement about the topic. This is mostly owing to the difficulties involved in making use of big data (Dubey et al., 2020). When processing big, unstructured datasets, Hazen, Boone, Ezell, and Jones-Farmer (2014) warned that decisions could go awry if data quality wasn't strictly monitored. However, despite the benefits, several academics in the field of management have voiced concerns about the application of data analytics to decision making (Albergaria & Jabbour, 2020; Ross, Beath, & Quaadgras, 2013). To better serve their stakeholders, most businesses, (Chen, Chiang, & Storey, 2012) There is a wealth of literature on the impacts of analytics capability on organizational performance (Wamba et al., 2017), but there has been less investigation into the effects of SCA capability on performance (Srinivasan & Swink, 2018). There is a significant knowledge gap in this area that has to be filled. Our second study topic is as follows: how does AI-SCAC affect operational and financial performance?

Our first two RQs focus on analysing direct impacts, which is important, but direct effects on their own can't always explain complex interactions in commercial settings (Eckstein, Goellner, Blome, & Henke, 2015). Scholars have hypothesized some conditions that may influence the direct consequences of skills in order to explain their varying impacts. The perspective is accurately reflected by contingency theory (Sousa & Voss, 2008). There hasn't been much thought given to, or research conducted on, the impact of higher-order capability on lower-order capability, either conceptually or empirically (Fainshmidt, Pezeshkan, Lance Frazier, Nair, & Markowski, 2016). Furthermore, environmental dynamism's (ED) moderating influence on paths connecting higher-order capability and lower-order capability, to handle ill-defend border conditions and the confounding effects of the dynamic capabilities, is limited (Schilke, 2014). As Schilke (2014) points out, environmental conditions are frequently linked with a high degree of ED when discussing dynamic capabilities. Recently, some academics have voiced doubts about the practical use of dynamic capacities theory (Eisenhardt & Martin, 2000). Proponents of contingency theory contend that the potential advantages of any organization's dynamic capabilities depend not only on the organization's structure but also on the situation in which these skills are used (Schilke, 2014) acknowledge the necessity for adjustments to the dynamic capabilities, which can be partially explained by external factors (Hrebiniak & Joyce, 1985). Schilke (2014), have highlighted ED's significance as a contextual variable in constructing organizational skills and improving performance. To date, research on the links between dynamic capabilities and organizational performance has mostly concentrated on the moderating effect of ED. However, the impact of ED as a moderator on the links between higher-order and lower-order skills is not discussed in the current literature (Fainshmidt et al., 2016). In order to fill this knowledge gap, we provide the following third research question: How does ED influence the connection between alliance management competence and AI-SCAC?

We have used information gathered from the automotive component manufacturing industry in the United States to answer our three RQs. Our theoretical framework is based on the contingency theory and the dynamic capability view of the firm (Eisenhardt & Martin, 2000; Hossain, Akter, Kattiyapornpong, & Dwivedi, 2020). Our research makes three primary contributions. As a first theoretical contribution, we analyse how a company's top-down approach to dynamism influences its bottom-up abilities. Second, we investigate how ED moderates the influence of higher-order dynamic capability on lower-order dynamic capability. In the third place, we explain in detail how SCA acts as a mediator between AMC and the organization's operational and financial performance.

2. Underpinning theories, theoretical model and research hypotheses

2.1. Dynamic capability view

The DCV is an expansion of the well-known resource-based perspective (RBV) (Barney, 1991). According to Helfat and Peteraf (2003), the RBV gives an explanation of competitive heterogeneity based on the concept that near competitors differ in their resources and capabilities in important and persistent ways. When applied to the business world, these variations translate to advantages and disadvantages. Despite considerable disagreement, the preceding statement does not imply a fixed perspective on resources within the framework of the resource-based paradigm. The DCV part of the RBV, adaptation and change since it entails developing, integrating, and reorganizing strategic resources and capabilities to create a sustainable competitive advantage. DCV is defined as "the firm's ability to integrate, build, and reconfigure internal and external skills to address quickly changing contexts. Dynamic capabilities are simple, experienced, unstable processes that are based solely on the quick learning gained from a specific circumstance to deliver unexpected results, and are hence well-suited to extremely uncertain contexts (Eisenhardt & Martin, 2000). As markets change, businesses may need to adapt by implementing new processes or routines that facilitate the incorporation, transformation, and renewal of both tangible and intangible resources into improved competencies (Eisenhardt & Martin, 2000). Two essential principles form the backbone of the DCV: Both (1) the importance of dynamic capabilities and (2) the impact of these talents on organizational performance are more readily apparent in the context of technologically innovative sectors. However, we see the lack of an explanation as to how the hierarchical ordering of dynamic capacities and the economic setting operate as variables causing divergent outcomes despite the widespread use of DCV and the expanding amount of work on the topic. Higher-order dynamic capacities are substantially more related to performance, as was found by Fainshmidt et al. (2016). There is a connection between higher-order dynamic capabilities and performance, but Schilke (2014) argues that lower-order dynamic capabilities play a role in mediating this connection. We therefore see AMC as a higher-order dynamic capability and the AI-SCAC as a lower-order dynamic capability for the purposes of our research.

2.2. Contingency theory

Contingency theory (CT) emphasizes the fit concept (Sousa & Voss, 2008). (Eckstein et al., 2015) argue that CT implies organizations adjust to unique contexts for competitive advantage. Thus, managers must analyse their firm's external and internal environment and choose appropriate actions (Volberda, Van Der Weerdt, Verwaal, Stienstra, & Verdu, 2012). CT explains how higher-order dynamic capabilities affect lower-order ones (Schilke, 2014). This enhances theoretical comprehension of dynamic capacities (Fainshmidt et al., 2016). Different definitions of fit can be used in CT-related research and should be clearly considered (Sousa & Voss, 2008). Informed by CT, we suggest that ED is a contingent variable, which explains how AMC influences AI-SCAC in the uncertain COVID-19 pandemic setting.

2.3. Environmental dynamism

Schilke (2014) argues that volatility (the rate and magnitude of change) and uncertainty are the two primary characteristics of ED. The drastic steps imposed by national governments to contain the COVID- 19 crisis, for instance, have caused widespread alterations in business structures (De Haas, Faber, & Hamersma, 2020). Citizen purchasing habits have been drastically altered as a result of these policies (Sheth, 2020). As a result of this abrupt shift in behavior, market demand has become unstable (Oehmen, Locatelli, Wied, & Willumsen, 2020). As a result, we may state that low-dynamism settings are characterized by low levels of change and nearly predictable market behavior (Sirmon, Hitt, & Ireland, 2007). Whereas extremely dynamic settings are characterized by extreme turbulence and frequent, fast change (Schilke, 2014). As a result of ED's influence, two competing schools of thinking have emerged about the relationship between an organization's dynamic capabilities and its performance. Scholars from the University of Chicago's First School of Management and Entrepreneurship stress the importance of embracing change in order to harness the full potential of companies (Weerawardena, Mort, Liesch, & Knight, 2007). The second school of thought contends that, despite the pressing need for resource reorganization, routine-based dynamic skills are not always sufficient for bringing about desirable change (Eisenhardt & Martin, 2000). After considering the evidence presented by Schilke (2014), we conclude that the degree to which opportunities to change exist and the organization's capacity to exploit these opportunities through routine-based change are both influenced by the environment's dynamism. Since there are so few opportunities for the organization to make good use of its dynamic capacities when ED is low, we contend that its effectiveness is also poor. The utility of dynamic talents is reduced under such conditions. However, when ED is strong, dynamic capabilities shine. As a result, dynamic capabilities have a significant bearing on the effectiveness of the company. We hypothesize that ED will have a large impact along the corridor connecting the AMC and the AI-SCAC.

2.4. Alliance management capability

The potential for AMC to help stakeholders effectively pool their strategic resources in a highly volatile and unsure setting is substantial (Schilke, 2014). There is much evidence in the existing literature demonstrating the importance of AMC in improving organizational performance (Schilke, 2014). Schilke (2014) argues that "Organizations with a strong alliance management capability possess routines that support various alliance-related tasks, such as partner identification and inter-organizational learning," (pp.183-184). These routines allow for the efficient implementation of inter-firm relationships. Accordingly, we contend that alliance management can take place across several projects in the B2B setting, including but not limited to data sharing, context and capacity analysis, resource mobilization, collaborative risk assessment, and the sharing of logistics infrastructure. Still, organizations struggle with keeping their partnerships strong. Problems like this are caused by misalignment (Lee, 2004). Management researchers have tried to determine how much time and money a company should put into creating an AMC and how that would affect the company's bottom line (Kohtamäki, Rabetino, & Möller, 2018).

2.5. *Artificial intelligence powered supply chain analytics capability*

With the advancement of technology in recent years, information systems are now essential, but insufficient, to bring about the desired levels of performance in a business (Jeble et al., 2018). Large amounts of data are now being collected in real-time in structured, semi-structured, and unstructured formats because to the rapid expansion of the internet, cellphones, and other developing technologies (Fisher, DeLine, Czerwinski, & Drucker, 2012). Thus, businesses must build analytics expertise on top of existing IT capability to turn this data into actionable insight and sustain competitive advantage (Davenport, 2014). The term "artificial intelligence-smart computing, analytics, and cloud" (AI-SCAC) describes a wide range of approaches to dealing with massive, complicated datasets and the difficulties inherent in doing so (Wamba & Akter, 2019). Data capture, storage, transfer, and sharing; system designs; data search, analysis, and visualization; and data analytics approaches are all crucial obstacles (Srinivasan & Swink, 2018). According to Srinivasan and Swink (2018), SCAC is a way for businesses to expand their analytics capabilities and speed up their processing of data. As a result, businesses gather information from a wide range of channels, which is then evaluated to yield insights that help managers make informed choices concerning supply chain operations. Building on the work of Srinivasan and Swink (2018), we argue that integrating cognitive technology with SCAC will result in improved managerial decision-making. So, for instance, supply chain managers will use cognitive technology to process complex information in order to predict changes in supply or demand patterns, which is especially useful during pandemic emergencies.

2.6. *Theoretical model and hypotheses development*

According to Eisenhardt and Martin (2000), a company's AMC and AI-SCAC, as seen through the lens of DCV, can be traced back to a variety of distinct business processes. As a result, management theorists have begun focusing on the context in which such nebulous "dynamic capabilities" actually exist, rather than attempting to measure such talents directly (Schilke, 2014). Empirical research into particular kinds of dynamic skills "sheds light not only on these specific processes, but also on the generalized nature of dynamic capacities," Eisenhardt and Martin (2000) (p. 1108).

The underlying assumptions of our study are based on two dynamic capacities that are subject to change: AMC and AI-SCAC. We view these as higher- and lower-order dynamic capacities, respectively, and propose them as means to reorganize the organization's resource base in the face of a pandemic catastrophe. Organizations can benefit from AMC because it allows them to better monitor market conditions and gain access to previously unavailable resources (Das & Teng, 2000). When used by businesses, AI-SCAC simplifies the analysis of massive amounts of data, allowing for more informed and timely supply chain decisions (He, Zhang, & Li, 2021). Inspired by the claims made by Fainshmidt et al. (2016) (p. 1349), we propose that the impact of higher-order dynamic capability on organizational performance occurs through the mediating effect of lower-order dynamic capability. The concept of a hierarchical grouping of dynamic capacities into multiple levels is vital but yet in its infancy. For this reason, we contend that organizational performance is affected by the interplay of dynamic capabilities across levels. We conceptually and empirically distinguish between AMC and AI-SCAC, with the former generating improved performance directly and indirectly through the latter. We use this method to examine how the placement of a company's dynamic capabilities in a hierarchy affects its efficiency. Moreover, by integrating ED as a contextual moderating factor, we hope to gain insight into the part ED plays in the dynamic capabilities-organizational performance link (Wamba, Dubey, Gunasekaran, & Akter, 2020).

2.6.1. *Alliance management capability (AMC) and AI powered supply chain analytics capability (AI-SCAC)*

AI-SCAC simplifies the complexities of the data needed for action (Srinivasan & Swink, 2018). The success of this endeavor, however, hinges on the accuracy of the data collected from a variety of channels (Hazen et al., 2014). The contribution of AMC in such a context can be substantial. In the context of humanitarian operations, Prasad, Zakaria, and Altay (2018) argue that organizations are best positioned to build and deploy systems and procedures in support of analytics if they have high levels of transparency and the ability to share information effectively. It is widely accepted that effective alliance management in challenging situations, such as a crisis, requires open communication between partners (Altay & Pal, 2014). Strong alliances give data and other technical support upon which analytics systems and processes work (Kamalaldin, Linde, Sjödin, & Parida, 2020), therefore companies that create AI-SCAC are also likely to invest in AMC, digitalization is considered as a source of future competitiveness due to its potential for unlocking new value-creation and income generation prospects," Kamalaldin et al. (2020) (p. 306) write. To reap the benefits of digitalization, both suppliers and consumers shift their focus from transactions centered on products to relationships based on services. This indicates that AMC can improve AI-SCAC, which in turn aids in gaining a competitive edge. Our hypotheses are based on what has been discussed above:

H_1: *AMC has positive and significant effect on AI-SCA.*

2.6.2. *AI-SCAC and operational/financial performance (OP/FP)*

Since "market competition for consumers, inputs, and capitals make organizational performance crucial for the survival" (Dubey et al., 2020), classical economic theory is the foundation for the majority of the earliest OP studies (Richard, Devinney, Yip, & Johnson, 2009) (p. 719). We therefore contend that OP represents the aggregate results of all enterprise efforts. This success is evaluated by how well it contributes to the organization's overall aim within a specified time frame (Lee & Huang, 2012). The ability to gain and maintain a competitive edge through outstanding performance is now essential to the survival of every business (Schilke, 2014). Management theorists claim that businesses can save money on things like overtime labor, lost sales, and excess inventory by employing rich and up-to-date current information to guide operational decisions and by generating better solutions rapidly (Dubey et al., 2020). Information system practices were found to have a positive and significant relationship with OP by Bayraktar, Demirbag, Koh, Tatoglu, and Zaim (2009), and a positive association between SCAC and OP was discovered by Srinivasan and Swink (2018) with organizational flexibility serving as a moderating influence. In addition, a substantial relationship between the degree to which big data analytics is used and the overall business/firm performance, as measured by the effectiveness of the firm's business processes. We propose that supply chain managers may maximize return on capital employed, decrease inventory, increase product quality, and speed up delivery thanks to the correlations we've established between these factors and AI-SCAC. In light of this, we propose the following hypothesis:

H$_{2a}$: *AI-SCAC has positive and significant effect on OP.*

H$_{2b}$: *AI-SCAC has positive and significant effect on FP.*

2.6.3. Moderating role of environmental dynamism (ED)

According to Schilke (2014), extensive alliance potential is dependent on ED, and sustaining an AMC necessitates considerable investments like forming a dedicated team to support the alliance activities. When an organization's ED is low, Rosenkopf and Schilling (2007) argue, it will have fewer opportunities to form strategic partnerships. Thus, we hypothesize that AMC has little effect on organizational performance under conditions of low ED. However, due to the fact that alliance management competency is predicated on routine activities that make use of the lessons learned from previous experiences, high ED may limit the value creation prospects in the supply chain network (Schilke, 2014). Therefore, we think it's important to study how AMC works in tandem with ED to boost the AI-SCAC. Adjustments to an organization's resources are necessary to keep up with the tempo of environmental change (ED) (Schilke, 2014; Wamba et al., 2020). Dynamic capabilities may provide businesses with benefits (Wamba & Akter, 2019), but those benefits are more likely to materialize in technologically dynamic sectors (Schilke, 2014). According to Weerawardena et al. (2007) (p. 294), businesses can "create cutting-edge knowledge-intensive goods, opening the road for their rapid market entry" thanks to their dynamic capacities. As a result, given the increased likelihood of needing to employ them in a rapidly shifting external environment, adaptability should be more highly valued (Schilke, 2014). In line with the work of Fainshmidt et al. (2016), contend that when ED is high, the influence of higher-order dynamic capabilities (i.e., AMC) on lower-order dynamic capabilities (i.e., AI-SCAC) grows. We assume that this is because this facet of the dynamic capabilities approach has been given less attention in the past, thus we hypothesize:

H$_3$: *High ED has a significant and positive effect on the path joining AMCs and AI-SCAC.*

3. Research design

Schilke (2014) three-stage research design served as our framework. We began by conducting interviews to learn more about the different kinds of organizational skills that are related to organizational resource configuration and their effects on organizational performance. Second, we built a survey-based evaluation tool. Data for both the dependent and independent variables in our study were collected and analyzed from the most relevant sources.

3.1 Qualitative interviews

Over the course of two weeks, we spoke with thirty-four high-ranking supply chain managers in the auto parts manufacturing sector via Zoom and Microsoft Teams. Thirty-five to forty minutes was the average length of each interview. Part one of the interview consisted of us asking managers what they know about the normal tasks that help their company respond quickly to shifting conditions outside the company. In particular, we questioned them on the measures they had taken in light of the COVID-19 pandemic. Executives stressed the significance of AMC and AI-SCAC. Second, we asked these managers if they felt these tasks were very important in ensuring good operational and financial success, confirming the validity of our research hypothesis. In addition, we pondered the impact of environmental shifts on AI-AMC. SCAC's. The majority of those we polled seemed to think our assumptions held some water. Some business executives have even claimed that the COVID-19 problem has sped up their digitization initiatives, with CEOs being more willing to invest in their company' supply chain analytics capabilities and related training programmes.

3.2 Survey

We chose car component manufacturers from the ACM database. Two major factors led to the selection of this sector: (1) the prevalence of alliances within it (Dussauge, Garrette, & Mitchell, 2004), and (2) the importance of supply chain analytics to its functioning. We worked with a marketing firm that consults with and collects data for businesses in India and elsewhere.

To make sure our questionnaire was easy to understand for our respondents, we ran a few tests before we started collecting data. The demographics of the test group were similar to those of the final survey participants. It took a lot of effort to get feedback from senior supply chain managers in vehicle manufacturing companies, and that was before the pandemic problem had hit and many managers were afraid to talk. Despite these challenges, we were determined to collect such feedback before publishing the main poll since we believe that pre-testing is essential for detecting and correcting language, clarity, and technical term difficulties. Fifteen managers in the manufacturing supply chain were used for a pilot survey. Brief interviews using Zoom/Microsoft Teams were conducted to address concerns with question interpretation. After making some small wording adjustments based on comments, the final survey was distributed.

Our marketing department sent out our survey by email to the 656 businesses included in the ACAMA database, which contains information on over 800 businesses. Using the key informant approach in two waves, we were able to acquire 167 usable replies from a diverse sample of respondents (Capron & Mitchell, 2009). The 25.46 percent response rate is in line with those of similar studies in the past (i.e. (Srinivasan & Swink, 2018; Wamba & Akter, 2019). Organizational and key informant data are summarized in Table 1. We included a question about their job title and length of service to ensure that the primary responses were appropriate (Kumar, Stern, & Anderson, 1993). More over two-thirds (67%) of those included in the final data set had been at their current employer for at least six years.

Nonresponse bias

We did a triple check for any non-response bias. The first step is to use Student's t-test to examine the differences between the early and late data collection waves (Armstrong & Overton, 1977). Table 1 displays the outcomes. Means for each respondent group did not differ significantly ($p > 0.05$) from those of the non-respondents. Second, we checked to see if there were any differences in the size of the businesses between the respondents and the ones who didn't return the questionnaire. In this case, there were no discernible variations in replies ($p > 0.05$). Finally, we followed Mentzer, Flint, and Hult (2001) and asked a random sample of the non-respondents to answer a single item for each construct. No significant differences were found between respondents and non-respondents for any issue using Student's t-tests of group means ($p > 0.05$). Inferring from this, we found no evidence of non-response bias in our study.

Table 1
Demographics

	Sample
Industry	
Auto component manufacturing	135
Firm Size	
<100 employees	27
100–249 employees	31
250–499 employees	33
500–999 employees	29
1000–4999 employees	8
≥5000 employees	7
Firm age (years)	
<5	14
5–9	41
10–19	38
20–29	28
>30	14
Job title of respondents	
Procurement Head	67
Logistics Head	31
Head of Production & Quality	21
Head of R&D	16
Tenure of the respondent in the organization (years)	
<1	15
2–5	47
6–10	51
≥10	22

3.3 Measures

Our constructs were evaluated using multi-item scales. Based on the current research, we modified our metrics. According to the recommendations of DeVellis and Thorpe (2021), we conducted in-depth interviews with 17 top-level managers to further hone the questionnaire items. Furthermore, we conducted preliminary testing on 23 managers to ensure the reliability of our instrument. We triangulated the management inputs with external data sources to ensure their accuracy (Homburg, Klarmann, Reimann, & Schilke, 2012; Schilke & Cook, 2015).

4. Data analysis

4.1. Measurement properties of constructs

Table 2 reports SCR and AVE for our multi-item structures. Convergent validity of our models is confirmed using SCR values. We followed the lead of Fornell and Larcker (1981) and investigated discriminant validity. Table 3 shows that the square root of AVE exceeds all values in the same row and column that are correlated. According to the criterion test, the HTMT values in Table 4 are all below the threshold (0.9). Using this, we verify the discriminant validity of our models (Henseler, Ringle, & Sarstedt, 2015). Overall, our constructions are reliable, valid, and robust enough for structural estimates.

Table 2
Scale Items

Constructs	Items	Loading	CR	AVE
IC	AMC1	0.71	0.76	0.61
	AMC2	0.73		
	AMC3	0.79		
	AMC4	0.78		
APC	AMC5	0.79	0.79	0.58
	AMC6	0.70		
	AMC7	0.81		
	AMC8	0.83		
IL	AMC9	0.83	0.73	0.53
	AMC10	0.84		
	AMC11	0.87		
	AMC12	0.91		
AP	AMC13	0.89	0.81	0.54
	AMC14	0.81		
	AMC15	0.76		
	AMC16	0.70		
AT	AMC17	0.83	0.73	0.56
	AMC18	0.77		
	AMC19	0.75		
AI-SCAC	AI-SCAC1	0.74	0.78	0.63
	AI-SCAC2	0.79		
	AI-SCAC3	0.80		
	AI-SCAC4	0.85		
	AI-SCAC5	0.78		
ED	ED1	0.86	0.71	0.64
	ED2	0.81		
	ED3	0.72		
	ED4	0.69		
	ED5	0.70		
OP	OP1	0.66	0.74	0.68
	OP2	0.73		
	OP3	0.78		
	OP4	0.81		
FP	FP1	0.87	0.70	0.51
	FP2	0.85		
	FP3	0.83		

4.2. Common method bias (CMB)

In order to reduce the potential for common method bias (CMB) in our survey-based cross-sectional data, we adhered to stringent procedures (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). To begin, we conducted the standard one-factor Harman's test. Some academics in the field of management, however, argue that Harman's one-factor test is insufficient and should not be considered irrefutable proof. In light of this, we implemented the second method, the correlation marker methodology, proposed by Lindell and Whitney (2001). As a means of filtering out CMB-induced associations, we substituted in a completely unrelated variable. Following the advice of Lindell and Whitney (2001, we also derived the statistically significant correlation values. Differences between the adjusted and unadjusted correlations are small. In light of these statistical findings, we conclude that CMB has no appreciable effect on our subsequent findings.

Table 3
Correlations

	AMC	AI-SCAC	ED	OP	FP
AMC	0.69				
AI-SCAC	0.61	0.71			
ED	0.45	0.29	0.79		
OP	0.39	0.35	0.38	0.78	
FP	0.32	0.21	0.40	0.48	0.85

4.3. Hypotheses testing

We tested our four research hypotheses as H1, H2a, H2b and H3. Table 5 withdraws the β coefficient of the paths and consistent p - values. Initially, we originate provision for H1, which tests the effect of AMC on AI-SCAC ($\beta = 0.31$; $p < 0.001$). Furthermore, we found provision for H2a ($\beta = 0.29$; $p < 0.01$). H2b, we found provision in the outcomes ($\beta = 0.25$; $p < 0.05$). We further tested the interaction influence of ED on the path linking AMC and IA-SCAC (H3). We found support for H3 ($\beta = 0.35$; $p < 0.001$).

Table 4
HTMT

	AMC	AI-SCAC	ED	OP	FP
AMC					
AI-SCAC	0.19				
ED	0.21	0.29			
OP	0.26	0.20	0.25		
FP	0.23	0.21	0.20	0.28	

On the basis of our findings, we come to the conclusion that the influence of higher-order dynamic capability on lower-order dynamic capability is amplified when there is a high level of environmental dynamism present. It has come to our attention that the control variable organizational size (OS) does not have a major impact on the model that we developed for this investigation. During the pandemic crisis, we analyzed these observations, and our conclusion was that the size of an organization does not alter the motivation of organizations to engage in AMC and AI-SCAC. Additionally, the alliance portfolio size has a favorable and considerable impact on the model that we used for this research.

Table 5
Hypothesis testing

Hypothesis	β	p-value	Results
H1	0.31	0.001	Supported
H2a	0.29	0.01	Supported
H2b	0.25	0.05	Supported
H3	0.35	0.001	Supported

5. Discussion

The dynamic capacities demonstrated during the pandemic crisis response were confirmed to be straightforward, experienced, and prone to instability (Colombo, Piva, Quas, & Rossi-Lamastra, 2021). Two main points of view form the basis of the DCV: In technologically dynamic industries for two reasons: (1) the value of dynamic capabilities is more immediately visible, and (2) the effects of dynamic capabilities on competitive advantage are more prominent. Yet, DCV does not explain why and how the hierarchical ordering of dynamic capabilities and the external environment context are essential elements in explaining variances in performance. The studies conducted by Fainshmidt et al. (2016) show that higher-order dynamic capabilities are significantly more strongly connected with performance than lower-order dynamic capabilities. Schilke (2014) makes the interesting observation that performance is partially mediated by higher-order dynamic capacities. In addition, Fainshmidt et al. (2016) suggest that higher-order dynamic capabilities have a larger effect on lower-order dynamic capabilities when ED is high. Schilke (2014) points out that the correlation is not linear, with medium ED situations producing superior performance outcomes. All of our investigation was built on these well-reasoned arguments from the academic community. We recognize that despite the widespread use of DCV, there are still substantial knowledge gaps. The urgent necessity to utilize the capabilities of data analytics to reduce supply chain disruptions caused by COVID-19 prompted our study. Most of the investigations have been theoretical or anecdotal, and the rising body of research has not produced any theory-driven empirical outcomes. To assist fill in the gaps, we formulated three research questions and sourced data from India's car parts producers to answer them. These results add a new perspective to our understanding of DCV in a global pandemic. The results of the tests of the hypotheses are summarized in Table 5. When we look at the results in Table 5, we can determine which claims made by our research hold water and which do not. The overall results of our research contribute to theoretical knowledge and offer substantial advice to supply chain managers, especially in the face of a pandemic emergency. Further, we think our work could lead to new research opportunities. Implications for theory, applications in practice, and caveats/future research prospects are discussed in more depth.

6. Implications to theory

Firstly, our study makes it clear that not all dynamic talents are the same and that they all need to be evaluated independently. Not much is known about the inner workings of dynamic capacities or the conditions under which they are most effective from a research standpoint. Big data analytics capacity has been seen as malleable in previous academic studies (Gupta & George, 2016; Mikalef et al., 2019). All of these studies frame big data analytics capability as a higher-order reflective construct or a hybrid reflective/formative one. As an added bonus, Srinivasan and Swink (2018) considered supply chain analytics to be a model of the real world. In spite of the many words written on AI-SCAC, we were unable to find any proof that DCV theory had ever been established to explain its emergence. To address this, we build on the theoretical work of Srinivasan and Swink (2018) by analyzing the interplay between AMC and AI-SCAC in the face of the extreme volatility brought on by the epidemic. As a result, our findings provide missing information concerning DCV borders that was previously identified by other studies (Fainshmidt et al., 2016).Second, our research offers hard evidence that AMC precedes AI-SCAC. As a causal factor of analytics capabilities, AMC is rarely acknowledged in the current research. Our data analysis supports the contingent view of DCV as a higher-order organizational capability, which is the position we take here. Our research adds to the literature by showing that AMC improves operational and financial performance despite low demand and government constraints on product movement thanks to the AI-mediating SCAC's role. Our findings add to the growing body of research suggesting that crisis-time investments in alliance management skill can yield positive outcomes thanks to the inherent flexibility of dynamic capabilities.

In addition, to the best of our knowledge, ours is the first investigation to examine how AMC, AI-SCAC, and productivity all tie in to the success of a business. Prior research has either examined the impact of organizational flexibility as a moderator (Wamba et al., 2017) or has examined the relationship between direct causality and organizational performance (Srinivasan & Swink, 2018). We underline the fact that, despite its widespread use, AMC has received very little attention from the field of organization research (Rothaermel & Deeds, 2006), mostly as a result of methodological limitations, based on a thorough examination of the relevant literature. In spite of these limitations, we have investigated AMC's crucial role in developing AI-SCAC, which has not been thoroughly investigated by organizational academics. We acknowledge the immaturity of our attempt to conceptualize AMC, but we think our work to date has raised some interesting questions about AMC and its impact on AI-SCAC.

7. Managerial implications

Our findings have important implications for management because they indicate that upper-level executives need to know the what, how, and when of investments in developing both higher- and lower-order talents. In this sense, the findings point the way for managers who are trying to make the most of analytics to glean actionable insights for making decisions about managing intricate supply chain networks. For instance, many companies put resources on developing AI-SCAC, but the returns on these expenditures are usually modest at best. Based on our findings, AMC seems to be a higher-level skill. Therefore, without AMC, it might be extremely difficult for businesses to turn AI-SCAC into the positive results that were hoped for. More importantly, in high ED, due to market volatility, companies may be unable to comprehend the complexities of demand and supply.

Our findings provide insights for decision-makers in poor nations to use in crafting policies that take advantage of dynamic capabilities to achieve better results during pandemic crises. Furthermore, they educate both managers and politicians on the critical role that external factors play. For automobile industry managers, the clarity and use of these findings are invaluable. Additionally, they provide intellectual stimulation and can be adopted by manufacturing firms in other industries. In addition, they instruct managers who are responsible for alliance management operations on how alliance management capacity can be a crucial precondition for AI-powered supply chain analytics performance. In this way, they illustrate why the company should put resources into developing crucial competencies including interdepartmental coordination, alliance portfolio coordination, interdepartmental learning, alliance reactiveness, and alliance transformation. Similarly, senior managers need to equip the right people to make a significant positive difference and deliver a return on investment in regards to AI-SCAC, while training managers need to prepare comprehensive training and development programmes to enhance the organization's learning and knowledge management capabilities. The APS has a considerable impact on the model, which in turn shows that the quality and quantity of alliance partnerships have a major role in determining the extent to which AI-SCAC benefits are realized.

Our research confirms the consensus among academics that, in times of rapid environmental change, companies need to redouble their efforts to communicate with their business partners in order to keep their level of openness at a high level. Further, it is crucial to maintain open communication among collaborators in order to foster effective collaboration. Because of the complexities and uncertainties that exist across organizational boundaries, the findings indicate that developing an effective alliance management competence is challenging. As a result, it should come as no surprise that most partnerships fail to produce the desired results, particularly in the context of maximizing the utility of AI-SCAC in times of pandemic crisis.

8. Limitations and further research directions

Our study has limitations. Cross-sectional data tested theories. Multi-informant data collection. Reduces data method bias. We examined AMC and AI-impact SCACs on organizational performance. Strategic alliances provide external resources, and new product creation helps enterprises update their product line. Finally, our study focused on experience-based, static routines and ignored organizational change. We recommend a qualitative approach to study alliance management, analytical capability, and crisis environmental changes. New topics require theoretical and empirical research.

Acknowledgement

The publication of this research has been supported by the Deanship of Scientific Research and Graduate Studies at Philadelphia University in Jordan.

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