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Research paper

Facilitating artificial intelligence powered supply chain analytics through alliance management during the pandemic crises in the B2B context

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ABSTRACT

The COVID-19 pandemic has disrupted global supply chains and exposed weak links in the chains far beyond what most people have witnessed in their living memory. The scale of disruption affects every nation and industry, and the sudden and dramatic changes in demand and supply that have occurred during the pandemic crisis clearly differentiate its impact from other crises. Using the dynamic capabilities view, we studied alliance management capability (AMC) and artificial intelligence (AI) driven supply chain analytics capability (AI-SCAC) as dynamic capabilities, under the moderating effect of environmental dynamism. We tested our four research hypotheses using survey data collected from the Indian auto components manufacturing industry. For data analysis we used Warp PLS 7.0 (a variance-based structural equation modelling tool). We found that alliance management capability under the mediating effect of artificial intelligence-powered supply chain analytics capability enhances the operational and financial performance of the organization. Moreover, we also observed that the alliance management capability has a significant effect on artificial intelligence-powered supply chain analytics capability under the moderating effect of environmental dynamism. The results of our study provide a nuanced understanding of the dynamic capabilities and the relational view of organization. Finally, we noted the limitations of our study and provide numerous research directions that may help answer some of the questions that arise from our study.

1. Introduction

> "*Thanks to the explosive expansion and advances of digital technologies, such as smart mobile phones, social media platforms, e-commerce, and so on, data are around in every organization. As the analytics capabilities of organizations develop rapidly, artificial intelligence tools, big data analytics, blockchain, and so on are all tools available and being used in the industry* (Araz, Choi, Olson, & Salman, 2020, p. 1316).

Supply chain analytics (SCA), via the use of cognitive technologies, such as artificial intelligence (AI), helps improve complex supply chain process decisions (Akter, Michael, Uddin, McCarthy, & Rahman, 2020; Asmussen & Møller, 2020; Boehmke, Hazen, Boone, & Robinson, 2020). Cognitive technologies capability enables machines to understand complex situations at high speed, whilst processing large amounts of data, and to learn and interact like humans (Duan, Edwards, & Dwivedi, 2019; Dwivedi et al., 2021; Gupta, Kar, Baabdullah, & Al-Khowaiter, 2018; Kelly, 2015) and Artificial intelligence-powered supply chain analytics (AI-SCA) has gained increased momentum during a pandemic crisis (Cankurtaran & Beverland, 2020; Ivanov, 2020). Motivated by the perceived importance of AI-SCA capability (AI-SCAC), we undertook a theory-driven study to examine antecedents of AI-SCAC and the effects of AI-SCAC on performance during the COVID-19 crisis. In recent times, AI-SCAC has been touted as a game-changer, especially as a means of dealing with the pandemic, with its use increasing significantly across all functional departments of the organization during this period of crisis (PYMTS, 2020; Sheng, Amankwah-Amoah, Khan, & Wang, 2020; Sharma, Adhikary, & Borah, 2020; Ivanov & Dolgui, 2020; The State of

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BI and Business Analytics Report, 2020). However, despite the rich body of literature on the use of AI-SCAC, empirical study is scant.

The COVID-19 crisis has affected customers' ability to pay for their goods and services and vendors are unable to produce and supply raw materials to meet demand (Queiroz, Ivanov, Dolgui, & Wamba, 2020). It has also significantly affected the accounts payable (AP), accounts receivables (AR) and days of sales outstanding (DSO). In a way, most organizations have experienced serious working capital management (WCM) issues that have been resolved largely via data analytics capability (PYMTS, 2020). Supply chain management scholars have noted that SCA capability has the potential to revolutionize the next generation of business (Hazen, Boone, Ezell, & Jones-Farmer, 2014; Schoenherr & Speier-Pero, 2015; Waller & Fawcett, 2013).

The pandemic resulting from COVID-19 has disrupted the entire supply chain, leading to shortages of essential items (Craighead, Ketchen Jr, & Darby, 2020; Ketchen Jr & Craighead, 2020; Ritter & Pedersen, 2020). In order to survive in such extreme uncertain times, organizations have been making significant efforts to adapt to new norms via the leveraging of relationships (Colombo, Piva, Quas, & Rossi-Lamastra, 2020; Crick & Crick, 2020) and by harnessing analytics capability (Ivanov, 2020). During the pandemic we have observed organizations having superior capabilities of managing alliances, demonstrating the successful use of analytics capability (Crick & Crick, 2020; Hanelt, Bohnsack, Marz, & Antunes Marante, 2020; Sheng et al., 2020). With the motives for forming such alliances including inter-organizational learning, accessing technology and complementary resources, and fostering innovation (Leischnig, Geigenmueller, & Lohmann, 2014; Rothaermel & Deeds, 2006), alliance management capability (AMC) is considered as a source of competitive advantage (Dyer and Singh, 1998; Schreiner, Kale, & Corsten, 2009; Sluyts, Matthyssens, Martens, & Streukens, 2011; Schilke, 2014). Although it is well understood that AMC has a strong influence on SCAs, the evidence for such influence is mostly anecdotal (Zhang, Meng, de Pablos, & Sun, 2019). Therefore, our study is one of the first to examine the effect of AMC on SCA capability. Furthermore, we argue that theory in this area remains underdeveloped, lacking grounding in established theoretical perspectives. Hence, we posit our first research question (RQ1): *what are the effects of AMC on AI-SCAC?*

The insights derived via processing large data can be utilized to improve both operational performance (Srinivasan & Swink, 2018; Dubey et al. 2019a; Kar & Dwivedi, 2020) and financial performance (Gupta, Drave, Dwivedi, Baabdullah, & Ismagilova, 2020; Mikalef, Boura, Lekakos, & Krogstie, 2019a, 2019b; Sena, Bhaumik, Sengupta, & Demirbag, 2019). Yet despite high levels of enthusiasm among practitioners, exploiting AI-SCAC for enhanced operational and financial performance is still a major challenge for supply chain managers, due to dealing with the complexities associated with utilizing big data (Gunasekaran et al., 2017; Dubey et al. 2019; Kinra, Hald, Mukkamala, & Vatrapu, 2020). Hazen et al. (2014) cautioned that if the quality of the data is not properly controlled then the outcome generated via processing large unstructured datasets might have a negative consequence on decision-making. So, despite the opportunities, management scholars have expressed caution related to the potential use of data analytics capability in their decision-making process (see, Agarwal & Dhar, 2014; Albergaria & Jabbour, 2020; Brown, Chui, & Manyika, 2011; Ross, Beath, & Quaadgras, 2013; Simsek, Vaara, Paruchuri, Nadkarni, & Shaw, 2019). Chen, Chiang, and Storey (2012) argue that in most cases organizations aim to use data analytics capability to improve their decision-making abilities to satisfy their stakeholders. Although, there exists a rich body of the literature on the effects of analytics capability on organizational performance (see, for example, Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Fosso Wamba et al., 2017; Wang & Wang, 2020; Bag, Gupta, Kumar, & Sivarajah, 2020), research on SCA capability on performance is limited (Srinivasan & Swink, 2018). This is a clear research gap, which needs to be addressed. We, therefore, posit our second research question (RQ2): *what are the effects of AI-SCAC on operational/finance performance?*

Analyzing direct effects, as is the focus of our first two RQs, is necessary, but the direct effects on their own often fail to fully explain complex relationships in business situations (Boyd, Takacs Haynes, Hitt, Bergh, & Ketchen Jr, 2012; Eckstein, Goellner, Blome, & Henke, 2015). To explain the differential effects of capabilities, scholars have assumed specific conditions that may influence the direct effects. This view is well captured by contingency theory (Sousa & Voss, 2008). Conceptual and empirical study of the effect of higher-order capability on lower-order capability is scant (Fainshmidt, Pezeshkan, Lance Frazier, Nair, & Markowski, 2016). Furthermore, the moderating effect of environmental dynamism (ED) on the paths joining higher-order capability and lower order capability, to address ill-defined boundary conditions and the confounding effects of the dynamic capabilities is limited (Fosso Wamba, Dubey, Gunasekaran, & Akter, 2020; Schilke, 2014). Schilke (2014) argues that in the case of dynamic capabilities, environmental conditions are often equated with a high degree of ED. In recent times, some scholars have expressed their reservations related to the notion of dynamic capabilities theory and its usefulness in practice (Eisenhardt & Martin, 2000). Advocates of contingency theory argue that the potential benefits of the dynamic capabilities of any organization depends not only on the organizational structure but also on the context in which these capabilities are exploited (Hitt, Ireland, & Palia, 1982; Schilke, 2014; Sirmon & Hitt, 2009). We recognize the need for an adaptation of the dynamic capabilities, which are to a certain extent explained by environmental forces (Eckstein et al., 2015; Hrebiniak & Joyce, 1985; Schilke, 2014). In recent times scholars have increasingly identified ED as an important contextual variable in building organizational capabilities and enhancing performance i.e., Helfat and Winter (2011), Schilke (2014) and Fosso Wamba et al. (2020). Most studies to date have focused on the moderating influence of ED on the paths joining dynamic capabilities and organizational performance. However, the existing literature is silent on the moderating effect of ED on the paths joining higher-order capabilities and the lower order capabilities (Fainshmidt et al., 2016). To address this research gap, we posit our third research question (RQ3): *what is the effect of ED on the path joining alliance management capability and AI-SCAC?*

To address our three RQs we have used data collected from the Indian auto components manufacturing sector. Our theoretical model is grounded in the dynamic capability view of the firm (Akter et al., 2016; Eisenhardt & Martin, 2000; Fosso Wamba et al., 2017; Hossain, Akter, Kattiyapornpong, & Dwivedi, 2020; Schilke, 2014; Teece, Pisano, & Shuen, 1997) and contingency theory (Lawrence & Lorsch, 1967; Tosi Jr & Slocum Jr, 1984). The main contributions of our study are threefold. Firstly, we make a theoretical contribution by examining the direct effect of the higher-order organizational dynamic capability on the lower order dynamic capability. Secondly, we attempt to explain the effect of higher-order dynamic capability on lower-order dynamic capability under the moderating effect of ED. Thirdly, we provide a nuanced understanding of how AMC affects the operational and financial performance of the organization under the mediating effect of SCA.

We have organized our paper into six sections. In the next sections, we present our underpinning theories, theoretical model, and hypotheses development. In the third section, we discuss our research design, outlining how we developed our measuring instrument, the sampling design, and the data collection strategy. We further present the demographic profile of our respondents and the results of the non-response bias test. In the fourth section, we present our data analysis using PLS-SEM. In the fifth section, we discuss the findings of our statistical analyses. In this section, we highlight our main contributions to theory and practice. We also outline the limitations of our study, which leads us to set out areas for further study and research questions which remain unaddressed. Finally, we draw the main conclusions from our study.

2. Underpinning theories, theoretical model and research hypotheses

2.1. Underpinning theories

2.1.1. Dynamic capability view (DCV)

Since the seminal work by Teece et al. (1997), scholarly interest in DCV has increased in management research. The DCV is regarded as an extension of the popular resource-based view (RBV) (Barney, 1991). Helfat and Peteraf (2003, p. 997) argue that "*the RBV provides an explanation of competitive heterogeneity based on the premise that close competitors differ in their resources and capabilities in important and durable ways. These differences in turn affect competitive advantage and disadvantage. Nothing in this premise necessarily implies a static approach to the resource-based view, notwithstanding some controversy in this regard*".

Helfat and Peteraf further argue that the DCV element of the RBV involves adaptation and change, because they build, integrate, or reconfigure the strategic resources and capabilities to generate a competitive advantage. Following Teece (1997, p. 516), we define DCV as "*the firm's ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments*". In the context of highly uncertain environments, dynamic capabilities are simple, experiential, unstable processes that are based purely on the quick learning gained from a given situation to produce unexpected results (Eckstein et al., 2015; Eisenhardt & Martin, 2000; Fosso Wamba et al., 2020; Mikalef, Krogstie, Pappas, & Pavlou, 2020). It may refer to specific process or routines that enable integration, conversion, or renewal of tangible and intangible resources into new competencies as markets evolve (Eckstein et al., 2015; Eisenhardt & Martin, 2000; Teece, 2007). Based on preceding discussions, we see that DCV has covered a long distance since the seminal work by Teece et al. (1997). The basic notion of the DCV converges around two main tenets: (1) the effects of dynamic capabilities on organizational performance, (2) the value of dynamic capabilities are more visible in the case of technologically dynamic industries (see, Fainshmidt et al., 2016). However, despite the high popularity of DCV and growing body of literature on the topic, we note the absence of an explanation as to how the hierarchical ordering of dynamic capabilities and the economic context serve as contingencies producing differential outcomes. Fainshmidt et al. (2016) found that higher-order dynamic capabilities are significantly more related to performance than lower-order dynamic capabilities. Schilke (2014) notes that the lower-order dynamic capabilities partially mediate the relationship between higher-order dynamic capabilities and performance. Hence, for our study, we conceive AMC as a higher-order dynamic capability and the AI-SCAC as a lower-order dynamic capability.

2.1.2. Contingency theory (CT)

Contingency theory (CT) is a mid-range theory based on the notion of fit (Sousa & Voss, 2008). Eckstein et al. (2015) argue that CT assumes organizations adapt based on specific situations they find themselves in and this adaptation generates competitive advantage. Thus, managers must carefully analyse their firm's external and internal environment and decide on the fit of alternative actions (Volberda, van der Weerdt, Verwaal, Stienstra, & Verdu, 2012). CT is a key theoretical lens for understanding the context under which higher-order dynamic capabilities effect lower-order ones (Fainshmidt et al., 2016; Schilke, 2014). Looking through such a lens provides enhanced theoretical understanding of the role of dynamic capabilities (Fainshmidt et al., 2016). Hence, we argue that in CT-related research, different concepts of fit can be employed and should be explicitly considered when conducting such studies (Sousa & Voss, 2008). Informed by CT, we argue that ED is a contingent variable, which offers a better understanding of how AMC affects AI-SCAC in the extremely uncertain environment resulting from the COVID-19 pandemic.

2.1.3. Environmental dynamism (ED)

Schilke (2014) argue that ED has two main characteristics: volatility (rate and amount of change) and uncertainty. For instance, the COVID-19 crisis has led to significant change in industry structures due to stringent measures taken by national governments to control the spread of the virus (de Haas, Faber, & Hamersma, 2020). These measures have significantly affected the consumption behaviour of citizens (Sheth, 2020). This sudden change in behaviour has resulted in the instability of market demand (Oehmen, Locatelli, Wied, & Willumsen, 2020). Thus, we can argue that environments with little dynamism are characterised by little change and the market behaviour is almost predictable (Sirmon, Hitt, & Ireland, 2007). In contrast, highly dynamic environments are characterised by highly turbulent environments, which often experience rapid and continuous change (Schilke, 2014). The effect of ED on the path joining dynamic capabilities and the organizational performance has led to two schools of thoughts. In the first school scholars advocate change, in the order to gain significant positive outcomes from utilizing the dynamic capabilities of organizations (Helfat et al., 2009; Weerawardena & Mavondo, 2011). The second school of thought argue that routine-based dynamic capabilities are not always sufficient for achieving beneficial change, although there is a significant need for the reconfigurations of resources (Eisenhardt & Martin, 2000). Following Schilke (2014) arguments, we understand that the environmental dynamism affects both the extent of opportunities to change and the organization abilities to exploit these available opportunities through routine-based change. Hence, we argue that when ED is low, the effectiveness of organizational dynamic capabilities are low, as there are hardly any occasions when these capabilities are properly utilized. In such situations, dynamic capabilities have limited usefulness. On the other hand, when ED is high, the usefulness of dynamic capabilities increases. In such case the impact of dynamic capabilities on organizational performance is high. In our study we posit that the effect of ED on the path joining AMC and the AI-SCAC will be significant.

2.1.4. Alliance management capability (AMC)

In a dynamic and highly uncertain environment, AMC holds great promise in terms of resolving complications that may prevent stakeholder's abilities to productively share their strategic resources in the form of activities and information (Schilke, 2014). Existing literature provides rich evidence in support of the significant role played by AMC in enhancing organizational performance (Schilke, 2014; Sluyts et al., 2011). Schilke (2014, p.183-184) 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, that facilitate an effective execution of inter-firm relationships*". Hence, we argue that alliance management may occur over one or more projects within the B2B context, for example, information exchange, context, and capacity analysis need assessment, resource mobilization, joint risk assessment, or sharing of logistics facilities. Nevertheless, organizations face challenges in maintaining an alliance with their partners. These challenges stem from poor alignment (Dubey et al., 2018; Lee, 2004). Management scholars have attempted to examine the extent to which an organization should invest to build AMC and the effect on organizational performance (Forkmann, Henneberg, & Mitrega, 2018; Kohtamäki, Rabetino, & Möller, 2018).

2.1.5. Artificial intelligence powered supply chain analytics capability (AI-SCAC)

In recent years, as technology has moved forward, information systems are necessary but not sufficient to achieve desired levels of organizational performance (Fosso Wamba & Akter, 2019; Jeble et al., 2018). With the rapid proliferation of the internet, smartphones, and other emerging technologies (RFID, sensors, Internet of Things, Cloud Computing, etc.), we have reached a new phase where large volumes of data are collected in real-time in structured, semi-structured and unstructured formats (Agarwal & Dhar, 2014; Fisher, DeLine, Czerwinski,

& Drucker, 2012). Therefore, it is imperative for firms to develop analytics capabilities, on top of existing IT capability, to convert this data into useful information and to retain competitive advantage (Davenport, 2014). AI-SCAC is an all-encompassing term for techniques to handling large complex data, as well as encompassing the inherent challenges of such data handling (Fosso Wamba & Akter, 2019). Critical challenges are related to data capture, storage, transfer & sharing, related to system architectures and search, analysis, and visualization related to data analytics methods (Dubey et al., 2020; Srinivasan & Swink, 2018; Venkatesh, 2021). Srinivasan and Swink (2018) argue that SCAC is an extension of traditional analytics capability that enables organizations to increase their information processing capability. Hence, firms collect data from various sources, which is analysed to provide insights to guide managers in making the right decisions related to supply chain processes. Extending Srinivasan and Swink (2018) arguments, we posit that the use of cognitive technology, along with SCAC, will lead to the decisions taken by the managers being more effective than in the past. So, for example, supply chain managers will process complex information, with the help of cognitive technology, to forecast changes in supply or demand patterns, especially during pandemic crises (Cortez & Johnston, 2020; He, Zhang, & Li, 2021).

2.2. Theoretical model and hypotheses development

Our theoretical model is shown in Fig. 1. From the DCV perspective, AMC and AI-SCAC is the dynamic capabilities of an organization, which Eisenhardt and Martin (2000) argue manifest themselves in different identifiable business processes. Hence, instead of quantifying vague dynamic capabilities, management scholars have started exploring the set of processes within which these dynamic capabilities exist (Schilke, 2014). Motivated by the theoretical arguments offered by Eisenhardt and Martin (2000, p. 1108), empirical study of specific types of dynamic capabilities, "*sheds light not only on these specific processes, but also on the generalized nature of dynamic capabilities*".

Our research hypotheses are grounded in two contingent dynamic capabilities: AMC and AI-SCAC. We conceive these as higher-order and lower order dynamic capabilities, respectively, and posit that they are ways to reconfigure the organizational resource base during a pandemic crisis. AMC helps the organization to sense the fluctuations in the market, as well as provide access to resources that lie beyond their reach (Crick & Crick, 2020; Das & Teng, 2000; Schilke, 2014). AI-SCAC enables organizations to process complex information to make effective and efficient supply chain decisions (Cortez & Johnston, 2020; He et al., 2021). Secondly, motivated by the arguments offered by Fainshmidt et al. (2016, p. 1349), who argue that "*just as there are different classes of resources, there are different levels of dynamic capabilities*", we suggest the impact of higher-order dynamic capability on organizational performance takes place under the mediating effect of lower-order dynamic capability. Hierarchical ordering of dynamic capabilities into different levels is an important aspect, yet remains underdeveloped as a concept (see, Ambrosini, Bowman, & Collier, 2009; Fainshmidt et al., 2016). Hence, we argue that the interaction of dynamic capabilities at different levels impacts on organizational performance. We differentiate, both conceptually and empirically, between AMC and AI-SCAC as being at different levels; with the former generating enhanced performance, both directly and indirectly, via AI-SCAC. In this way we analyse how the hierarchical ordering of dynamic capabilities makes a difference to organizational performance. Furthermore, we seek clarity regarding the role of ED in the dynamic capabilities-organizational performance link, by including ED as a contextual moderating factor (Fainshmidt et al., 2016; Fosso Wamba et al., 2020; Schilke, 2014).

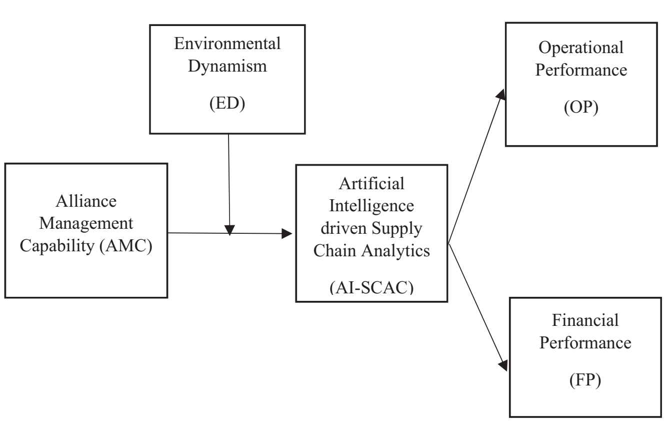

Fig. 1. Theoretical Model.

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

AI-SCAC processes the complex information required to decision making (Srinivasan & Swink, 2018). However, its success depends upon the quality of information derived from various sources (Hazen et al., 2014). In such a situation, the role of AMC can be crucial. Prasad, Zakaria, and Altay (2018) argue that, in context to humanitarian efforts, high levels of transparency and effective information-sharing capabilities position organizations to develop and deploy systems and processes for supporting analytics capabilities. In complex environments like a crisis, information sharing among partners is often considered critical for better alliance management (Altay & Labonte, 2014; Altay & Pal, 2014). In addition, organizations that develop AI-SCAC are also likely to invest in AMC, as strong alliances provide data and other technical support upon which analytics systems and processes operate (Kamalaldin, Linde, Sjödin, & Parida, 2020). Kamalaldin et al. (2020, p. 306) further argue that "*digitalization is viewed as a source of future competitiveness due to its potential for unlocking new value-creation and revenue-generation opportunities. To profit from digitalization, providers and customers tend to move away from a transactional product-centric model to relational service-oriented engagement*". This suggests that AMC can enhance AI-SCAC, which, in turn, helps achieve competitive advantage. Based on these preceding discussions, we hypothesize the following:

H1: AMC has positive and significant effect on AI-SCA.

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

Most of the early studies devoted to OP is rooted in classical economic theory (Dubey et al. 2019a), with OP being regarded as one of the most important variables in management research, as "*the market competition for customers, inputs, and capitals make organizational performance essential for the survival*" (Richard, Devinney, Yip, & Johnson, 2009, p. 719) Hence, we argue that OP is the sum of accomplishments achieved by all businesses. These accomplishments are measured in terms of meeting an organizational goal within a given period (Lee & Huang, 2012). A competitive advantage with superior performance has become a vital element of an organization's ability to survive (Schilke, 2014). Management scholars argue that by using rich and up-to-date current information to inform operational decisions and by developing better solutions quickly, organizations can avoid expensive courses of action, such as overtime production, lost sales, and excess inventories (Srinivasan & Swink, 2018; Dubey et al. 2019a). Bayraktar, Demirbag, Koh, Tatoglu, and Zaim (2009) found a positive and significant relationship between information system practices and OP; and Srinivasan and Swink (2018) found a positive association between SCAC and OP under the moderating effect of organizational flexibility. Further, Ayinder et al. (2019a, 2019b) found a significant association between the level of big data analytics adoption and overall business/firm performance, via the operations of its business processes. Because of these suggested links between variables, we argue that AI-SCAC enables supply chain managers to reduce working capital, maximise return on capital employed, improve inventory turnover ratio, enhance product quality, and improve product delivery. Hence, we hypothesize it as:

H2a. *: AI-SCAC has positive and significant effect on OP.*

H2b. *: AI-SCAC has positive and significant effect on FP.*

2.2.3. Moderating role of environmental dynamism (ED)

Schilke (2014) argues that building and maintaining an AMC requires significant investments, for instance, in creating a dedicated team to support the alliance operations and that the extent of alliance opportunities is contingent on ED. Rosenkopf and Schilling (2007) suggest that when the ED is low, organizations score relatively lowly in terms of alliance opportunities. So, we postulate that the impact of AMC on organizational performance is low in the case of low ED. Conversely, high ED may reduce the value creation opportunities in the supply chain network because the alliance management capability rests on routinized practices that utilize the lessons drawn from previous experiences (Anand & Khanna, 2000; Schilke, 2014). Hence, we believe that the role of AMC in improving the AI-SCAC, under the moderating influence of ED, is worth investigating. Environmental dynamism (ED) requires changes in an organization's resource base to align with the external changes in the environment (Fainshmidt et al., 2016; Fosso Wamba et al., 2020; Mikalef et al., 2019a, 2019b; Schilke, 2014). Although organizations may derive potential benefits from their dynamic capabilities (Fosso Wamba & Akter, 2019), benefits are more likely realized in technologically dynamic industries (Schilke, 2014). Weerawardena et al. (2007, p. 294) argue that dynamic capabilities allow organizations to "*develop cutting-edge knowledge-intensive products, paving the way for their accelerated market entry*". Thus, in the face of frequent change in the external environment, dynamic capabilities should have more value; because such a context increases the opportunity to exercise dynamic capabilities (Schilke, 2014). Following, Fainshmidt et al. (2016) and other arguments, we argue that the impact of higher-order dynamic capabilities (i.e., AMC) impact on lower-order dynamic capabilities (i.e., AI-SCAC) increases when high ED is present. This aspect of the dynamic capabilities view has received less attention in prior literature; thus, we hypothesize:

H3: High ED has a significant and positive effect on the path joining AMCs and AI-SCAC;

Consistent with various management scholars' arguments, we consider organization size and age as appropriate control variables for our study (see, Schilke, 2014; Srinivasan & Swink, 2018; Dubey et al. 2019a; Fosso Wamba et al., 2020). In addition, we have controlled for the organization's alliance portfolio size (Schilke, 2014).

3. Research design

We used the three-staged research design, as suggested by Schilke (2014). Firstly, we conducted interviews to understand various types of organizational capabilities relevant to organizational resource configuration and their effects on organizational performance. Secondly, we developed a survey-based instrument. Thirdly, we gathered and analysed data for the dependent and independent variables of our study from appropriate organizations.

3.1. Qualitative interviews

We conducted 26 interviews, via Zoom/ Microsoft Teams, with senior-level supply chain managers from the auto components manufacturing industry. Each interview lasted between 30 and 45 min. In the first part of the interview, we asked managers to share their understanding of types of routine activities that enable their organization to adapt to rapid external changes. In particular we asked them about activities taken in response to the COVID-19 crises. Managers highlighted the important role of AMC and AI-SCAC. In the second part, we confirmed the appropriateness of our research hypotheses by asking these managers how critical the activities were for achieving high levels of operational and financial performance. Moreover, we asked how a change in the environment influence the AMC on AI-SCAC. There was considerable agreement among interviewees as to the relevance of our proposed hypotheses. Some managers also suggested that the COVID-19 crisis has accelerated their digitalization programs and that top leaders in their companies are now more positive to invest in their supply chain analytics capability and associated training programs.

3.2. Survey

We chose auto component manufacturing organizations registered on the database of the Auto Components Manufacturers Association of India (ACMA). This industry sector was chosen for reasons: (1) alliances are common in this industry (Dussauge, Garrette, & Mitchell, 2004); (2) the supply chain analytics capability plays a key role in the industry (Jeble et al., 2018); (3) the ACMA is the apex body in India that represents automotive components manufacturing industry both nationally and globally. We procured the assistance of a professional marketing firm that provides services related to data collection and consulting to many organizations in India and abroad.

Prior to collecting data, we pre-tested our questionnaire to assure that respondents understood and our wordings and to avoid any confusion. We identified respondents with similar profiles as those from the main survey for the pre-testing. Although, it was very time intensive process to collect responses from several senior supply chain managers in automobile manufacturing companies, especially during pandemic crisis as many managers were not willing to participate in the process. However, despite these challenges, we were determined to gather such inputs, as we believe pre-testing is an essential step to identify and fix any issues related to language of statements, clarity or use of technical terms prior to the launch of main survey. In view of these considerations, a survey was pretesting with a group of fifteen supply chain managers working in manufacturing firms in the Pune region of India (a hub of auto-component manufacturing firms). Short interviews via Zoom/ Microsoft Teams were conducted to discuss problems encountered in interpreting questions as and when needed. Minor changes were done to the wording of questions, as per feedback received, and a final survey was launched.

Our questionnaire was initially sent out by professional marketing team on our behalf, via e-mail, to 656 organizations in the ACAMA database, which contains details of over 800 firms. After two waves of data collections, using the key informant method to ensure diversity in the respondents (Capron & Mitchell, 2009), we finally received 167 usable responses. The response rate of 25.46% is consistent with previous studies of a similar nature i.e., Srinivasan and Swink (2018), Dubey et al. (2019), Fosso Wamba and Akter (2019) and Gupta et al. (2020). We provide the characteristics of participating organizations and key informants in Table 1. To examine the appropriateness of the key respondents, we included an item in the questionnaire to know about their tenure and job title (Kumar, Stern, & Anderson, 1993). Overall, 67% of the participants in the final data set had been associated with their organization for more than six years (see Table 1).

3.3. Nonresponse bias

We checked for non-response bias in three ways. Firstly, by comparing the responses from the two waves of data collection, using Student's *t*-test: an early wave and a late wave (Armstrong & Overton, 1977). The results are shown in Table 1. We observed no significant difference between respondents and non-respondents ($p > 0.05$) across the means for each respondent. Secondly, we examined whether the non-respondents were different from those that returned the questionnaire, in terms of organization size. Here we found no significant differences in responses ($p > 0.05$). Finally, following Mentzer, Flint, and Hult (2001), we randomly selected people from the non-respondents' sample and asked them to answer one item for each of the constructs, as shown Fig. 1. Based on a sample of 28 non-respondents, the Student's *t*-

Table 1
Sample characteristics ($N = 167$).

	Sample (Wave 1)	Sample (Wave 2)
Industry		
Auto component manufacturing	93	74
Firm Size		
<100 employees	17	16
100–249 employees	22	14
250–499 employees	18	18
500–999 employees	15	11
1000–4999 employees	13	8
≥5000 employees	8	7
Firm age (years)		
<5	8	9
5–9	7	6
10–19	34	23
20–29	26	22
>30	18	14
Job title of respondents		
Procurement Head	32	28
Logistics Head	25	22
Head of Production & Quality	23	13
Head of R&D	13	11
Tenure of the respondent in the organization (years)		
<1	10	9
2–5	20	16
6–10	45	38
≥10	18	11

tests of group means yielded no significant differences between respondents and non-respondents for any question ($p > 0.05$). We therefore drew an inference that non-response bias is not a potential issue in our study.

3.4. Measures

We adopted multi-item scales to measure our constructs (see Fig. 1). We adapted our measures from existing literature. Following the suggestions of DeVellis (2016) we further refined the questionnaire items via in-depth interviews with 17 senior managers. We further pre-tested our instrument with 23 managers. To assure reliability we triangulated the inputs obtained from the managers with complementary data sources (Homburg, Klarmann, Reimann, & Schilke, 2012; Schilke & Cook, 2015). The next sections describe the measures.

3.4.1. Alliance management capability (AMC)

We used a five-dimensions, reflective construct to measure AMC, as developed by Schilke (2014) and Schilke and Goerzen (2010). The dimensions are: (a) inter-organizational coordination; (b) alliance portfolio coordination; (c) inter-organizational learning; (d) alliance proactiveness; and (e) alliance transformation (Schilke, 2014, p. 191).

3.4.2. AI powered supply chain analytics (AI-SCAC)

For AI-SCAC we modified the measures developed by Srinivasan and Swink (2018). This is a five items reflective construct. We included items to understand how organizations used advanced techniques powered by cognitive technology to process useful information related to supply chain decisions from large and complex data sets. From a visualization point of view, we included items to measure the extent to which managers use dashboards to interpret the extracted information to gain insights from other managers involved in their supply chain networks. Further, we measured how the information enables managers take alternative decisions, in cases of supply shortages and demand fluctuations resulting from the COVID-19 crisis.

3.4.3. Environmental dynamism (ED)

To capture ED, we adapted measures developed by Schilke (2014) and we further confirmed our items based on the scale developed by Miller and Friesen (1982), which resulted in a five-item reflective construct. The items include measuring whether: a change in production modes is present, a changing external environment is continuously impacting the demand for products, digitalization is rapidly changing business practices, disasters like COVID-19 are highly unpredictable and, finally, in the current pandemic, organizations are rapidly changing their business models.

3.4.4. Organizational performance

We measured OP outcomes using items developed by Srinivasan and Swink (2018) and Dubey et al. (2019). For FP we took the items from Cochran and Wood (1984), Vickery, Jayaram, Droge, and Calantone (2003) and Richard et al. (2009).

All constructs and their measuring items are listed in Appendix A.

3.5. Control variables

3.5.1. Organization size (OS)

Management scholars suggest that OS might play an important role in enhancing organizational performance, by facilitating the access to a lower cost of capital, whilst simultaneously reducing operational risk (Chang & Thomas, 1989; Schilke, 2014; Srinivasan & Swink, 2018; Dubey et al. 2019a). Schilke (2014) further argues that OS influences the organization's dynamic capabilities, with larger organizations being able to invest in resources to develop their change routines. Hence, we use OS as a control variable, which we measured in terms of number of full-time employees.

3.5.2. Alliance portfolio size (APS)

In addition to OS, we used APS as a control variable, reflecting the fact that as well as the size of the individual organization, the size of the alliances formed could also facilitate enhanced performance - for the same reasons as outlined in the previous section. The past research has found significant association between the number of firm's alliances and the organizational performance (Powell, Koput, & Smith-Doerr, 1996). Following Jiang, Tao, and Santoro (2010) and Schilke (2014) suggestions we measured APS as the organization's total number of alliances. We used the logarithmic value to reduce the skewness in answers.

4. Data analysis

We used Warp PLS 7.0 software to analyse our data (see, Dubey et al., 2021; Kock, 2019), which is based on Partial Least Squares (PLS) method. Moshtari (Moshtari, 2016, p. 1549, c.f. Peng & Lai, 2012, p. 468) argue that "*PLS is a prediction oriented statistical tool that helps researchers to understand the predictive validity of the exogenous constructs*", which is appropriate, as our study examines the effect of AMC on AI-SCAC and the effects of AI-SCAC on OP/FP. Where there is no empirical evidence anticipating a relationship, as is the case with AMC and AI-SCAC, PLS-Structured Equation Modelling (SEM) is highly recommended (see, Akter, Fosso Wamba, & Dewan, 2017; Hult et al., 2018; Peng & Lai, 2012; Rigdon, Sarstedt, & Ringle, 2017). We followed Peng and Lai (2012) and Kock (2019) suggestions to evaluate the proposed model in two stages: (a) checking the validity and the reliability of the measurement model; (b) analyzing the structural model.

4.1. Measurement properties of constructs

Table 2 reports scale composite reliability (SCR) and average variance extracted (AVE) for our multi-item constructs (see, Fig. 1). Based on the SCR values we confirm that our constructs possess desired convergent validity (i.e., $\lambda i \geq 0.5$; $SCR \geq 0.7$ & $AVE \geq 0.5$) (Fornell & Larcker, 1981). We examined the discriminant validity of the constructs

Table 2
Measurement properties ($N = 167$).

Constructs	Items	λi	Variance	Error	Scale composite reliability (SCR)	Average Variance Extracted (AVE)
IC	AMC1a	0.75	0.56	0.44	0.85	0.58
	AMC1b	0.75	0.56	0.44		
	AMC1c	0.77	0.60	0.40		
	AMC1d	0.77	0.60	0.40		
APC	AMC2a	0.89	0.80	0.20	0.95	0.83
	AMC2b	0.94	0.89	0.11		
	AMC2c	0.91	0.83	0.17		
	AMC2d	0.90	0.81	0.19		
IL	AMC3a	0.74	0.54	0.46	0.92	0.73
	AMC3b	0.87	0.76	0.24		
	AMC3c	0.89	0.79	0.21		
	AMC3d	0.92	0.84	0.16		
AP	AMC4a	0.90	0.81	0.19	0.93	0.77
	AMC4b	0.90	0.81	0.19		
	AMC4c	0.70	0.49	0.51		
	AMC4d	0.98	0.95	0.05		
AT	AMC5a	0.97	0.95	0.05	0.94	0.83
	AMC5b	0.97	0.95	0.05		
	AMC5c	0.77	0.59	0.41		
AI-SCAC	AI-SCAC1	0.66	0.44	0.56	0.91	0.67
	AI-SCAC2	0.77	0.60	0.40		
	AI-SCAC3	0.77	0.59	0.41		
	AI-SCAC4	0.93	0.86	0.14		
	AI-SCAC5	0.94	0.88	0.12		
ED	ED1	0.80	0.63	0.37	0.88	0.61
	ED2	0.77	0.60	0.40		
	ED3	0.78	0.60	0.40		
	ED4	0.67	0.45	0.55		
	ED5	0.87	0.75	0.25		
OP	OP1	0.92	0.84	0.16	0.96	0.85
	OP2	0.95	0.91	0.09		
	OP3	0.93	0.86	0.14		
	OP4	0.89	0.79	0.21		
FP	FP1	0.96	0.93	0.07	0.98	0.93
	FP2	0.97	0.94	0.06		
	FP3	0.97	0.93	0.07		

Notes: IC, inter-organizational coordination; APC, alliance portfolio coordination; IL, inter-organizational learning; AP, alliance pro-activeness; AT, alliance transformation; AI-SCAC, artificial intelligence powered supply chain analytics capability; ED-environmental dynamism; OP, operational performance; FP, financial performance; λi, factor loadings; SCR, scale composite reliability; AVE, average variance extracted.

following Fornell and Larcker (1981) suggestions. We found that the square root of AVE (see the leading diagonal of Table 3) is greater in magnitude than all the correlated values in the same row and column. Further, using criterion test, the HTMT values (see, Table 4) are much below the cut off value (0.9). Hence, we confirm that our constructs possess sufficient discriminant validity (Henseler, Ringle, & Sarstedt, 2015). Overall, the tests undertaken show our constructs possess sufficient reliability and validity and are sufficiently strong to enable structural estimates.

Table 3
ConstructPlease provide a definition for the significance of bold in Table 3. correlations (N = 167).

	AMC	AI-SCAC	ED	OP	FP
AMC	***0.87***				
AI-SCAC	0.01	***0.82***			
ED	0.10	0.14	***0.78***		
OP	−0.22	−0.31	−0.36	***0.92***	
FP	−0.07	−0.09	−0.15	0.02	***0.96***

Notes: AMC, alliance management capability; AI-SCAC, artificial intelligence powered supply chain analytics capability; ED-environmental dynamism; OP, operational performance; FP, financial performance.

Table 4
HTMT values (N = 167).

	AMC	AI-SCAC	ED	OP	FP
AMC					
AI-SCAC	0.27				
ED	0.25	0.29			
OP	0.21	0.11	0.21		
FP	0.31	0.36	0.56	0.17	

Notes: AMC, alliance management capability; AI-SCAC, artificial intelligence powered supply chain analytics capability; ED-environmental dynamism; OP, operational performance; FP, financial performance.

4.2. Common method bias (CMB)

As survey-based cross-sectional data may suffer from common method bias (CMB) (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Podsakoff & Organ, 1986), we followed strict procedures to minimize the CMB effect. Firstly, we undertook the traditional single factor Harman's test (single factor explained nearly 26.2% of the total variance). However, some management scholars believe that Harman's single factor test is not sufficient and may not be treated as conclusive evidence. Hence, we undertook the second procedure, suggested by Lindell and Whitney (2001), which is popularly known as the correlation marker technique. We adopted an unrelated variable to partial out correlations that were a result of CMB. Additionally, we further extracted the significant values of correlations, as suggested by Lindell and Whitney (2001). There are minimal differences between the adjusted and unadjusted correlations. Hence, based on these statistical findings, we infer that CMB does not seriously influence our remaining results.

Following Kock's (2019) suggestion we determined the nonlinear bivariate causality direction ratio (NLBCDR). "*The NLBCDR measures the extent to which bivariate nonlinear coefficients of association provide support for the hypothesized directions of the causal links in the proposed theoretical model* "(Kock, 2012, p.52–53). We observed a NLBCDR of 0.91, which is significantly above the threshold value ≥0.7. Hence, we argue that causality is not an issue. We further provide the values for model fit and quality indices supporting this conclusion [see, average $R^2 = 0.51$; Tenenhaus GoF = 0.67].

4.3. Hypotheses testing

We examined our four research hypotheses as H1, H2a, H2b and H3. Table 5 provides the β co-efficient of the paths and corresponding *p*-values. Firstly, we found support for H1, which examines the effect of

Table 5
Structural Estimates (N = 167).

Hypothesis	Effect of	Effect on	β	p-value	Results
H1	AMC	IA-SCAC	0.32	<0.0001	supported
H2a	IA-SCAC	OP	0.28	<0.0001	supported
H2b	IA-SCAC	FP	0.17	<0.005	supported
H3	ED*AMC	IA-SCAC	0.17	<0.05	supported
	Control variables				
	OS	OP	0.027	>0.05	Not supported
	OS	FP	0.013	>0.05	Not supported
	APS	OP	0.17	<0.005	Supported
	APS	FP	0.21	<0.005	Supported

Notes: AMC, alliance management capability; AI-SCAC, artificial intelligence powered supply chain analytics capability; ED-environmental dynamism; OP, operational performance; FP, financial performance; OS, organizational size; APS, alliance portfolio size.

AMC on AI-SCAC (AMC → AI-SCAC) ($\beta = 0.32$; $p < 0.0001$). Secondly, we found support for H2a (AI-SCAC→OP) ($\beta = 0.28$; $p < 0.0001$). Addressing H2b (IA-SCAC→FP), we found support in the results ($\beta = 0.17$; $p < 0.05$). These findings are all consistent with previous literature (see, Kamalaldin et al., 2020; Srinivasan & Swink, 2018)). We further tested the interaction effect of ED on the path joining AMC and IA-SCAC (H3). We found support for H3 ($\beta = 0.27$; $p < 0.0001$). Our findings here support Fainshmidt et al. (2016)'s arguments.

Based on our results we argue that the effect of higher-order dynamic capability on lower-order dynamic capability is enhanced in the presence of high environmental dynamism. We note that the control variable organizational size (OS) does not have a significant effect on our study model. We interpreted these observations during the pandemic crisis and conclude that the size of the organization does not affect the motivation of organizations to invest in AMC and AI-SCAC. Furthermore, the alliance portfolio size (APS) has a positive and significant effect on our study model.

5. Discussion

The response to the pandemic crisis confirms dynamic capabilities as being simple, experiential, and unstable processes that are the outcome of the learning process (Colombo et al., 2020). The tenets of the DCV revolves around two key perspectives: (1) the effects of dynamic capabilities on competitive advantage, (2) the value of dynamic capabilities are more visible in the case of technologically dynamic industries (see, Fainshmidt et al., 2016). Despite its popularity in literature, DCV remains silent on how the hierarchical ordering of dynamic capabilities and the external environment context serve as contingencies producing different performance outcomes. Fainshmidt et al. (2016) argue that higher-order dynamic capabilities are significantly more linked to performance than lower-order dynamic capabilities. Similarly, Schilke (2014) notes that the lower-order dynamic capabilities partially mediate the relationship between higher-order dynamic capabilities and performance. Fainshmidt et al. (2016) further argue that the effect of higher-order dynamic capabilities on lower-order dynamic capabilities is more pronounced in the presence of high ED. Schilke (2014) observes that the relationship is not linear, with the performance outcome higher in the case of medium ED. We took these scientific debates as the foundation of our study. We recognize that despite the increasing use of DCV, the boundaries are yet to be understood. Our study was motivated by the significant use of data analytics capability to minimize the supply chain disruptions resulting from COVID-19. Despite increasing in volume, the existing literature has failed to provide theory-driven empirical results, with studies being purely conceptual or anecdotal in nature. Hence, we posited three guiding research questions to address research gaps and we addressed the questions with the help of data gathered from the Indian auto component manufacturing industry. The results paint an original and interesting picture of DCV during a pandemic (see Tables 2–5). Table 5 provides a summary of the hypotheses testing. Based on Table 5, we see which statements of our study are supported and which are not supported. In totality, the findings generated in our study offer some useful contributions to theory and provide rich guidance to supply chain managers, especially during such a pandemic crisis. We further believe that our study may open new avenues for research. In the remainder of this section, we elaborate on implications for theory, practice, and limitations/further research directions.

5.1. Implications to theory

Firstly, our study enhances understanding of how dynamic capabilities are distinct and cannot all be grouped into one homogeneous category. Previous studies have not provided a clear understanding of how dynamic capabilities behave and under what conditions they generate better results. Previously scholars have conceptualized big data analytics capability as dynamic in nature (see, Akter et al., 2016; Gupta & George, 2016; Mikalef et al., 2019a, 2019b). All these studies have viewed big data analytics capability as a higher-order reflective construct or as a combination of both reflective and formative constructs. Srinivasan and Swink (2018) further conceptualized supply chain analytics as a reflective construct. However, among the rich debate on the topic, we found that DCV theory has not been developed to explain the antecedent of AI-SCAC. To address this and building on previous studies (see, Fainshmidt et al., 2016; Schilke, 2014) we extend Srinivasan and Swink's (2018) theoretical contribution to understand how AMC, as a higher-order dynamic capability, influences AI-SCAC, as a lower order dynamic capability, under the presence of high volatility caused by the pandemic. Hence, our findings provide a nuanced understanding of DCV boundaries and contribute to addressing the gap noted by some scholars (see, Eisenhardt & Martin, 2000; Fainshmidt et al., 2016; Schilke, 2014).

Secondly, our study provides empirical evidence that AMC acts as an antecedent to AI-SCAC. The existing literature rarely acknowledges AMC as a causal element of analytics capability. We argue that our statistical results lend weight to the contingent view of DCV, which is regarded as higher-order organizational capability. Our findings contribute to theory by identifying that AMC, under the mediating effect of the AI-SCAC, enhances operational and financial performance, despite poor demand and restrictions imposed by governments on the movement of products. Hence, we provide further evidence that dynamic capabilities may produce excellent results if the stakeholders invest in alliance management capability during such a crisis.

Thirdly, our study is the first to test the relationship between AMC, AI-SCAC, and organizational performance. Most of the previous studies have tested a direct causal relationship to study organizational performance (Akter et al., 2016; Fosso Wamba et al., 2017) or under the moderating effect of organizational flexibility (Srinivasan & Swink, 2018). Based on an extensive review of salient literature, we highlight that, despite immense popularity, AMC has not attracted much attention from the organization researchers (Rothaermel & Deeds, 2006), which is mainly due to methodological constraints. Despite these constraints we have examined how AMC has a significant role in building AI-SCAC, which is yet unexplored by organizational scholars. Whilst we recognize that our attempt towards conceptualizing AMC is in its early stage, we believe that our efforts to date raise some new questions related to the AMC and, specifically, its influence on AI-SCAC.

5.2. Managerial implications

In terms of managerial implications, our results suggest that, when considering investments in building higher-order capabilities and lower-order capabilities, senior managers need to understand the details in terms of the *what, how and when*. In this respect the results provide directions to managers engaged in exploiting analytics capability to enable them to extract useful information to inform decision making related to managing complex supply chain networks. For instance, many organizations invest in building AI-SCAC, yet despite these, often substantial, investments, most do not yield strong positive returns. Our results suggest that AMC is a higher-order capability. Hence, in the absence of AMC, organizations may face enormous challenges to translate AI-SCAC into the successful outcomes which they initially expected. Moreover, in high ED, due to volatility in the market, organizations may fail to make sense of the demand and supply uncertainties.

Our results offer guidance to policymakers involved in formulating policies for developing countries to understand how dynamic capabilities can be exploited to gain superior outcomes during a pandemic crisis. They further inform managers, as well as policymakers, of the important contingent role external conditions play. These results are explicit and particularly useful to managers engaged in the automotive sector. They are also conceptually stimulating and may be transferred to manufacturing organizations in other sectors. Furthermore, they provide guidance to managers engaged alliance management activities, as to the how alliance management capability can be an important antecedent of AI-powered supply chain analytics capability. Hence, they show how the organization must invest in building important capabilities, such as: inter-organizational coordination, alliance portfolio coordination, inter-organizational learning, alliance pro-activeness, and alliance transformation. Similarly, training managers must prepare comprehensive training and development programs to improve organizational learning and knowledge management capabilities; and senior managers must empower the right people to make a significant positive difference and deliver a return on investment in relation to AI-SCAC. The APS has significant effect on the model which suggests that the partnering capabilities and the number of alliance partners significantly influences the benefits realized from the AI-SCAC.

Our results support the previous findings of scholars that during a period of high environmental dynamism, the efforts of organizations to interact with their partners should be re-doubled to maintain a high degree of transparency. Moreover, there should be continuous interactions with partners to improve collaboration, which is an essential success factor. The results show that alliance management capability is difficult to build, due to the complexities and uncertainties that exist across organizational boundaries. Hence, it is not surprising, therefore, that most alliances among partners fail to generate expected outcomes, especially in context to leveraging the potential of AI-SCAC during pandemic crisis.

Following, the arguments of Levitt and March (1988) relating to the "*experience curve*", AMC is built over the time via repeated engagements. The learning effects literature has shaped the operations management literature (Yelle, 1979), and the arguments made then remain true in the present case. AMC is the outcome of the continuous investment; however, in the wake of the sudden pandemic crisis, the importance of swift trust has been identified as an important driver of AMC (Tatham & Kovács, 2010; Dubey et al. 2019b; Schiffling, Hannibal, Fan, & Tickle, 2020). Our results provide a framework that may act as a blueprint for the manufacturing sector to assess and improve alliance management capability and AI-powered supply chain analytics capability, as well as increased organizational and financial performance.

5.3. Limitations and further research directions

Like any other previous studies, our study has its limitations. These limitations and unanswered research questions raise new questions that may help advance the theoretical boundaries. The limitations and future research directions are outlined below.

Firstly, our study utilized cross-sectional data to test the research hypotheses. As is common with such research designs, our study used single-informant data. Such data contributes to common-method bias (see, Ketokivi & Schroeder, 2004). Moreover, it is difficult to assess the causality among the hypothesized relationships using cross-sectional data. Therefore, due to the nature of the data, we could not further assess the variable effects of ED on the path joining AMC and AI-SCAC, as this requires collecting data via a longitudinal study (see Schilke, 2014). Hence, we strongly recommend such a study to comprehensively address unanswered questions relating to causality and common-method bias. Further, following Ketokivi and Schroeder (2004) suggestions, we recommend the use of a multi-informant instrument to gather data. This will help minimize the common method bias in the data.

Secondly, we examined the role of AMC and the AI-SCAC on organizational performance. However, other capabilities may be studied in this context i.e., strategic alliances and new product development capabilities may further explain variations in organizational performance, as they are essential ways to reconfigure organizational resources. The external resources may be obtained via strategic alliances, whereas the new product development capabilities may help organizations to update their product portfolio.

Thirdly, our data were gathered from the Indian auto components manufacturing industry. Hence, we caution readers that the results of our study should be interpreted in the context of this industry and generalization needs be doing with caution. We, therefore, encourage future replication studies that may test our findings in other settings, possibly incorporating a greater number of different industries, countries, and/or time periods to ensure a higher level of variance of the AMC and the analytics capability.

Finally, our study adopted a rather narrow definition of the contingent DCV, focused on experience-based, rather static routines and excluded more flexible forms of organizational change. Hence, we recommend the use of a qualitative approach to understanding the interplay of alliance management, analytics capability, and environmental changes, to understand the differential outcomes during a crisis. We believe, therefore, there are several unanswered and new questions that warrant further theorizing and empirical investigation.

6. Conclusions

In conclusion, we suggest that DCV, which is one of the most popular theories among management scholars, requires further development in some areas, which is the rationale for our study. Specifically, the behaviour of dynamic capabilities and the effect of ED on their performance outcomes are yet to be fully understood. We believe that emerging technologies as dynamic capabilities, such as AI, are far more complex in terms of their management, than capabilities based on traditional and well-established technologies. Hence, our findings suggest that future organizational scholars seeking to expand the boundaries of DCV theory ought to focus on explaining how some dynamic capabilities yield superior results beyond expectations, whilst other such capabilities produce poor outcomes. To do this we believe a more integrated approach, supported by other organizational theories, may be a fruitful avenue for further research.

Appendix A. Operationalisation of constructs

Constructs	Items	Statement	Source
IC	AMC1a	*We maintain strong coordination with our alliance partner during crisis.*	Schilke (2014, p. 189)
	AMC1b	*We assure that our tasks fit well with our alliance partner during crisis.*	
	AMC1c	*We assure that our work is well synchronized with our alliance partner during crisis.*	
	AMC1d	*We have regular interaction with our alliance partner despite lockdown.*	
APC	AMC2a	*We assure good coordination with all our partners during crisis.*	Schilke (2014, p. 189)
	AMC2b	*Maintain good synergy among our partners portfolio during crisis*	
	AMC2c	*We have accurately defined our interdependencies during crisis*	
	AMC2d	*We identify any overlaps between us*	
IL	AMC3a	*We assure that we learn from our partners during pandemic crisis*	Schilke (2014, p. 189)
	AMC3b	*We have desired level of competence to absorb new knowledge to navigate pandemic crisis*	
	AMC3c	*We have adequate routines to analyse the information obtained from alliance partners during pandemic crisis*	
	AMC3d		

(*continued on next page*)

(*continued*)

Constructs	Items	Statement	Source
		We can successfully integrate our existing knowledge with the information's that we have obtained from each partner to navigate pandemic crisis	
AP	AMC4a	*We do not compete with our partners especially during pandemic crisis*	Schilke (2014, p. 189)
	AMC4b	*We often take initiatives to reach out to our partners with a strong proposal to navigate pandemic crisis*	
	AMC4c	*We are far more proactive in comparison to our competitors in terms of exploring possible opportunities for alliance with the partners to minimize the negative consequences of pandemic crisis*	
	AMC4d	*We actively monitor environments to explore possibilities of new partnership with our partners*	
AT	AMC5a	*We do not give much importance to contractual agreements if it act as a barrier in our partnerships.*	Schilke (2014, p. 190)
	AMC5b	*We continuously modify our agreement based on the environment*	
	AMC5c	*We are flexible to change based on partners request especially during crisis*	
AI-SCAC	AI-SCAC1	*We use cognitive computing to improve our decision making to navigate pandemic crisis*	Adapted from Srinivasan and Swink (2018) & Dubey et al. (2020)
	AI-SCAC2	*We often make cognitive interpretation of the information extracted using data analytics to mitigate the disruption resulting from pandemic crisis*	
	AI-SCAC3	*We often integrate our data gathered from multiple sources to extract meaningful information*	
	AI-SCAC4	*Our dashboard helps managers to understand the cognitive computing outputs of complex data to make effective decision*	
	AI-SCAC5	*We have installed dashboard applications to our managers communication devices*	
ED	ED1	*We have changed our production capacity based on demands*	Schilke (2014, p. 189)
	ED2	*The current demand during crisis is changing continuously*	
	ED3	*Marketing strategies are changing rapidly during crisis*	
	ED4	*The crisis creates high degree of unpredictability in terms of demand and supply*	
	ED5	*We are rapidly changing our business models to respond to the crisis*	
OP	OP1	*Delivery on time*	Srinivasan and Swink (2018); Dubey et al. (2019)
	OP2	*Order fulfilment lead time*	
	OP3	*Inventory turnover ratio*	
	OP4	*Capacity utilization*	
FP	FP1	*EBIDTA (Earnings Before Interest, Depreciation, Taxation and Amortization*	Schilke (2014, p. 189)
	FP2	*ROI (Return on Investment)*	
	FP3	*ROS (Return on Sales)*	

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