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Understanding the influential and mediating role of cultural enablers of AI integration to supply chain

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ABSTRACT
Artificial Intelligence (AI) has been claimed to offer transformational power across industries and sectors. To date, research has largely focused on the technical characteristics of AI and its influence on organisational capabilities. Despite the hype surrounding AI, there is a scarcity of rigorous research that examines the organisational and behavioural factors that foster AI integration in supply chains is lacking. This quantitative study addresses this gap in knowledge by developing a research hypothesis that examines the relationships between supply chain culture and AI. We extend the generalisability of culture to provide novel insights about AI-driven supply chains that have not been reported in previous studies. The findings demonstrate the influential role that cultural enablers have on the successful integration of AI technologies in supply chains, which has implications for operations and supply chain management.

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Artificial intelligence; AI; supply chains; culture; operations management

1. Introduction

The general concept of supply chain (SC) relationships has been present in the academic lexicon for over 40 years. More recently, organisations have increasingly realised the importance of developing closer ties with fewer suppliers through a process of supplier categorisation (Cadden et al. 2015; Sánchez-Flores et al. 2020; Skipworth et al. 2015). The outcome of these closer relationships has resulted in the development of strategic buyer-supplier relationships with a small number of key suppliers to achieve sustained competitive advantage (Chicksand et al. 2012; Holgado de Frutos, Trapero, and Ramos 2020; Sako 1992). A key characteristic of these strategic SC relationships is technology integration (Cadden et al. 2020; Holgado de Frutos, Trapero, and Ramos 2020). However, a paradox remains. It is reported that new technology integration has the potential to add business value to an organisation and its SC by combining resources, coordination systems, increased data sharing, reduced costs, reduced lead times and increased service and quality (Brandon-Jones and Kauppi 2018). Yet, technology integration along the SC, be it technologies such as connected Enterprise Resource Planning (ERP) systems, e-procurement systems (e.g. Electronic Data Interchange), or Radio Frequency Identification (RFID) have all largely failed to deliver the desired business value (Brandon-Jones and Kauppi 2018; Zhan and Tan 2020).

Indeed, there is much hype that AI may deliver the game changing results to efficient and effective SC management, from the order management (i.e. forecasting), to order fulfilment (i.e. optimisation and utilisation), to order delivery (i.e. logistics and route planning) (Baryannis, Dani, and Antoniou 2019a; Ben-Daya, Hassini, and Bahroun 2019; Calatayud, Mangan, and Christopher 2019; Kamble and Gunasekaran 2020; Ivanov, Dolgui, and Sokolov 2019; Spanaki et al. 2020). For example, AI is being used for vendor matching and strategic sourcing. Keelvar's sourcing software uses machine learning for recognition of tendering documents and category specific e-Sourcing bots to help select suppliers against a set of KPIs. Amazon also uses AI throughout its SC for decision making and to automate tasks that were previously required human input.

Despite this hype and long-standing history of the operations and supply chain management (OSCM) field, a number of legitimate concerns have been raised, which could inhibit the successful deployment and use of AI in the context of OSCM.

First, the reported business value of AI is largely based on anecdotal evidence that is driven by technology and

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business consultants who may be bias to these results, which lack the theoretical basis to consolidate findings (Mikalef and Gupta 2021). Understanding how organisations will use AI to generate actionable insights that create business value is critical to sustaining competitive advantage (Berns et al. 2009; Iglesias, Markovic, and Rialp 2019; Pappas et al. 2018). Yet, if previous implementations of new technologies have not delivered the expected business value, there is a high risk that organisations may not realise the full potential of AI, which is predicted to account for nearly a quarter (24%) of global GDP by 2025 (World Economic Forum).

Second, Remko (2020) raises concern that there is a gap between understanding of OSCM in academic literature and that in practice. For example, in the context of SC resilience, studies tend to be conceptual in nature, and have made limited use of existing theoretical and new frames to advance knowledge (Ivanov and Dolgui 2020; Scholten, Stevenson, and van Donk 2019).

Third, which is related to the previous two points, the lack of theoretical development limits the accumulative body of knowledge (cf. Metcalfe 2004; Weick, Sutcliffe, and Obstfeld 1999). This lack of cumulative tradition resonates with the issue of 'fragmented adhocracy', which has previously overshadowed other research communities (Adam and Fitzgerald 2000; Banville and Landry 1989; Hirschheim, Klein, and Lyytinen 1996).

Fourth, the OSCM field has been criticised for not engaging in digital technologies, such as AI, and big data analytics (BDA) (Hofmann 2017; Vidgen, Shaw, and Grant 2017; Mortenson, Doherty, and Robinson 2015). For example, AI has received relatively little attention in the context of SC research, in general (Baryannis et al. 2019b). Hence, it makes sense to import insights from other disciplines into OSCM (Van Der Vegt et al. 2015) as it breaks down existing walls between OSCM and other disciplines (Liberatore and Luo 2010).

Fifth, numerous calls to action have been made for increased rigorous research on the influence of AI on SC performance (Baryannis, Dani, and Antoniou 2019a; Ben-Daya, Hassini, and Bahroun 2019; Calatayud, Mangan, and Christopher 2019; Dubey et al. 2019; Papadopoulos et al. 2017; Sivarajah et al. 2017; Spanaki et al. 2020).

These insights into how to bridge the human-machine interface (Liao et al. 2017) along the SC will be an important foundation for exploring and developing resilient SCs as they become increasingly more complex and intertwined (Ivanov and Dolgui 2020).

In this study, these concerns are addressed by focusing on SC culture, which enables us to provide novel, yet important theoretical and practical contributions to the OSCM field (Van Der Vegt et al. 2015).

The position of this study is that for the successful integration of AI, firms need to look beyond traditional technical enablers (i.e. security, technical skills, compatibility of systems) and business enablers (i.e. long term contracts, high quality of information) (Harland et al. 2007; Brandon-Jones and Kauppi 2018) to cultural and behavioural enablers (i.e. embracing of new technologies, trust, openness to change, autonomy, and a culture of information sharing). The influential role of culture as an enabler to SC success has increasingly being recognised by the research community (Cadden et al. 2015, 2020b; Losonci et al. 2017; Wiengarten et al. 2015). Yet, although culture is mentioned inferentially in the technology integration literature as a key enabler, there are limited empirical studies that investigate this concept (Ben-Daya, Hassini, and Bahroun 2019; Dasgupta, Shrein, and Gupta 2019; Huo, Han, and Prajogo 2016; Schniederjans, Curado, and Khalajhedayatia 2020).

To this end, the aim of this study is to 'examine the level to which supply chain culture can act as a key enabler to successful AI technology integration'.

This paper is structured as follows. First, a review of literature related to AI and SC culture and performance is presented. Next, the rational for development of the hypothesis is outlined, as well as the research methodology. Then, the analysis and findings are provided, followed by a discussion of findings. Contributions research and practice is outlined. The paper ends with implications, future research and a conclusion.

2. Theoretical framework

2.1. *Evolution of AI in modern operations and supply chain management*

Since its establishment as a relatively unknown academic discipline in the 1950s (Haenlein and Kaplan 2019; Lohr 2016), AI technologies have become a focal point of discussion in contemporary business (Dubey et al. 2019; Sivarajah et al. 2017; Spanaki et al. 2020). International Data Corporation (IDC) predicts that global spending on AI will be nearly \$98 Billion in 2023, more than double the \$37.5 billion that was spent in 2019.

AI has been claimed to offer transformational power across industries, ranging from enhanced business operations and productivity (Tarafdar, Beath, and Ross 2019; Faulds and Raju 2020) to reinventing business models (Duan, Edwards, and Dwivedi 2019) to organisational operations (Haenlein and Kaplan 2019) to decision-making (Duan, Edwards, and Dwivedi 2019; Paschen, Wilson, and Ferreira 2020; Power, Cyphert, and Roth 2019) to changing the nature of work (Schwartz et al. 2019) and increased predictive intelligence (Gawankar, Gunasekaran, and Kamble 2020; Kamble and Gunasekaran 2020; Ivanov, Dolgui, and Sokolov 2019).

Anecdotal evidence indicates that AI can fundamentally reshape existing operational practices and tasks (Dubey et al. 2019; Wamba-Taguimdje et al. 2020; Wamba et al. 2018) and that applications of AI will play an influential role in rebuilding and reconfiguring global operations and SC (Baryannis et al. 2019b; Dwivedi 2019; Koh, Orzes, and Jia 2019; Queiroz et al. 2019; Roscoe, Cousins, and Handfield 2019). Indeed, recent studies on AI have deepened our understanding of AI in the contexts of OSCM yet, scaling AI usage could encounter significant bottlenecks that remain under studied (Spanaki et al. 2020). For example, failure to scale up from pilot implementations of AI applications can result in unclear business value as managers fail to estimate the potential impact of the pilot on the manufacturing processes and define success criteria accurately (Dogru and Keskin 2020).

There is no single universal definition of AI, an umbrella term referring to the digital technologies performing activities, tasks and decisions normally performed by human intelligence (Pomerol 1997). We adopt the definition provided by Haenlein and Kaplan (2019, 5), that AI is 'a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation'. This definition is pertinent to the context of this study as it captures the overlap between AI and business analytics capabilities. This overlap includes leveraging large data, employing advanced technology and analysis tools, and using advanced statistical methods to extract value (Davenport 2018a). AI and business analytics capability is an emergent technological capability that is enforcing new organisational capabilities focusing on technology for the collection and analyses of real-time data (Davenport 2018b; Mikalef et al. 2020). For example, BDA capabilities refer to an organisation's ability to capture and analyse data towards the generation of 'actionable insights' by effectively deploying its data, technology and resources through organisation-wide activities (Mikalef et al. 2020).

A number of studies highlight the importance and value of quality information sharing in the context of effective SCM and higher performance (Huo, Haq, and Gu 2021; Wamba et al. 2015; Yu and Cao 2020; Li and Lin 2006; Li et al. 2006), and in use of AI-based technologies (Ali et al. 2017; Kache and Seuring 2017; Baryannis, Dani, and Antoniou 2019a; Spanaki et al. 2018; Papadopoulos et al. 2017). It is this multidisciplinary approach of AI, which is based on data sharing, gathering and analytics that has brought the potential organisation-wide transformational power of AI to the attention of OSCM field (Baryannis et al. 2019b; Spanaki et al. 2018).

Table 1. Application of AI to supply chain activities.

AI technology	Application in supply chains	Source
Machine learning	• Demand forecasting • Vulnerabilities • Risk management	• Carbonneau, Laframboise, and Vahidov (2008) • Gu, Dolan-Gavitt, and Garg (2017) • Baryannis, Dani, and Antoniou (2019a)
Expert systems	• Professional contracts • Risk management	• Shokouhyar et al. (2019) • Soleymani and Nejad (2018)
Robotics	• Advanced automation • Scheduling	• Viswanadham (2002) • Sadik and Urban (2017)
Natural language processing	• Supply chain maps • Advanced automation	• Wichmann et al. (2020) • Dash et al. (2019)
Machine vision	• Defective product detection	• Benbarrad et al. (2021) • Ireri et al. (2019)
Speech recognition	• Demand forecasting	• Kilimci et al. (2019) • Torres-Franco (2021)

In the context of OSCM, the increase in the frequency and impact of global events (i.e. natural and man-made disasters) has prompted organisations to critically evaluate their capabilities for resource reallocation and SC resilience through data-driven approaches (Remko 2020; Wamba and Akter 2019; Giannakis et al. 2019). Data-driven technological approaches, such as AI and BDA capability in organisations could draw on unstructured data to enhancing adaptive SC capability to cope with future interruptions from global events (Dubey et al. 2019; Papadopoulos et al. 2017).

There are six main AI technologies that fall under the umbrella of AI, namely, machine learning, expert systems, robotics, natural language processing, machine vision, and speech recognition (Dejoux and Léon 2018). Table 1 lists how each of these technologies have been applied to specific SC activities.

The potential impact of AI technologies is expected to be far reaching, affecting every corner of the factory and SC (Dennehy 2020; Baur and Wee 2015). For example, machine learning can support data-driven decision-making in pre-production, production, processing, and distribution stages of agricultural SCs (Sharma et al. 2020). Prior research has examined the role of AI for effective and efficient SCM, including forecasting (Chien, Lin, and Lin 2020), configuration and optimisation (Abbasi et al. 2020; Fragapane et al. 2020), forecasting (Chien, Lin, and Lin 2020), risk management (Baryannis et al. 2020; Soleymani and Nejad 2018), collaboration between human operators and AI-based systems (Klumpp 2018), increased operational efficiency in replenishment policies (Priore et al. 2019), and supplier selection (Zhao and Yu 2011; Choy et al. 2004). While such studies have made valuable contributions, knowledge about the influential and mediating role of culture is limited.

2.2. The evolution of supply chain management

Supply Chain Management (SCM) as a term was first introduced into mainstream literature in the early 1980s (Harland 1996; cited by Kotzab et al. 2011; Xu et al. 2017). Ever since, there has been much debate by academics concerning the term SCM (Cadden et al. 2020a; Cousins, Lawson, and Squire 2006). Traditionalists regard SCM as merely strategic purchasing, with a focus on developing partnerships with both first and second tier suppliers (Larson and Halldorsson 2002). There are also those who refer to purchasing and SCM interchangeably (Giunipero and Brand 1996; Cousins, Lawson, and Squire 2006). Others view purchasing as a subset of SCM and have an embedded perspective (Stock and Lambert 2001). However, a definition for SCM that is widely accepted by the academic community is an organisational concept whose primary objective is to integrate and manage the sourcing, flow and control of materials using a total systems perspective across multiple functions and multiple tiers of suppliers (Monczka, Trent, and Handfield 1998; cited by Larson and Halldorsson 2002, 36).

There is a general consensus of the impact that SCM has on the financial and operational performance of firms (Skipworth et al. 2015; Xu et al. 2017; Zhang and Cao 2018). As far back as the early 1990s, a landmark study into supplier categorisation by Sako (1992) was instrumental in unveiling a novel approach and thinking into the buyer-supplier relationship management field. This concept and approach lay underutilised until recent times (Cadden et al. 2015). However, as firms are increasingly looking for competitive advantage, the focus on supplier relationships has re-appeared with renewed vigour and promise to deliver this much craved competitive advantage. Many firms have now shifted their mind-set in regard to the purchasing function, from one of an operational and tactical function to one which is strategic in nature (Cadden et al. 2020b; Kim and Nguyen 2018). Further, this shift in focus within the purchasing function coupled with increasing globalisation, technological change, and shortening product life cycles since the mid-1990s (Cadden et al. 2020a; Kim and Nguyen 2018; Tan, Lyman, and Wisner 2002), has resulted in firms developing closer ties with fewer suppliers through a process of supplier rationalisation (Kim and Nguyen 2018; Phillips et al. 2006). The outcome of these closer relationships has resulted in the development of collaborative or strategic SC relationships with a small number of key suppliers as a means to achieve sustained competitive advantage (Kim and Nguyen 2018; Chicksand et al. 2012; Lamming, Caldwell, and Phillips 2004; Sako 1992).

2.2.1. Supply chain culture

The antecedents of culture can be traced back to the field of anthropology (Kluckhohn 1951). However, culture entered the academic lexicon in the late 1970s (Pettigrew 1979). The two most influential writers of their time in the area of organisational culture were Edgar Schein and Gerard Hofstede. Schein's work on organisational culture (also referred to as corporate culture) began in the 1980s with an infamous 'ice-berg' model detailing the layers of organisational culture (Schein 1985). The model proposed that culture is difficult to measure, complex to understand change, and has many different layers. Yet, the artifacts level is widely recognised amongst researchers as most visible layer. At this level, manifestations of organisational culture are most measurable. This concurs with work by Hofstede (1980) who also recognises a visible manifestation level (which he broadens to the term practices). Within the practices level, Hofstede includes Symbols (signs and slogans which provide instant recognition) for example, Audi's 'vorsprung durch technik' (Barley 1983), Heros those in the organisation who are inspirational figures and 'exemplify the values' (Cadden et al. 2010), such as Richard Branson or Bill Gates (Hofstede et al. 1990; Wilkins 1984), Rituals (Hatch 1993; Hofstede et al. 1990; Schein 1985) and artefacts.

Hofstede et al. (1990) devised a cultural audit tool which allows organisations to measure organisational culture at the practices level. Despite its limitations with validation, this tool is widely recognised and used within the literature (Cadden et al. 2010, 2020a; Pothukuchi et al. 2002). There are 35 questions across six key sub dimensions within the practices tool. These consist of process versus results (rule driven versus result driven); Employee versus Job (caring about the individual or job orientated); Open versus closed (constructive organisations versus a defensive organisation); Tight versus loose (controlling organisation versus empowerment and flexibility); Norm versus pragmatic (achievement based versus following standards); and Market versus Internal (customer focused or internally focused). Hofstede et al.'s (1990) tool was updated in 2000 by Verbeke to address the much-quoted validation issues (Verbeke 2000).

Beneath the 'artefacts' or 'practices' layer of organisational culture is the 'values' level. The values literature has long been an area of major contention. The challenge lies between what is one's own values versus what are work values, and the criticality of these both being similar. Much work in the area of person-fit (O'Reilly, Chatman and Caldwell 1991) discusses how important it is to recruit personnel who hold similar values to those of the firm. Values in the work sense are defined as 'the end state people desire and feel they ought to be able to realise through working' (Nord et al. 1988, 2). While Rokeach (1973, 14) suggests personal values are 'organisation of principles and rules to help one choose between alternatives, resolve conflicts and make decisions'. Hofstede et al. (1990) believes values are hard but not impossible to change, and that by the age of seven a person's values are already engrained. Applying this concept to organisational and inter-organisational relationships poses the following questions: Can an organisation change an employee's values through a process of socialisation of culture? Can an organisation change suppliers' values through early involvement and absorptive capacity? It would seem interesting and promising to apply Rokeach's definition of a person's value system in a SC context. Could a set of SC values help organisations 'choose between alternatives, resolve conflicts and make decisions'? Rokeach believes that through self-confrontation values can be changeable. This self-confrontation takes the form of giving individuals feedback and they will therefore become more self-aware of their sub conscious and through this self-awareness can alter their mindset and value system.

There has been much written on the cultural clashes between integrating firms in the research field of mergers and acquisitions (Cartwright and Cooper 1993; Weber and Camerer 2003). It is widely recognised that a lack of cultural fit can result in lower productivity, higher labour turnover, and customer responsiveness (Cadden et al., 2020a; 2015). Albeit the literature within the field of organisational cultural fit is mature, there are still a large number of unanswered questions in how this may be applied in a SC setting. For example, how best can cultural fit be measured across partnership SC organisations? How best can cultural fit be achieved between two or more integrating SC organisations? Which cultural dimensions are most important? Which aspects of culture should firms concentrate on in order to achieve high performance outcomes for all participants?

The research on Mergers and Acquisitions has provided a useful foundation. For example, the ability to integrate firms is regarded as the most important factor in determining overall success (Cartwright and Cooper 1993). Further, the participation of the personnel involved and creating an atmosphere of cohesiveness is both a challenge and the most rewarding (Haspeslagh and Jemison 1991).

In SC relationships, cultural fit is increasingly a major area of interest as firms are beginning to recognise the positive influence of cultural fit on successful buyer supplier performance outcomes (Cadden et al., 2020a; Phillips et al. 2006). In the context of this study, SC cultural fit is defined as the 'shared values, beliefs and behaviour patterns which permeate within and between each supply chain partner organisation resulting in mutually desired performance outcomes' (Cadden et al. 2010).

Many firms involved in strategic buyer supplier relationships must now look beyond the traditional economic indicators alone to achieve desired performance outcomes (Karunaratne et al. 1996; Larsson and Lubatkin 2001; Lee and Yu 2004; Weber et al. 1996; Weber et al. 2003). These relationships highlight the importance of shared values such as trust, commitment, adaptability and communication as increasingly important in achieving high-performance outcomes for integrating firms (Cullen 2000; Dolan and Garcia 2002; Douma 2000). Organisations have begun to realise the importance of investing more joint resources into developing an environment where shared values can thrive. Buyer supplier practices such as cross functional teams, joint workshops, joint sports-days and barbeques; widely recognised as visible manifestations and a conduit to permeate shared values (Hofstede et al. 1990; Schein 1985; Trice and Beyer 1993), are increasingly investigated as mechanisms embed a SC culture of high performance (Cousins, Lawson, and Squire 2008).

Such an environment creates a culture of performance management throughout the SC, which removes the fear of cause and effect, resulting in performance as a behaviour rather than an organisational outcome (Neely 2002; cited by Cadden et al. 2011). Therefore, research would suggest that cultural fit between the SC partners should therefore result in performance improvement.

Research has been conducted on the role of culture within a SC context. For example, Whitfield and Landeros (2006) assessed 12 business units and 112 buyers in the US. They found that achievement and affiliative based cultures where there is a constructive cultural style and where members are 'encouraged to interact' results in increased supplier engagement. Mello and Stank (2005) devised a theoretical framework attempting to define cultural dimensions of use when implementing SC initiatives. Liu et al. (2010) looked at the role of institutional pressure on the firm's ability to adopt internet enabled SCM systems, and how such effects are moderated by organisational culture. They found that differing elements of organisational culture had differing impacts. A flexible orientation negatively moderated the effects of coercive pressures and positively moderated the effect of

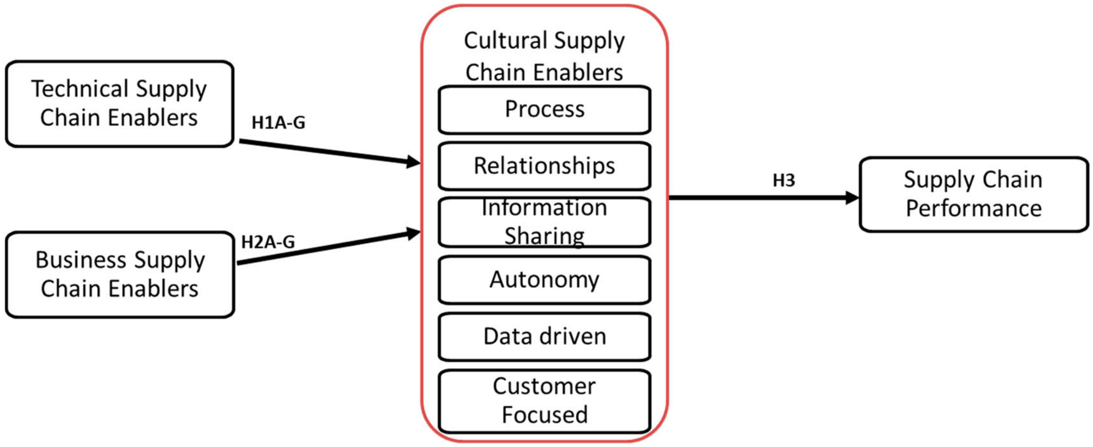

Figure 1. SCHAIN model (Supply Chain Holistic Artificial Intelligence Nexus).

mimetic pressures. The finding that firms are not just economically rational but are socially rational is another interesting finding. Lui and Lui (2009) conducted a study of 225 matched dyads in China and found that performance is enhanced when relational mechanisms are used.

2.2.2. Supply chain performance

Whilst operations performance is widely adopted within firms, and typically includes the standard cost, service and quality metrics within the boundaries of the firm, SC performance is more difficult to measure and manage due to the boundary spanning activities, locus of control and visibility along the SC. However, with firms increasingly aware of the benefits of strategic SC relationships, researchers are calling for more nuanced and empirical studies which include SC performance measures. Further, whilst traditional financial measures, such as return on investment, market share, earnings before interest and tax, and sales growth (Cadden et al., 2020a; Yilmaz, Alpkan, and Ergun 2005) have been widely reported, a number of studies have reported that firms may be able to maximise the potential of their SC performance by increased integration (Cadden et al. 2015; Gunasekaran, Patel, and McGaughey 2004). It is therefore posited that SC performance measures need to extend the standard operational measures into a SC setting; measures such as operating cost, inventory costs, flexibility, delivery performance, and cost reduction initiatives (Ahmad and Schroeder 2003; Cadden et al., 2020a; Gunasekaran, Patel, and McGaughey 2004; Zhan and Tan 2020).

3. Hypotheses development

This section presents three sets of research hypotheses examining the relationships between the technical and business enablers of Artificial intelligence (AI) and Business Analytics (BA) and their influence on SC culture. A third and final set of hypotheses seeks to explore how the aforementioned interlinkages influence operational performance. Figure 1 outlines the testable model in this study.

3.1. Hypothesis H1A-H1G: technical enablers of AI and BA and their influence on SC culture

Davenport (2018a) argues that AI and BA capability development may be significantly enhanced in companies that adopt an analytical or results driven approach to business operations. In a SC context, Jha, Agi, and Ngai (2020) observe that firms which are systemically and technically integrated with their suppliers via existing technologies such as ERP and internet enabled technologies such as cloud computing may find the transition to big data and AI less operationally demanding (Gunasekaran et al. 2017; Jha, Agi, and Ngai 2020). This is because such organisations already display an orientation towards a result-based and data-driven culture as they are technologically integrated with their suppliers and customers and possess basic data integration capabilities i.e. ERP (Chan et al. 2006; Chae, Olson, and Sheu 2014a; Jha, Agi, and Ngai 2020). For instance, a study by Ghobakhloo (2020) found that operations technology maturity and cybersecurity maturity were found to be key determinants of smart manufacturing and digital technology implementation. A study by Ivanov et al. (2017) highlighted the importance of collaborative cyber-physical system principles, which will combine both 'information and material subsystems' to arrive at robust and integrative decision-making process along the SC. Moreover, in relation to BA specifically, the use of predictive analytics often requires historical or real-time factual data in order to develop predictive forecasts, which in turn can be used to manage SC risk and identify the most efficient suppliers and profitable customers (Chan et al. 2006; Brintrup et al. 2020).

In terms of AI specifically, both Priore et al. (2019) and Davenport (2018a) argue that the successful implementation of AI models such as machine learning, generally requires historical training datasets from SC participants in order to develop learning algorithms (Chan et al. 2006). The aforementioned learning algorithms can then make intelligent case-based choices on inventory replenishment as well as predictions on supplier performance (Chan et al. 2006; Priore et al. 2019). Liao et al. (2017) refers to the Human-Machine interface as being critical in developing collaboration. This practice requires the open sharing of both supplier and OEM data in order to facilitate AI decision making (cf. Chan et al. 2006; Brintrup et al. 2020). For instance, Čudanov and Jaško (2012) found that new ICT adoption was typically higher in results based cultures (as opposed to process or people based cultures) where the focus is on sharing measurable performance outcomes between departments and across the SC. Moreover, as AI may often augment or replace the human aspects in the SC, the use of AI and BA will be more suited to pragmatic, results-based SC cultures, where the idea is to improve outcomes/results by any means necessary, as opposed to adhering to pre-defined processes or standards (Verbeke 2000; Cadden et al., 2020a; Ivanov and Dolgui 2019; Preindl, Nikolopoulos, and Litsiou 2020). For example, Ivanov and Dolgui (2019) reported that Low Certainty Need SC can have an impact on managing risk and resilience. To this end, process flexibility and structural variety were recognised as two key characteristics to support resilience and recovery resource allocation. Therefore, it can be argued SC analytics and AI will be suited to both data-driven and results-oriented SCs, that are flexible, as opposed to the rigidity of being strictly process oriented SCs (Ivanov and Dolgui 2019; Yu et al. 2018; Wamba and Akter 2019).

Leading on from the previous arguments, a comprehensive systematic literature review study by Calatayud, Mangan, and Christopher (2019), found that the internet of things (Iot) and AI are the technologies most frequently associated with the autonomous and predictive capabilities in future SCs. Traditionally, the degree to which a SC may have been described as autonomous related to the idea that suppliers were not required to be monitored, as long as they met and shared their weekly targets or performance targets (Hoyt and Huq 2000). Increasingly however, the processes within SCs are becoming increasingly autonomous in the technological sense, with many traditional human roles being supplemented or overtaken by self-thinking artificial intelligence (Fatorachian and Kazemi 2020; Schulze-Horn et al. 2020). For instance, robotic process automation (RPA) is a form of AI based software tools used to partially or fully automate human activities that are largely rule based and repetitive (Davenport 2018a). In procurement management, digital bots can be applied on top of the existing SAP infrastructure to lessen the analytical burden on responsible personnel in areas such as contract writing and the uploading of contracts, thus allowing personnel to focus attention on supplier negotiations (Deloitte 2018). Furthermore, Fatorachian and Kazemi (2020) highlight that in cyber physical environments, machines have self-controlling and self-diagnostic capabilities and can detect variations in production or assembly performance through the use of sensors. Interestingly, BA can be combined with this data to predict and forecast machine breakdowns and schedule maintenance appointments (Fatorachian and Kazemi 2020). This type of data must be shared throughout operations and the SC, underlining the need for technologically integrated SCs to facilitate autonomous AI (Brintrup et al. 2020; Sanders 2014). For instance, both Chan et al. (2006) and Brintrup et al. (2020) highlight that in order to develop an AI enabled knowledge platform to simulate SC risk, data is required from both suppliers and the OEM. Hence, it's argued that AI and BA will be more suited to autonomous or loose SC structures, which are facilitated by a high degree of information sharing and technological integration (Chae et al. 2014b; Moyano-Fuentes, Sacristán-Díaz, and Garrido-Vega 2016; Davenport 2018a; Fatorachian and Kazemi 2020). Furthermore, Ivanov and Dolgui (2020) report on Intertwined Supply Networks (ISNs), as being open systems that include structural dynamics, and firms and SCs will express a range of behaviours through interconnectedness and role changing. In the world of digitisation, understanding these key behaviours and roles and how the SC or network mutates will be key to 'survivability' and firm success.

Finally, in order to effectively integrate BA and AI initiatives within the SC, close relationships with both suppliers and customers are fundamental to building both trust and knowledge surrounding the implementation of BA and AI systems with suppliers (Gupta et al. 2019). More specifically, in relation to data-driven SCs, relationships are fundamental to gathering data from suppliers and customers in a secure and ethical manner (Bienhaus and Haddud 2018; Preindl, Nikolopoulos, and Litsiou 2020). For example, the sharing of information across the SC is not new for manufacturing organisations and is built on the foundation of trust and long-term relationships with buyers, suppliers and customers (Chiarini and Kumar 2020). Robust supplier relationships are important technical enablers for AI and BA as both Barton and Court (2012) and Jha, Agi, and Ngai (2020) highlight that a key challenge for using business analytics is to make big data secure, trustworthy and understandable to all participants in the SC (cf. De Cremer, Nguyen, and Simkin 2017). Employees or suppliers may be initially reluctant to use big data since they may not have appropriate skills to harness and utilise such data or because the data is not channelled to all members in the SC (Harland et al. 2007; Jha, Agi, and Ngai 2020). Moeuf et al. (2020) advocate that training is the most important factor for success in SME adoption of industry 4.0 technologies. However, Sony and Naik (2020) argue that such technologies will inevitably change job roles, so training must be customised to fit these new roles. Moreover, in relation to AI specifically, trust in the new ways of working must be created in buyer-supplier relationships. Schulze-Horn et al. (2020) argue that AI should not be seen as a rival or replacement of the human personnel, instead it should be seen as a facilitator of a more effective and efficient SC. For instance, Brandon-Jones and Kauppi (2018) highlight that process enhancement and usability are important enablers of technology acceptance within e-procurement adoption. Therefore, trust based collaborations with key suppliers should be made in order to demonstrate the *technical practicality* and usefulness of AI and BA in the SC.

Business analytics can also facilitate enhanced customer integration and therefore influence the SC to become more market oriented (Sanders 2014; Chavez et al. 2017). For instance, BA an AI applications can be used to better synchronise the SC with customers' expectations in terms of limiting inventory stock-outs through analytical modelling, and implementing more accurate forecasting methods (Chavez et al. 2017). Moreover, BA and AI can be used in terms of segmenting the customer into more targeted marketing groups through the use of predictive analytics (Fatorachian and Kazemi 2018). Finally, as AI and data analytics can analyse large amounts of customer data quickly (often in real-time) from existing CRM (Customer Relationship Management) and website databases, firms Implementing AI and BA will quickly be able to facilitate enhanced customisation of orders as well as the introduction of new products using BA (Choy et al. 2004; Davenport 2018a; Fatorachian and Kazemi 2020; Vidgen, Shaw, and Grant 2017; Zhan and Tan 2020). In other words, the combination of BA and AI with existing CRM systems can help the SC be market oriented and responsive to changing customer demands (Gupta et al. 2019; Wamba and Akter 2019).

In summary, the technical enablers of AI and BA will influence supply chain culture to be more; (H1a) results oriented rather than process oriented, (H1b) more relationship oriented towards both suppliers and customers as opposed to closed, (H1c) more disposed towards information sharing as opposed to being disconnected, (H1d) more autonomous rather than OEM dependant, (H1e) more data-driven rather than job-focused more, and finally, (H1f) more market focused as opposed to internally focused.

3.2. Hypothesis H2A-H2G: business related enablers of AI and BA and their influence on SC culture

Dubey, Gunasekaran, and Childe (2019b) argues that flexibility oriented organisational cultures (as opposed to control cultures) are more likely to have the capacity to respond to the changes introduced by AI and BA. Interestingly, this proposition is supported in a subsequent study by Dubey, Gunasekaran, and Childe (2019b), in which is found that that organisational flexibility is a key enabler in the path linking big data analytics capability and SC agility. Gupta et al. (2019) also refer to *supplier* relationship flexibility (i.e. the supplier's ability and willingness to accept the volume and variety of information as well as the ability and desire to integrate buyers' systems) as key facets of overall SC flexibility in smart SCs. It can be argued that the relationship found by Dubey, Gunasekaran, and Childe (2019b) between flexibility, BA and agility may be due to the observation that SC agility is focused on organisational responsiveness to customer demand and therefore largely results oriented (Gunasekaran et al. 2017, 2018). Hence, the flexibility to gather data from many different sources i.e. across business functions and from suppliers/customers, as opposed to storing data in silos, will enable the firm to make more efficient and informed decisions using BA (Dubey, Gunasekaran, and Childe 2019b; Gunasekaran et al. 2018; Preindl, Nikolopoulos, and Litsiou 2020; Srinivasan and Swink 2017; Zhan and Tan 2020). As Gupta et al. (2019) argue, a flexible structure is required for the optimum information flow in smart SC (cf. Lee 2004). As BA is largely data-driven (Quoc Viet, Behdani, and Bloemhof 2020; Jha, Agi, and Ngai 2020), organisational flexibility will facilitate the rapid capture and analysis of customer and inventory data, thus enabling faster SC response times i.e. agility (Dubey, Gunasekaran, and Childe 2019b; Wamba and Akter 2019). Conversely, in process or control oriented environments, information flow and data analysis may be restricted due to an adherence to rigid rules and silo based thinking (Samson and Terziovski 1999 Ivanov and Dolgui 2019). Finally, firms with flexible work methods will be more likely to have the capacity and adaptive capabilities to foster AI and its sub systems (Gunasekaran et al. 2018; Dubey, Gunasekaran, and Childe 2019b). AI in turn will supplement agility and faster response times by freeing up human capacity to respond to customer requirements (Deloitte 2018; Davenport 2018a). Therefore, it can be argued that business flexibility as an enabler of AI and BA, will influence the SC to be more results oriented, data-driven and autonomous.

A second key enabler of AI and BA relates to organisational alignment and coordination capabilities (Sony and Naik 2020). More specifically, this relates to the synchronisation and integration of the entire organisation in order to produce and share high quality data related to performance (Akter et al. 2016). Gupta et al. (2019) find that in addition to the *acquisition* of data outlined in the previous paragraph, the correct *deployment* of information within smart SCs is important for the effective use of BA and AI. In other words, an aligned and integrated organisation should provide more accurate and context specific organisational information for effective strategic decision making within the realm of BA and AI (Chae et al. 2014b; Akter et al. 2016; Chiarini and Kumar 2020; Cohen 2015; Jha, Agi, and Ngai 2020). For example, a firm which has integrated systems between the SC and CRM, can use BA to analyse customer feedback and complaints to specifically examine how SC decision making can improve customer satisfaction such as lead-time reduction and more customisation choices (Cohen 2015; Akter et al. 2016). Moreover, firms can identify organisational value streams though BA (O'Neill and Brabazon 2019) and automate those processes which do not add customer value using AI (Deloitte 2018). Hence BA and AI require organisational alignment and coordination which will in turn influence the SC to be more disposed toward information sharing between both internal departments and SC partners (Akter et al. 2016; Yu et al. 2018).

Finally, relationship oriented organisations which have strong links to both suppliers and customers will facilitate the adoption of BA and AI in their SCs. Previous research suggests that organisations which develop close relationships with their suppliers and customers can build trust alongside learning-based collaborations, thereby facilitating a high degree of SC integration (Handfield and Christian 2002; Liker and Choi 2004). This in turn will facilitate the joint introduction of new initiatives, systems and processes (i.e. build-to order), allowing the organisation to more effectively reduce costs, increase flexibility, enhance response times and improve quality (Liker and Choi 2004; Krause, Handfield, and Tyler 2007). From an AI and BA perspective, close relationships with suppliers and customers also gives the focal firm access to valuable data which in turn be used by BA and AI to enhance both supplier and customer relationships (Chavez et al. 2017; Zhan and Tan 2020). As Davenport (2018a) illustrates, in the supplier domain, probabilistic matching using machine learning can help to unify disparate and siloed data sources into one integrated system, while in the customer space, machine learning can be applied to CRM data to produce detailed propensity models which allow the sales teams to decide which customers to offer which products, thereby enhancing customer relationships (Davenport 2018a; Gupta et al. 2019). While Zhan and Tan (2020) find that integrated data siloes are linked to idea generation for new product development which in turn can satisfy existing customers and attract new customers. In this sense, the adoption of BA and AI will influence SCs to be more relationship oriented and market focused.

In summary the business enablers of AI and BA will influence supply chain culture to be more; (H2a) results oriented rather than process oriented, (H2b) more relationship oriented towards both suppliers and customers as opposed to closed, (H2c) more disposed towards information sharing as opposed to being disconnected, (H2d) more autonomous rather than OEM dependant, (H2e) more data-driven rather than job-focused more, and finally, (H2f) more market focused as opposed to internally focused.

3.3. *Hypothesis H3A-H3G: supply chain culture and operating performance*

This section will now propose a final set of research hypotheses which examine the impact of the cultural related enablers of AI and BA on operating performance. As prior research has found that organisations have struggled with new technology adoptions in the past (Harland et al. 2007), It is imperative to determine how a BA and AI enabled culture can impact operational performance (Ferraris et al. 2019; Bordeleau, Mosconi, and De Santa-Eulalia 2020).

In relation to results-oriented and data-driven cultures, Verbeke (2000) and Cadden et al. (2020a) highlight that firms that display a results orientation are often concerned with performance outcomes and data-sharing and therefore will not typically set rigid rules or standards which often define process-based cultures (Čudanov and Jaško 2012; Bortolotti, Boscari, and Danese 2015). In other words, results oriented firms are more flexible in their operations and SC (Ivanov and Dolgui 2019). As a consequence, results oriented cultures are predisposed to the sharing of data between internal departments and with SC partners and this is made possible through the use ERP and cloud computing (Chae, Olson, and Sheu 2014a). These technologies in turn, enable the *accessibility* of real-time business data which is important in agile SC settings (Čudanov and Jaško 2012; Huang and Handfield 2015; Jha, Agi, and Ngai 2020). In such data-rich environments, BA and advanced modelling can utilise such data management resources and SCM planning initiatives to improve data accuracy and data deployment thereby improving operational and firm performance (Chae et al. 2014b; Gupta et al. 2019; Wamba and Akter 2019). For instance, Chae, Olson, and Sheu (2014a), find that when integrating BA, data management resources are be stronger predictors of SC performance than IT planning resources. More importantly however, is that both sets of resources are related to SC planning satisfaction and SC performance i.e. on-time delivery, order fulfilment and flexibility (product mix and volume). Additionally, Chavez et al. (2017) finds that data-driven SCs are positively associated with multiple manufacturing capability dimensions (i.e. quality, delivery, flexibility and cost), which in turn, leads to customer satisfaction improvement. Interestingly, delivery appears to have no significant effect on customer satisfaction in the study. In relation to AI, Brintrup et al. (2020) apply machine learning and BA algorithms to historical firm datasets to predict SC risk. The authors show that using largely quantitative engineering variables related to the firms SC agility performance, the algorithm can predict late orders with 80% accuracy. Moreover, Priore et al. (2019) develop an AI based algorithm that determines the best inventory replenishment rule around 88% of the time, which in turn leads to a reduction of operating costs against static alternatives. Hence, it's argued that firms in results and data-driven cultures are more likely to have the data resources and a flexible organisational structure in place to facilitate BA and AI, which in turn will enhance SC performance in terms of cost, lead-times, flexibility and fulfilment (Chae, Olson, and Sheu 2014a; Chavez et al. 2017; Priore et al. 2019).

In relation to information sharing within the SC, Fatorachian and Kazemi (2020) postulate that information sharing SCs which have a high level of SC coordination, alignment and information connectivity, will facilitate the integration of AI and BA and thus enhance SC performance in areas such as inventory management, procurement and production (cf. Wamba and Akter 2019). For example, Gunasekaran et al. (2017) find that SC connectivity and information sharing under the mediation effect of top management commitment, are positively related to big data and predictive analytics acceptance (BDPA) which, in turn, are positively related to BDPA assimilation and SC performance (i.e. customer responsiveness, enhanced delivery precision and lower costs). From a supplier perspective, a study by Fuchs et al. (2018) finds that frequent and adequate information sharing in the SC also contributes significantly to supplier performance (i.e. lead-time, order fill capacity and delivery flexibility).

Finally, more recent studies (cf. Zheng et al. 2021; Gunasekaran et al. 2018; Fatorachian and Kazemi 2020) conclude that information sharing Industry 4.0 technologies such IoT, cloud computing and RFID, which enable information transfer in the SC, should also facilitate automated business processes. For example, in order for AI to make more accurate prediction on inventory replenishments, AI requires historical and real time data which in turn can be used in conjunction with BA to reduce costs and SC risks and improved lead-times (Chan et al. 2006; Priore et al. 2019). Information sharing SCs are therefore key for both integrated BA systems and autonomous AI in support of SC operation and visibility. This in turn will enable SC flexibility, reduce risk, increase autonomy and speed in terms of responding to customer or market requirements (Gunasekaran et al. 2018; Ivanov et al. 2018).

In relation to SC autonomy specifically, Davenport (2018a) argues that in SCs defined by a high degree of autonomy and flexible work methods, AI is the next logical step in SCM and is capable of performing human-based tasks in the SC such as contract development (Davenport 2018a; Deloitte 2018; Gunarsekaran et al. 2018). This AI enabled autonomy will in turn will facilitate SC flexibility, freeing up capacity for employees to focus on key SC issues such as lead-times and customer satisfaction (Davenport 2018a). Moreover, in terms of the relationships between SC autonomy and cost and lead-time reductions, a case based research study by Gunarsekaran et al. (2018) highlights that agile manufacturers in the sample were seeking to move to programmable, intelligent automation to enable a wider range of machining and assembly operations, thus negating the changeover costs associated with flexible automation. The performance effects of technological automation are also supported by Nevo and Wade (2011) and Priore et al. (2019) who find that technology enabled automation and AI based learning can lead to improved operational performance in terms of reducing SC costs and lead-times and enhancing flexibility.

Hence it's argued that firms in autonomous and information sharing SCs are more likely to have coordinated and aligned information resources combined with an orientation towards operational flexibility and autonomy, which will in turn enable BA and AI to enhance SC performance in terms of cost, lead-times, flexibility and fulfilment (Gunarsekaran et al. 2018; Dubey, Gunasekaran, and Childe 2019b; Fatorachian and Kazemi 2020; Jha, Agi, and Ngai 2020).

In terms of SC relationships and market orientation, Wamba and Akter (2019) find that along-side the SC technical enablers of BA, SC talent, which includes relational knowledge (i.e. teaching others and working in a collaborative environment), is an enabler of SC analytics capabilities. The results suggest that such capabilities can facilitate SC agility which, in turn is positively related to customer retention and increased sales growth. Moreover, Gupta et al. (2019) find that in intelligent supply chain environments, customer and supplier relationships positively moderate the relationship between agile project management and SC flexibility. In relation to market orientation, Davenport (2018a) argues that AI can generate and test analytical models at faster rates, which increases the ability to develop new products, reduce led-times and enhance features and performance of existing products. For instance, Duan, Cao, and Edwards (2020) show that BA directly improves environmental scanning which in turn helps to enhance a firm's innovation (new products and services).

Finally, a study by Zhan and Tan (2020) finds that analytical infrastructure enabled managers to integrate isolated information silos in big data analytics to serve as inputs for new product ideas and to aid decision-making in relation to competence sets to support new product development. These previous studies provide evidence of an increased focus on the customer in relationship and market focused firms after BA and AI implementation. Overall, it can be said that the ability of AI and BA to analyse large amounts of data with precision, can lead to shorter lead-times, greater SC flexibility, and improved customer orientation ultimately leading to enhanced customer satisfaction (Nevo and Wade 2011; Chavez et al. 2017; Davenport 2018a; Fatorachian and Kazemi 2020).

In summary, organisational cultures that are more; (H3a) results oriented rather than process oriented, (H3b) more relationship oriented towards both suppliers and customers as opposed to closed, (H3c) more disposed towards information sharing as opposed to being disconnected, (H3d) more autonomous rather than OEM dependant, (H3e) more data-driven rather than job-focused more, and finally, (H3f) more market focused as opposed to internally focused, will have a greater positive impact on operational performance.

4. Methodology

4.1. Research context and research instrument development

A deductive survey approach was deemed appropriate for this study as this approach allows for theory testing of an a priori model and enhances external validity and thus generalisation. This approach is also consistent with other digital technology studies in the domain (Dubey et al. 2019; Brandon-Jones and Kauppi 2018).

Pilot Study: In order to develop and validate our research instrument, we employed a multi-step process (Churchill 1979). This included a detailed and in-depth literature analysis of the various themes under study, namely (i) supply chain technology enablers, (ii) supply chain business related enablers, (iii) supply Chain cultural enablers, and (iv) supply chain performance. Relevant constructs, operational definitions, and scale measurement items were generated during this phase. As appropriate, reliable and validated scale items from previous studies were included in the study (Churchill 1979; see Appendix). Table 2 highlights the research constructs developed in this phase and the key literature consulted.

The constructs included (i) supply chain technology enablers, (ii) supply chain business related enablers, (iii) supply chain cultural enablers, and (iv) supply chain performance. Pre-validated measures from previous research formed the foundation of the study constructs into this study. Appropriate refinement and development of scale items were applied as appropriate to this study. Further, we conducted a set of semi structured interviews to pre-test the scales with key informants to

Table 2. Research study constructs.

Construct	Key literature consulted
Supply chain technology enablers	Brandon-Jones and Kauppi 2018; Cai, Jun, and Yang 2010; Harland et al. 2007; Cadden et al. 2015; Dubey et al. 2020; Wamba-Taguimdje et al. 2020; Zhan and Tan 2020
Supply chain business related enablers	Brandon-Jones and Kauppi 2018; Harland et al. 2007; Cadden et al. 2015; Wu et al. 2006; Zhan and Tan 2020
Supply chain cultural related enablers	
Sub dimensions	
1. Results	Cadden et al. 2020; Hofstede et al. 1990; Soosay and Highland 2015; Verbeke 2000
2. Relationships	Cadden et al. 2020; Cai, Jun, and Yang 2010; Hofstede et al. 1990; Verbeke 2000
3. Information sharing	Cadden et al. 2020; Hofstede et al. 1990; Gillani et al. 2020; Verbeke 2000
4. Autonomy	Cadden et al. 2020; Hofstede et al. 1990; Verbeke 2000
5. Data driven	Cadden et al. 2020; Gupta and George 2016; Hofstede et al. 1990; Verbeke 2000
6. Customer focused	Cadden et al. 2020; Hofstede et al. 1990; Verbeke 2000
Supply chain performance	Cousins, Lawson, and Squire 2008; Cadden et al. 2015; Gunasekaran, Patel, and McGaughey 2004

enhance the validity of the study. This was via contacting 10 SC managers whilst being cognisant of ensuring representation across sub sector, organisational size and turnover. Contact was either via face to face or video calls to add additional validity to the study. This process enabled refinement, rewording and substitution of scale items along with additional items added in the study context, thus allowing for content validity. Finally, the questionnaire was pilot tested in a class of final stage students studying MSc in Supply Chain Management and 5 SC academics. Minor adjustments to the scales were made resulting in a robust questionnaire (Drucker 2005). This resulted in the operationalisation of relevant constructs (including definitions and scale items: see Appendix 1).

Supply Chain Technology Enablers: This construct investigates the key supply chain technology enablers. Previous work (cf. Brandon-Jones and Kauppi 2018; Cai, Jun, and Yang 2010; Cadden et al. 2015; Dubey et al. 2020; Harland et al. 2007; Wamba-Taguimdje et al. 2020; Zhan and Tan 2020) supported the development of this scale. Key themes such as having the appropriate technical skills and capabilities, having the appropriate cyber security infrastructure, having experience and trust in technology adoption in the supply chain form this construct. This construct includes 7 items.

Supply Chain Business Related Enablers: This construct investigates the key supply chain business related enablers. Previous work by Brandon-Jones and Kauppi 2018; Harland et al. 2007; Cadden et al. 2015; Wu et al. 2006; Zhan and Tan 2020 supported the development of this scale. Key themes such as having the finances to implement new digital technologies, having insights to supplier and customer buying habits to support digital technology implementation, having cross functional teams and joint decision making along the supply chain and having flexibility in the supply chain form this construct. This construct includes 5 items.

Supply Chain Cultural Enablers: This construct investigates the key supply chain cultural related enablers and is deemed central to the success of AI and digital technology implementation in support of supply chain performance success. Primarily sub dimension foundations were adopted from previous studies (e.g. Cadden et al, 2020a; Hofstede et al. 1990; Verbeke 2000). Each by date order adding additional context, reliability and validity to the measures. As culture is an ambiguous and multifaceted construct. Supply Chain Cultural Enablers has been deconstructed into 6 sub dimensions as per other inter-organisational cultural research studies (e.g. Cadden, Marshall, and Cao 2013, 2020b; Pothukuchi et al. 2002). Each sub dimension ranges from 5–8 items.

Supply Chain Performance: This scale was developed from previous supply chain performance measures (Cousins, Lawson, and Squire 2008; Cadden et al. 2015; Gunasekaran, Patel, and McGaughey 2004). This construct includes 5 items.

A number of recognised control variables in supply chain research where included. These were sales turnover, industry sector, organisational size, and length of relationship. These have been shown in previous supply chain studies to increase the validity and generalisability of the results (Cadden et al. 2020b).

4.2. Data collection

The UK manufacturing sector was deemed the most appropriate sector to exhibit the phenomenon of interest, as has been proven in previous supply chain development studies (Cadden et al. 2020b; Brandon-Jones and Kauppi 2018). A national UK manufacturing database was accessed as the population. The database had over 10,000 firms. Therefore, a number of filters were applied. Firstly, companies under 100 employees and firms under £5 million were excluded. This filtering returned a sample of 3214 companies (when anomalies were removed). A random sample of 1200 companies were selected to complete the study. The survey was developed online and an e-link to the study was forwarded based on job role (supply chain manager or equivalent). Participants were encouraged to complete the questionnaire with consideration of the perceived enablers to AI and digital technology integration with one of their key strategic suppliers. Previous research has demonstrated that self-reporting survey instruments enable participants to record their perceptions of reality (Beugelsdijk, Noorderhaven, and Koen 2009). This is fundamentally important in a study that includes supply chain cultural enablers where behaviours and attitudes are posited to be key enablers to supply chain success. The online survey included an initial GDPR statement to ensure confidentiality and anonymity, a personalised pre-study pre-brief, a specific instruction guide, and the offer that a management report summary of the study would be made available to the respondents' post study, if they wished. A reminder email was forwarded one week later, followed by a telephone call and reissuing of the survey 3 and 7 weeks after initial online contact for non-respondents, as per Dillman's Tailored Design Method (Dillman 2007).

5. Analysis and findings

5.1. Data screening

Prior to full scale data analysis, a data screening exercise was undertaken in two stages. Firstly, any responses where missing data exceeded a 10% threshold were

Table 3. Sample characteristics.

Business unit sales volume	*N*	%
< £50 m	147	56.3
£50 m – £100 m	47	18
£100 m – £250 m	29	11.1
O£250 m – £500 m	19	7.3
£500m – £1 billion	11	4.2
Over £1bn	8	3.1
Total	*261*	*100*
Number of employees	*N*	%
100–499	182	69.8
500–999	51	19.5
1000+	28	10.7
Total	*261*	*100*

removed (Hair et al. 2010b). This resulted in the initial sample of 323 responses received being reduced to 271. The remaining data set still had some missing values but less than 5% on a single variable, which is commonly reported as of minimal concern (Amabile 1983) and includes values missing completely at random (MCAR) (Hair et al. 2010a). To ensure that the remainder of the responses and the missing data were MCAR, Little's MCAR test was then conducted. This was returned as significant (if not significant, missing values are replaced by using the mean value replacement). As a result, all responses with missing data were completely removed, leaving a total of 261 responses.

5.2. Respondent profile and survey biases

A response of 26.1% was returned which was deemed reasonable and exceeds the level of 20% reported by Malhotra and Grover (1998) as an acceptable response rate in survey research and consistent with other survey research in the area (Cadden et al., 2020b; Marshall et al. 2015). The characteristics of the sample data returned is listed in Table 3.

To evaluate the presence of non-response bias, two tests were conducted. First, a t-test was conducted to compare early ($n = 182$) and late ($n = 97$) respondents on all measures. All 54 indicators were evaluated by comparing the two groups through an independent t-test. The t-test results yielded eight statistically significant differences at $p < 0.05$ (two-tailed) for early respondents and late respondents: lean practice 1 and 2, process 1, open 1 and 3, loose 5, market 4, and operational performance 4. And then, for the rest of 46 indicators, the t-test result did not find significant difference between the two respondent groups. Consequently, nonresponse bias does not appear to be a major problem for the whole research while caution should be exercised in applying the findings. In addition, potential common method bias (CMB) was tested by following the Harman one-factor test (Podsakoff and Organ 1986) and including all the measurement items in a single principle component factor analysis with unrotated solution. CMB exists when a single factor emerges or accounts for most of the shared variance among the variables. Therefore, common method bias does not seem to be an issue.

5.3. Reliability

Results of the Cronbach Alpha reliability tests are presented in Table 4. All scales were deemed reliable as they exceeded the 0.7 α (Nunally 1978) and exceed the reliabil-

Table 4. Convergent validity and internal consistency reliability.

Construct	Indicator	Loading	Indicator reliability	Composite reliability	Cronbach's α	AVE
Technical AI supply chain enablers	TSCE1	0.72	0.74	0.89	0.86	0.73
	TSCE2	0.65	0.76			
	TSCE3	0.81	0.79			
	TSCE4	0.74	0.73			
	TSCE5	0.65	0.81			
	TSCE6	0.72	0.62			
	TSCE7	0.82	0.63			
Business AI supply chain enablers	BSCE1	0.74	0.75	0.74	0.72	0.78
	BSCE2	0.68	0.80			
	BSCE3	0.72	0.78			
	BSCE4	0.56	0.83			
	BSCE5	0.58	0.73			
Results	RES1	0.61	0.78	0.80	0.77	0.82
	RES2	0.62	0.84			
	RES3	0.65	0.82			
	RES4	0.74	0.83			
	RES5	0.71	0.81			
Relationships	REL1	0.63	0.75	0.91	0.88	0.73
	REL2	0.65	0.83			
	REL3	0.53	0.82			
	REL4	0.75	0.79			
	REL5	0.69	0.72			
	REL6	0.72	0.56			
	REL7	0.58	0.72			
	REL8	0.51	0.67			
Information sharing	IS1	0.66	0.64	0.84	0.81	0.71
	IS2	0.72	0.72			
	IS3	0.68	0.63			
	IS4	0.72	0.72			
	IS5	0.65	0.73			
	IS6	0.81	0.81			
Autonomy	AUT1	0.71	0.83	0.84	0.81	0.76
	AUT2	0.77	0.81			
	AUT3	0.75	0.72			
	AUT4	0.62	0.73			
	AUT5	0.72	0.69			
Data driven	DD1	0.72	0.76	0.82	0.79	0.74
	DD2	0.71	0.72			
	DD3	0.61	0.81			
	DD4	0.75	0.65			
	DD5	0.78	0.73			
	DD6	0.80	0.75			
	CUS1	0.66	0.68			
	CUS2	0.71	0.81			
Customer Focused	CUS3	0.57	0.71			
	CUS4	0.62	0.72	0.88	0.83	0.73
	CUS5	0.75	0.80			
	CUS6	0.58	0.64			
	SCPER1	0.85	0.82			
	SCPER2	0.75	0.85			
Supply chain Performance	SCPER3	0.71	0.87	0.92	0.89	0.84
	SCPER4	0.81	0.80			

Table 5. Descriptive statistics, correlations, and average variance extracted.

	Mean	S.D.	1	2	3	4	5	6	7	8	9
1 Tech	3.07	0.81	**0.85**								
2 Bus	3.34	0.73	0.68**	**0.88**							
3 Res	3.02	0.87	0.50**	0.71**	**0.90**						
4 Rel	3.08	0.76	0.41**	0.65**	0.54**	**0.86**					
5 IS	3.21	0.77	0.70**	0.60**	0.57**	0.42**	**0.84**				
6 Aut	3.32	0.89	0.75**	0.54**	0.43**	0.51**	0.65**	**0.87**			
7 DD	3.36	0.77	0.60**	0.32**	0.52**	0.63**	0.72**	0.64**	**0.86**		
8 Cust	3.14	0.64	0.72**	0.63**	0.40**	0.62**	0.51**	0.63**	0.71**	**0.85**	
9 Perf	3.85	0.71	0.58**	0.43**	0.62**	0.61**	0.59**	0.39**	0.62**	0.71**	**0.91**
10 Size			.091	.053	−.017	−.055	.011	.023	−.082	.067	.041
11 Industry			.021	−.034	−.065	−.41	−.071	.013*	−.003	−.041	.054

**Correlation is significant at the 0.01 level (2-tailed).
*Correlation is significant at the 0.05 level (2-tailed).
Diagonal values are the square root of the AVE.

ity of Hofstede's initial study (1990) and are in common with Verbeke (2000) and Cadden et al. (2011, 2020b).

5.4. Validity

A number of key steps were taken to ensure validity in this study. These scales are adapted and modified from previous studies. Face validity was assured by using the method advised by Fink and Litwin (1995; cited by Verbeke 2000, 592). A set of untrained eyes (a class of 50 MBA students) was given a definition of key constructs, Technical Supply Chain Enablers and Business Supply Chain Enablers, along with a mixed up copy of the questionnaire. In total, 36/50 (72%) correctly categorised the items within the appropriate scales. This concurs with Verbeke's (2000) results; and ensures face validity in this study. Construct validity is assessed by principle component analysis with Varimax rotation, which is a widely recognised method to assess for constructs validity (Spector 1992). All items loaded against their constructs above 0.5 and were deemed suitable (Nunnally 1978) and are presented in Table 5.

Convergent and discriminant validity were then tested. Firstly, a Fornell-Larcker criterion (Fornell and Larcker 1981) was conducted to measure if the square root of AVE value for each construct is greater than the correlation of the construct with any other construct. This was true in this sample (Table 5). Secondly, discriminant validity was assessed by using inter-factor correlations. The results were lower than the 0.7 standard and within an acceptable range (Anderson and Gerbing 1988) which provides confidence that multicollinearity is not an issue in this study.

5.5. Confirmatory factor analysis

Lisrel 8.8 was used to estimate the model parameters using robust full information maximum likelihood based on a matrix of variances and covariances. Following the guidelines suggested by Hoyle and Panter (1995) the goodness of fit for each model was assessed using a range of fit indices including the Satorra–Bentler scaled chi-square (S-Bχ2), the Tucker-Lewis index (TLI; Tucker and Lewis 1973), and the Comparative Fit Index (CFI: Bentler 1990). A non-significant chi-square, and values greater than .95 for the TLI and CFI are considered to reflect acceptable model fit. In addition, the Root Mean Square Error of Approximation (RMSEA: Steiger, 1998) with 90% confidence intervals (90% CI) were reported, where a value less than .05 indicates close fit and values up to .08 indicating reasonable errors of approximation in the population (Jöreskog and Sörbom 1996). The standardised root-mean-square residual SRMR: (Jöreskog and Sörbom 1996) has been shown to be sensitive to model mis-specification and its use recommended by Hu and Bentler (1999). Values less than .08 are considered to be indicative of acceptable model fit (Hu and Bentler 1999). Finally, as illustrated, in terms of the methodological approach, this paper performs CFA and SEM. Several papers which have explored the themes of organisational culture and digital transformation have favoured the above approach, limiting the need for additional types of regression analysis (see for instance; Bortolotti, Boscari, and Danese 2015; De Sanctis et al. 2018; Sousa-Zomer, Neely, and Martinez 2020).

5.6. Model fit

The model used all variables from the data collection as shown in Figure 1: technical supply chain enablers, business supply chain related enablers, six supply chain cultural enablers, and the supply chain performance measure. The model fit was acceptable ($\chi^2 = 2.35$, df $= 2$, $p = .35$; CFI $= .986$; TLI $= .98$; RMSEA $= .04$; SRMR $= .02$). The chi-square was reported as non-significant. The CFI, TLI, RMSEA and SRMR all met the

Table 6. Standardised regression co-efficients (standard error) for the initial part of the SCHAIN Model (Hypothesis H1 and H2) technical AI and business AI enablers and cultural AI enablers.

	Results	Relationships	Information sharing	Autonomy	Data driven	Customer focused
Technical AI supply chain enablers	.62 (.05)*	.83(.04)**	.51 (.06)*	.15 (.11)	.22 (.05) **	.18 (.09)
Business AI Supply Chain Enablers	.17 (.07)	.38 (.05)**	.54 (.09)*	.63 (.07)**	.10 (.11)	.41 (.06)**

*$p < .05$; **$p < .01$.

Table 7. Standardised regression co-efficients (standard error) for the final part of the cultural model (Hypothesis H3).

	Supplier operational performance
Results	.42 (.11)**
Relationships	.36 (.06)**
Information sharing	.18 (.13)
Autonomy	.17 (.05)
Data driven	.48 (.10)**
Customer focused	.26 (.07)*

*$p < .05$; **$p < .01$.

criteria for acceptable fit. These results also confirm that the constructs tested in our study meet the criteria for unidimensional. The model estimates are presented in Tables 6 and 7.

6. Discussion

To date, studies linking AI and BA to OSCM have been quite limited (Frederico et al. 2020). Therefore, this study sought to explore the interlinkages between the technical and business enablers of AI and BA and their relationships with organisational culture and operational performance (See Figure 2).

The findings of H1a-H1f highlight that the technical enablers of AI and BA are positively linked with organisational cultures which are results focused, relationship oriented, information sharing and data-driven. Hence, the first three hypotheses i.e. H1a (Results), H1b (Relationships), H1c (Information sharing) are all supported alongside H1e (Data-Driven). Conversely, the relationships between the technical enablers of AI alongside autonomous (H1d) and customer orientated cultures (H1f) were found to be insignificant. Overall, the results paint a clear picture; on a technical level, SC relationships and the sharing of information and data (i.e. Data-Driven) throughout the SC are pivotal to the initial construction of analytical and AI infrastructure (Gupta et al. 2019; Jha, Agi, and Ngai 2020; Liao et al. 2017). Previous research supports this logic, as AI applications such as machine learning require rule-based training datasets, often acquired from integrated ERP and SCM systems (Jha, Agi, and Ngai 2020; Brintrup et al. 2020). Moreover, a results culture can be helpful in terms of cross-functional collaboration, ensuring that the correct data is collected, shared and distributed throughout the operations and SC in order to meet end goals (Čudanov and Jaško 2012). Additionally, Čudanov and Jaško (2012) find that results-oriented cultures can provide guidelines regarding desired changes in management orientation for firms implementing new technologies. This can also relate to the governance of data, specifically in terms of developing the cross-channel SC structures for the sharing of data to implement AI systems (Tallon, Ramirez, and Short 2013; De Oliveira and Handfield 2019). Finally, Srinivasan and Swink (2017) find that external trust-based relationships with suppliers and customers can enhance SC information visibility and help integrate isolated data silos in SCs (Srinivasan and Swink 2017). Moreover, such relations are crucial for building trust and eroding resistance to AI, specifically by demonstrating the practicality of such technologies and by reducing fears of humans being replaced by AI (Brandon-Jones and Kauppi 2018; Klumpp 2018; Schulze-Horn et al. 2020). The insignificant relationships at the technical level with the autonomy and customer dimensions, are not unexpected since data integration and accessibility are perhaps more important than autonomy and market focus at the technical level (Srinivasan and Swink 2017; Jha, Agi, and Ngai 2020). In other words, the focus is on developing integrated information and data streams within the SC, establishing governance procedures for the sharing of data, and working with suppliers to implement AI applications and synchronise the SC (Srinivasan and Swink 2017; Zhan and Tan 2020). On a technical level, a market focus may therefore take a back seat initially in favour of upstream infrastructural and informational integration (Davenport 2018b).

In relation to H2a-H2f, the findings indicate that the business enablers of AI and BA are positively linked with organisational cultures which are relationship oriented, autonomous, market oriented and disposed toward information sharing. Hence Hypotheses H2b, H2c. H2d, and H2f are all significant. Conversely, the hypotheses related to results orientation (H2a) and data-driven (H2e) cultures are not. Accordingly, the results suggest that at the business level, the focus appears to be on the combination and utilisation of AI and BA technologies alongside business level capabilities (Liu, Prajogo, and Oke 2016; Popovic et al. 2018; Conboy et al. 2020; Jha, Agi, and Ngai 2020). This would explain the insignificance of the results

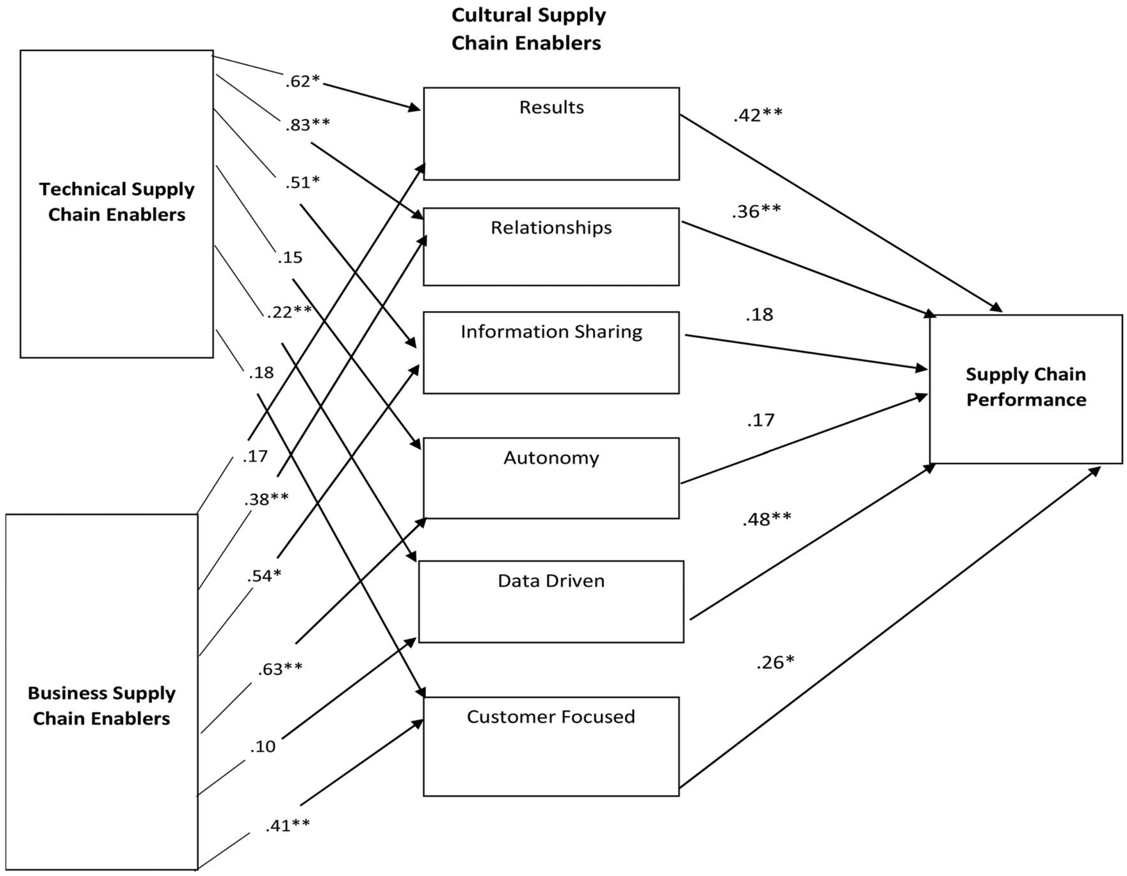

Figure 2. Hypothesis test results.

and data driven dimensions at this level as the technical enablers of AI such as cross functional data streams and rule-based training datasets should theoretically already be in place (Popovic et al. 2018; Jha, Agi, and Ngai 2020). The goal now is to combine technical resources with business level processes. i.e. enabling autonomous AI to enhance flexibility (Autonomy), using BA and AI applications to segment customers and enhance customer relationships (Market orientation) and finally, leveraging integrated data streams to share information in order facilitate SC alignment and responsiveness (Information sharing) (Liu, Prajogo, and Oke 2016, 2021; Davenport 2018a; Dubey et al. 2018; Popovic et al. 2018; Calatayud, Mangan, and Christopher 2019; Baryannis, Dani, and Antoniou 2019a). Indeed, the results suggest that information sharing, and relationship orientation also play a key at the process level. This observation supports the work of Tallon, Ramirez, and Short (2013) and Mikalef et al. (2020) who find that the relational aspects of data governance, i.e. data accessibility and information sharing, is associated with a range of intermediate and process-level benefits. This may include for example the sharing of real-time data to enhance decision-making which, in turn, can facilitate SC agility outcomes at the operational level i.e. the early identification of SC disruptions (De Oliveira and Handfield 2019; Dubey et al. 2018; Conboy et al. 2020). Moreover, Liu, Prajogo, and Oke (2016) find that there is a positive relationship between SC technology utilisation and firm performance and this increases with the level of information sharing between SC partners. Finally, Mikalef et al. (2020), link BD governance and information sharing to firm level innovation capabilities. Hence, the governance of data also plays an important role at the process level in terms of adapting and aligning SC structures in order to leverage the benefits of AI applications at the firm level (Tallon, Ramirez, and Short 2013; Mikalef et al. 2020).

Relationship orientation was also found to be significant at the process level. This finding is supported by Gupta et al. (2019) who find that customer and supplier relationships play a key role in intelligent SC, linking agile project management to organisational flexibility. In other words, strong SC relationships can facilitate AI and BD support for suppliers, thereby facilitating collective business level and SC outcomes (i.e. flexibility and alignment) (Harland et al. 2007; Dubey et al. 2018; Gupta et al. 2019). Finally, AI and BD were also linked to autonomy and customer orientation at the process level. In relation to autonomy specifically, Davenport (2018a) highlights that once the technical enablers of AI are in place, AI can facilitate increased SC autonomy. For instance, Priore et al. (2019) show that AI applications such as machine learning can be used to facilitate autonomous inventory replenishment, while Brintrup et al. (2018) find that machine learning can be used to predict late orders from suppliers with over 80% accuracy. Lastly, the results suggest that BDA and AI applications have a positive association with a customer orientation at the process level. This is not surprising as BD is linked to increased firm level innovation (Mikalef et al. 2020), which, in turn, is important for new product offerings and improvements to existing products lines (Davenport 2018a). BD and AI applications have also been also linked to improved quality, cost and delivery outcomes stemming from more efficient, flexible and agile internal processes, ultimately leading to enhanced customer satisfaction (Gunasekaran et al. 2017; Dubey et al. 2018; Priore et al. 2019).

Finally, Hypotheses H3a-H3f explore the role of organisational culture on supplier operational performance (See Table 7).

The final set of hypotheses examine how the combination of the technical enablers of BA and AI combine with the business-related indicators, to influence culture, and ultimately, SC operational performance. More specifically, as Conboy et al. (2020) argue, the co-specialisation of BA and AI applications with firm level SC capabilities i.e. flexibility, coordination and innovation, could lead to key operational enhancements. Firstly, the results suggest that organisational cultures which are results based (H3a), relationship oriented (H3b), data-driven (H3e) and customer focused (H3f) are associated with improved SC operational performance. Conversely, information sharing (H3c) and autonomous cultures (H3d) were not shown to be related to SC Performance. The positive relationship between results-based cultures and data-driven cultures with SC performance is logical. The aim of both types of culture is to facilitate the flow of information in the SC through flexible, cross-channel structures and integrated data streams which, as Hoyufman (2017) and Conboy et al. (2020) argue, inform real-time decision making (data velocity) and enhanced operational outcomes i.e. SC agility (i.e. lead-times, operating costs) (Čudanov and Jaško 2012; Fuchs et al. 2018; Priore et al. 2019). Moreover, both Chae, Olson, and Sheu (2014a) and Chavez et al. (2017) link data-driven SCs to improved performance in terms of quality cost, delivery, flexibility as well as overall customer satisfaction. Secondly, the positive linkages between relationship-oriented cultures and SC performance are not surprising in the context of this study, as a key finding is that relationship orientation was the single dimension that is significant across both the technical and business levels of AI implementation as well as positively related to operational performance. The linkages with operational performance stem for the observation that SC relationships, in combination with AI and BA, constitute an important firm level resource that enhances SC performance through greater SC alignment, flexibility and supplier/customer orientation (Whitten, Green, and Zelbst 2012; Chavez et al. 2017; Davenport 2018a; Gupta et al. 2019; Hüseyinoğlu, Kotzab, and Teller 2020). More specifically, SC relationships can facilitate access to siloed SC data (i.e. data variety) (Anshari et al. 2019; Gupta et al. 2019), which can be used to enhance SC outcomes i.e. flexibility (Gupta et al. 2019; Conboy et al. 2020). This finding is supported by Gupta et al. (2019) who found that relationships play a key role in the link between agility and SC flexibility outcomes in intelligent SC (i.e. supplier willingness to adopt to new systems and manage volume and product changes). Hüseyinoğlu, Kotzab, and Teller (2020) also find a positive link between the quality of SC relationships and SC operational outcomes i.e. a faster operating cycle, enhanced delivery performance and the flexibility to react to changing market conditions. Finally, Sodero, Jin, and Barratt (2019) report that the social and relational aspects of BA such as user involvement shapes BDA to fit organisational structures, and that such adaptive capabilities can facilitate enhanced operational performance in the SC (cf. Whitten, Green, and Zelbst 2012). Finally, the results suggest there is a positive relationship between customer orientation and SC performance. This finding is supported by Chavez et al. (2017) who find that data driven SCs can enhance operational flexibility, cost and quality dimensions ultimately improving overall customer satisfaction levels (Chavez et al. 2017). Moreover, AI and BA and can also enable automated 24hr customer service, thereby improving service-level efficiency and flexibility (Davenport 2018a; Conboy et al. 2020). Finally, research by Mikalef et al. (2020), demonstrates that when mediated by data governed structures, BA can facilitate radical innovative capabilities, which, in turn, can facilitate greater customer choice and enhanced customer value through new product and service innovations (Davenport 2018a; Conboy et al. 2020).

7. Implications for OSCM research and practice

By empirically investigating the role of AI in SC management performance, this study advances the research and practice on the applications of AI and BDA in OSCM (Bag et al. 2020; Gunasekaran et al. 2017; Gunasekaran et al. 2018; Khanra, Dhir, and Mäntymäki 2020; Padadopoulos et al. 2017; Wamba et al. 2018). In particular, this study makes several key contributions.

First, the findings highlight the importance of relationships with the multiple stakeholders of the SC when implementing AI and BDA. This pertains to enforcing trust and security (Spanaki et al. 2019), mitigating personnel's potential fears related to becoming replaced by AI as well as the importance of building joint resources and capabilities within the SC, and the need to implement relevant technologies across the supply network (Klumpp 2018; Jarrahi 2018). From a technical vantage point, relationships can facilitate information sharing and data-driven process across the SC. From a business vantage point, AI and BDA can provide benefits in operational performance in the form of e.g. reduced lead times and greater flexibility (Gupta et al. 2019; Hüseyinoğlu, Kotzab, and Teller 2020).

Second, our findings underscore that the implementation of AI applications for SC management essentially takes places on two levels: technical and business. With respect to the technical level, implementing AI requires that the organisation's IT infrastructure is capable of handling AI. At this level, there is less focus on autonomy and customers. On the business level in turn the customer focus and autonomy play a key role since firms typically seek to boost SC performance in terms of e.g. flexibility, agility and responsiveness to customer needs (Dubey, Gunasekaran, and Childe 2019b; Priore et al. 2019). Collectively, these two key contributions of the study point towards the importance of SC socialisation (Cadden et al. 2020a, 2020b). While the contractual premises and SC processes are often strategic-level decisions, the operational level activities play a critical role in a successful employment of AI in SCM.

From a theoretical standpoint, the findings of this study underscore the importance of SC relationships (cf. Gupta et al. 2019; Hüseyinoğlu, Kotzab, and Teller 2020) as well as looking at AI in SC management from a socio-technical perspective (cf. Kull, Ellis, and Narasimhan 2013). Specifically, since AI can easily be considered a threat by the employees at various levels, ensuring organisational buy-in and overcoming potential user resistance remain in the management agenda also with respect to implementing AI in SCM. At the business and operational levels, SC relationships facilitate cross channel data accessibility as well as the coordinated adoption and use of BDA and AI applications in the SC. Accordingly, SC Relationships therefore constitute an important cospecialised asset, which has important operational outcomes in terms of SC flexibility and alignment (Gupta et al. 2019; Conboy et al. 2020). Indeed, the results suggest that when implementing AI, SC relationships lead to enhanced SC performance in terms of reductions in lead-times and costs and improvements in SC responsiveness and flexibility.

Secondly, the findings also underline the importance of the relational aspects of data governance (Tallon, Ramirez, and Short 2013; De Oliveira and Handfield 2019; Mikalef et al. 2020) not just at the technical level, but also at the business level in terms of how data artifacts are governed and utilised to support AI implementation (Tallon, Ramirez, and Short 2013; Mikalef et al. 2020). For example, the results suggest that information sharing and the integration of isolated information silos in the SC have important technical and process level outcomes i.e. the creation of rule-based datasets and, at the process level, the sharing of real-time data to enhance SC agility i.e. reduced lead-times and responsiveness to product demand changes (De Oliveira and Handfield 2019; Dubey, et al 2019b; Conboy et al. 2020) Conversely, unlike relationship orientation, information sharing is not related to SC performance directly, rather it plays an important contextual role in terms of the implementation and usage of AI. This finding was also reported by Baihaqia and Sohalb (2013).

8. Contributions to OSCM research and practice

This study makes a number of key contributions to advancing knowledge for OSCM research and practice. *First*, the most salient theoretical contribution of this research is that it provides novel insights of the key cultural enablers that support successful AI integration in SCM. Understanding cultural enablers is pertinent to this study as the concept 'culture' is frequently misused in the SC and technology integration literature or studied at an abstract level (Cadden et al. 2020b). *Second*, theoretical understanding of the relational view of the firm is advanced by explaining how SC cultural enablers assist in supporting high-performing SC that are difficult to imitate or procure (Barney 1991; Cousins, Lawson, and Squire 2006; Dyer and Singh 1998). *Third*, a methodological contribution is made by developing and testing the model of SC culture which provides in-depth insights that are relevant in OSCM research. Fourth, as our study builds upon extant OSCM literature, it provides a deeper understanding of AI integration in SC, as well contributes to the tradition of accumulative building of knowledge (cf. Adam and Fitzgerald 2000; Metcalfe 2004; Weick, Sutcliffe, and Obstfeld 1999, 2008).

A key contribution to OSCM practice is the provision of a rigorous study that provides insights that can be easily adapted when adopting and integrating AI and other digital technologies in order to achieve high SC performance outcomes. For example, the results of this study underline the importance SC relationships in AI implementation and how they enable technical and business level outcomes as well as operational outcomes in terms of reducing SC costs and lead-times and enhancing SC flexibility. Further, the study provides practitioners with a holistic understanding about AI and digital technology integration within their SCs to assist in developing a SC AI strategy that is aligned to their corporate strategy and culture.

9. Conclusion, limitations and future research

As with all studies, we acknowledge there are limitations in this study. Addressing these limitations provides avenues for future research in the area. First, with respect to research design, the data are cross-sectional which inhibits examining how the focal constructs and the associations between these constructs evolve over time. To address this limitation, future research could adopt longitudinal research designs. Second, we relied on self-reported measures which can lead to biases. As a result, future research could explore how to incorporate other measures such as financial information and system log data in the research designs. Moreover, future research could take a more detailed examination of required resources and configurations of these resources when implementing AI for SCM purposes. For example, future studies could examine how the resource needs and resource configurations may differ across industry sectors and between small and larger organisations. There is a need for additional research focusing specifically on the SC performance impact of different AI applications such as autonomous AI-powered manufacturing, load forecasting, and vehicle schedule. Future research could examine how the resources required change across time-periods as operations become more autonomous i.e. pre- and post-implementation. There is a need for more studies to examine SC performance impacts of AI particularly in the relationship between autonomous AI manufacturing and operating performance. Finally, with SCs continually evolving and marketplaces competitive and dynamic, there is a need to bridge the advances within operational research techniques, such as mathematical optimisation and modelling, such as simulation theory and control, stochastic programming, neural networks (Wichmann et al. 2020; Shokouhyar et al. 2019; Ivanov et al. 2018) with operations management techniques, such as qualitative case study research in order to better understand how synergies and symbiotic SCs can evolve. Future research could investigate how these two disparate research paradigms could intertwine to reduce risk, increase collaboration and performance, and result in SCs powered by technology yet driven by people.

To conclude, we proposed that firms need to move beyond the traditional technical and business enablers (Harland et al. 2007; Brandon-Jones and Kauppi 2018) when integrating AI, by recognising the influential role of culture. Our study highlights the importance of developing and maintaining relationships when implementing AI into SC networks.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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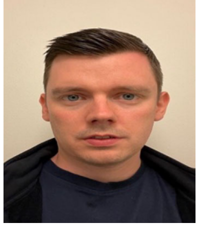

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Appendix: Survey measures (Each measured using a 1- -5 Likert scale, where 1 is strongly disagree and 5 is strongly agree)

I.V 1 (Technical related enablers) References: (Brandon-Jones and Kauppi 2018; Cai, Jun, and Yang 2010; Harland et al. 2007; Cadden et al. 2015; Dubey et al. 2020; Wamba-Taguimdje et al. 2020; Zhan and Tan 2020)

All our strategic supply chain partners will fully embrace appropriate AI technologies and business analytics over the next 3 years

All our strategic supply chain partners will trust appropriate AI technologies and business analytics over the next 3 years

All our strategic supply chain partners will be open to change in how we adopt appropriate AI technologies and business analytics over the next 3 years to better share data and information

All our strategic supply chain partners will implement appropriate AI and business analytics technologies over the next 3 years
safely and securely

All our strategic supply chain partners will have the IT capabilities and skills to implement new appropriate AI technologies and business analytics over the next 3 years

All our strategic supply chain partners have experience in implementing appropriate digital technologies and business analytics

All our strategic supply chain partners have the necessary IT and internet infrastructure to operate and maximise the potential of appropriate AI technologies and business analytics over the next 3 years

I.V 2 (Business related enablers) References: (Brandon-Jones and Kauppi 2018; Harland et al. 2007; Cadden et al. 2015; Wu et al. 2006; Zhan and Tan 2020)

All our strategic supply chain relationships are flexible and we can opt out of or easily amend contracts with non IT ready supply chain partners to adopt AI and business analytics ready partners;

Our supply chain can accommodate the cost to implement appropriate AI technologies and business analytics over the next 3 years

Our supply chain provides a high quality of information

Our supply chain shares knowledge on current supplier and customer buying habits that will support AI technologies and business analytics over the next 3 years

Our supply chain has regular cross functional team meetings that support joint supply chain decision making to support appropriate AI technologies and business analytics over the next 3 years

Cultural related enablers

1. Results – References: (Cadden et al. 2020; Hofstede et al. 1990; Soosay and Highland 2015; Verbeke 2000)

When confronted with problems suppliers help each other

The tasks of supplier employees that are absent are taken over by colleagues

Requests from other departments are carried out without delay

On special projects there is always cooperation between the various supply chain participants

Suppliers are encouraged to contribute by coming up with their own ideas

2. Relationships (Adapted from Cadden et al. 2020; Cai, Jun, and Yang 2010; Hofstede et al. 1990; Verbeke 2000)

Our supply chain relationships are built on trust

Whenever supply chain partners employees at any level are ill, or have personal problems, we ask after their problems with interest

Supply partners are encouraged to go to courses, seminars and conferences to help their personal development

If there are personal conflicts affecting our supply chain partners, we will offer to help to solve these problems

With respect to birthdays, marriages and births in our supply chain, we show a personal interest

In supply chain matters that directly involve our supply partners, their opinions are sought and listened to

We are quick to compliment supply partners on a job well done

We conduct our business collaboratively (and share demand forecasts and customer requirements timely) to ensure our supply partners work doesn't become too pressurised

3. Information sharing – References: (Cadden et al. 2020; Hofstede et al. 1990; Gillani et al. 2020; Verbeke 2000)

If we have a criticism of a supplier it is discussed openly with them

Supply chain partners are encouraged to express criticisms of our company directly to the supply chain management leaders in our company

Suppliers employees are asked for constructive criticism to help us perform better

We share information openly and honestly with our supply partners (be in cost, service, quality)

We feel appropriate AI technologies and business analytics will enhance our culture of Information sharing along the supply chain

Effectiveness of information sharing guidelines in understanding and enhancing knowledge of each participant in the supply chain

4. Autonomy – References: (Cadden et al. 2020; Hofstede et al. 1990; Verbeke 2000)

We rarely monitor our daily supply partners performance as long as they meet their weekly targets they are autonomous

If a supply partner is a little late for an appointment with us, they will never be reprimanded as we are more concerned with the bigger picture of performance

If a supply partner is unavailable for personal reasons during working hours, we don't micro manage or question this

In joint projects and joint asset specificity relationships where we provide financial support, we don't monitor the supply chains costs in receipt detail, but believe their reports

We allow supply chain partners to take executive decisions on key supply chain issues that may affect us also, such as inventory management and selection of tier 2 suppliers

5. Data driven – References: (Cadden et al. 2020; Gupta and George 2016; Hofstede et al. 1990; Verbeke 2000)
We use data to deliver results rather than focus on procedures
The suppliers business shares its key data to help contribute much to society
The suppliers business actively shares its key data to honours its ethical responsibilities:
We base our supply chain decisions on data rather than on instinct
We are willing to override our own intuition when data contradict our viewpoints
We continuously assess and improve our supply chain management in response to insights extracted from data

6. Customer focused – References: (Cadden et al. 2020; Hofstede et al. 1990; Verbeke 2000)
The satisfaction of the customers is measured regularly
Product promotions and actions by the competition are reported in detail
Consumers preferences are investigated thoroughly
The company provides products and services that meet the needs of the various customer segments
The future needs of the customers are discussed extensively with our supply partners
In talks with supply chain partners, we discuss the future needs of the customers

Supply chain performance – References: (Cousins, Lawson, and Squire 2008; Cadden et al. 2015; Gunasekaran, Patel, and McGaughey 2004)
In the past 3 years, our planning and fulfilment process time has improved due to our supply chain relationships
In the past 3 years, on time delivery has improved due to our supply chain relationships
In the past 3 years, conformance to product specifications have improved due to our supply chain relationships
In the past 3 years, our flexibility to respond to changing customer demands has improved due to our supply chain relationships
In the past 3 years, increasing number of successful cost reduction initiatives have resulted due to our supply chain relationships