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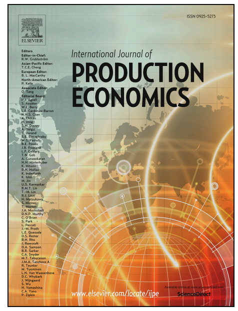

Supply chain analytics adoption: Determinants and impacts on organisational performance and competitive advantage

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Supply Chain Analytics Adoption: Determinants and Impacts on Organisational Performance and Competitive Advantage

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Abstract

Despite manufacturing companies recognising the potential benefits associated with the adoption of Supply Chain Analytics (SCA), only a few firms adopt data-based decision-making processes due to fundamental technical, organisational and environmental challenges. In this regard, this research explores the determinants influencing SCA adoption and the impacts on firm performance and competitive advantage. Specifically, the Technological, Organisational, and Environmental (TOE) framework was applied to identify the key determinants influencing SCA adoption. Data was collected from 217 executives working in the UK manufacturing sector through a questionnaire-based survey. The research model was tested using a quantitative approach, i.e., Partial Least Squares Structural Equation Modelling. Surprisingly, none of the identified technological factors leads manufacturing companies to adopt SCA. On the contrary, organisational and environmental factors have a crucial role in influencing supply chain and logistics managers to adopt SCA. This research also emphasises and validates the importance of SCA adoption in improving firm performance and fostering competitive advantage. On evaluating SCA adoption, supply chain managers should concentrate on aspects other than technological competence. Manufacturing companies looking to make investment decisions regarding SCA adoption should mainly consider organisational and environmental factors; hence, SCA systems can be used effectively and efficiently. This study is the first to explore the TOE framework regarding the adoption determinants within an SCA context along with its implications on organisational performance and competitive edge.

Keywords: Supply Chain Analytics; TOE Framework; Acceptance and Adoption; Survey; Manufacturing Industry.

1. Introduction

The COVID-19 pandemic highlighted that unexpected and rare events which cause supply chain disruptions are not "black swans" (Avishai, 2020); thus, appropriate planning is required to ensure flexibility and continuity of operations. In order to manage such uncertainties, managers mainly rely on instinct and experience; however, critical decisions shall be made based on Supply Chain Analytics (SCA) to increase resilience (Golan et al., 2020) whilst improving operational efficiency and effectiveness. SCA help companies improve operational performance (Mubarik et al., 2019), foster supply chain innovation (Shamout, 2019), and promote sustainability (Zhu et al., 2018). According to PRNewswire (2020), the SCA market is projected to grow from US$3.5 billion in 2020 to US$8.8 billion by 2025.

Although applying SCA might associate with benefits such as supply chain transparency (Chae and Olson, 2013), the development and implementation of analytics are still nascent (Bowers et al., 2017). It is argued that a lack of SCA capabilities exists that could enable manufacturing companies to leverage available data and information sources and generate valuable insights for their business operations (Tiwari et al., 2018). According to a Hackett Group (2018) survey, 66% of supply chain managers believe that analytics capabilities are crucial to their business operations. However, companies currently only use basic visualisation tools and techniques to chart available data, whilst there is a need to shift towards predictive analytics. Moreover, data reliability, consistency, and interoperability issues are the main challenges that hinder SCA adoption (Tsolakis et al., 2020). Last but not least, there is a need for employees to develop data analysis skills to identify issues across end-to-end supply network operations (Bowers et al., 2017).

Despite the vivid interest among practitioners in the adoption of SCA, the research on this area is limited (Bonnes, 2014; Schoenherr and Speier-Pero, 2015). Specifically, empirical research on SCA adoption to understand the inmate reluctance of manufacturing companies is still in its infancy (Mubarik et al., 2019). Chen et al. (2015) applied a modified 'Technology-Organisation-Environment' (TOE) framework and focused only on a few factors impacting SCA adoption (e.g., competitive pressure only in the environmental dimension). However, additional latent variables need to be further tested, such as partner support, security and privacy issues. Moreover, no study has explored the impact of SCA adoption on firm performance and competitive advantage. To this end, this research aims to explore the factors influencing supply chain, operational and logistics managers' decision to adopt SCA via attempting to address the following research questions:

- **RQ1** – What factors influence organisational adoption of supply chain analytics?
- **RQ2** – What are the implications of adopting supply chain analytics on organisational performance and competitiveness?

In order to tackle these queries, this research first reviewed the extant literature on SCA. Thereafter, a research model was developed based on the TOE framework, which enables the consideration of factors that can influence SCA adoption. Then, the research model was tested by collecting data from 217 manufacturing firms in the UK. The gathered data was analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM).

The contribution of this research in the Operations Management field is twofold. First, this research developed a holistic model that captures all main factors that impact SCA adoption. Second, this research unveils SCA adoption's implications to organisational performance and competitive advantage, based on a robust analysis of primary evidence from the manufacturing sector.

The remainder of the paper is structured as follows: First, an overview of the SCA literature and the theoretical underpinning is provided in Section 2. Next, the research model and hypotheses developed based on the TOE framework are presented in Section 3, while the applied research methodology in this study is discussed in Section 4. Following that, Section 5 presents the analysis of the gathered primary data. Finally, a discussion of the results, implications, limitations and directions for future research are provided in Section 6.

2. Literature Review and Theoretical Underpinning

2.1 Big Data Analytics

According to Barbosa et al. (2018), Big Data analytics (BDA) refers to the application of advanced analytic approaches such as predictive methods, statistics, data mining, Artificial Intelligence (AI) in very large and unstructured data sets. Previous studies focused on the dynamic capabilities needed to operationalise BDA. For example, Mikalef et al. (2018) conducted a systematic literature review that showed the mechanisms that enable companies to use BDA and achieve a competitive advantage. The study findings set future research directions around six key themes, namely: (i) resource orchestration of BDA; (ii) decoupling BDA capability from big data-enabled capabilities; (iii) bounded rationality of BDA; (iv) turning BDA insights into action; (v) trust of top managers in BDA insights; and (vi) business value measurement. Moreover, Wamba et al. (2015), based on a systematic review and case study research, developed a conceptual framework and highlighted that companies need to develop advanced capabilities and asses (e.g., information systems, human resources, supply chains) and resolve issues around data policies, technology, and industry structure, to adopt BDA successfully.

Moreover, other studies tried to identify factors that could lead to BDA adoption. Drawing upon the TOE framework, Nam et al. (2019) explored BDA adoption in Korea. The authors found that: (i) environmental factors can trigger the initiation stage of BDA; (ii) organisation factors influence the adoption and assimilation of BDA; and (iii) technological factors affect all adoption stages. Yadegaridehkordi (2020) also adopted the TOE framework and identified the key factors affecting big data adoption in the tourism industry in Malaysia and its implications on firm performance. The study revealed that the adoption of big data is influenced by relative advantage, IT expertise, management support and external pressure. Maroufkhani et al. (2020) explored the determinants of BDA adoption in SMEs in Iran, which include complexity, uncertainty and insecurity, trialability, observability, top management support, organisational readiness, external support. The study further identified the impact of BDA adoption on marketing and financial performance. Furthermore, Mikalef et al. (2018) utilised complexity theory in the case of BDA investments in Greece and found that different configurations of resources and contextual factors lead to diverse performance gains. Wamba et al. (2020) concluded that BDA could improve supply chain functioning and performance, but these effects rely on the level of environmental dynamism.

2.2 SCA Adoption Enablers, Barriers and Implications

The first paper on SCA, identified as part of this research, was published in 2013. Notably, many publications are found during the period 2017-2019, thus indicating an emerging research area (see Table 1). Specifically, 63% of the relevant articles are empirical in nature, with the primary elaborated research method being a survey, while the rest 37% are theoretical, i.e., literature reviews or conceptual papers.

Table 1: Theories applied to the study of supply chain analytics.

[Insert Table 1 about here]

Regarding the theoretical lenses that have been used to study SCA, the 'Resource-Based View' and 'Dynamic Capability' theories are prevalent (Chae and Olson, 2013; Barbosa et al., 2018; Wamba and Akter, 2019). Other theories that have been sporadically applied include 'Network Theory', 'Organisational Information Processing' Theory, 'Stakeholder Theory' and 'Knowledge-based View'.

The concept of SCA is not adequately defined, and it is used interchangeably with terms such as 'big data analytics' and 'business analytics' within the business and academic communities (Srinivasan and Swink, 2018). SCA has been characterised as a set of capabilities (e.g., management, talent, technology) or as qualitative and quantitative tools, techniques, and methods (Brintrup et al., 2019; Souza, 2014; Wamba and Akter, 2019). Mubarik et al. (2019) combined these two perspectives and defined SCA as the capability of a firm to analyse data by utilising quantitative techniques. However, the authors' definition focuses only on data analysis capabilities and quantitative methods. Furthermore, studies recognise distinct SCA types, namely: descriptive and diagnostic analytics, predictive analytics, and prescriptive analytics (Zhao, 2019). Considering the aforementioned views, this research regards SCA as:

"*A set of capabilities and qualitative/quantitative techniques utilised to analyse traditional data and big data to inform decision-making in operations to achieve improved supply chain performance and competitive advantage*".

Several authors referred to the capabilities and resources needed for SCA implementation (Bowers et al., 2017; Mubarik et al., 2019; Wamba and Akter, 2019). For example, Chae et al. (2014) found that three sets of resources are imminent for SCA, i.e., performance management resources, IT-enabled planning resources, and data management resources. Herden et al. (2020) focused only on identifying inhibitors to SCA adoption. The study did not explore the relationships between inhibitors and adoption, or any impact on performance or competitive advantage, while the findings cannot be generalised. Another study highlighted that technical capacity, competitive landscape, and intra-firm power dynamics are essential in building BDA capability in supply chain management (Jha et al., 2020).

Chen et al. (2015) applied a modified TOE framework by positioning top management support as a mediator between organisational factors (i.e., organisational readiness) and environmental factors (i.e., competitive pressure). The authors found that in dynamic environments, the use of BDA influences business growth to an even greater degree, while organisational and environmental factors indirectly influence BDA utilisation through top management support. Moreover, Chen et al. (2015) focused mainly on the technological dimension by regarding the expected benefits and technology compatibility.

A key observation from the literature analysis is that most extant studies focused on a few factors impacting SCA adoption and did not consider factors such as skills, partner support, security and privacy issues. Additionally, most studies highlighted the importance of technological factors; however, the effect of organisational and environmental factors should be further explored (Chen et al., 2015). Thus, the need to further analyse the drivers of SCA adoption exists, while organisational and environmental factors have to be tested in future research models.

Implications of SCA adoption, such as resilience and supply chain efficiency, have also been investigated in extant studies (Table 2). Few empirical studies focused on the SCA impact on performance. For example, Chae et al. (2014) developed and tested a model to enhance the understanding of the role of SCA in planning satisfaction and operational performance. Gunasekaran et al. (2017) found that BDA can minimise costs and improve agility and supplier relationships. Evidence showed that BDA implementation also improves supply chain transparency (Zhu et al., 2018). Several studies further supported that companies adopting

SCA can achieve competitive advantage (Wang et al., 2016a); however, none of these studies tested or explored the relationship between SCA adoption and competitive edge. A systematic literature review from Mikalef et al. (2017) also emphasised the lack of theoretical-driven research on the link between BDA and competitive advantage.

Table 2: Implications of supply chain analytics.

[Insert Table 2 about here]

Few studies tried to understand the drivers and barriers of BDA adoption in different industries or even individual corporate departments, e.g., Mikalef et al. (2019) focused on IT managers. However, there is a need to explore the factors impacting the adoption of big data holistically from a supply chain management perspective. Based on the studies discussed above, no study comprehensively explored the supporting and inhibiting factors to SCA adoption and its implications on organisational performance and competitive edge. In order to support our arguments and build a relevant research model to be tested, the TOE framework was employed.

2.3 TOE Framework

A range of internal (e.g., firms' size) and external (e.g., competitor pressure) factors hinder companies from implementing IT-based innovations. Several authors have explored the adoption of various technologies such as ERP, RFID, business analytics and blockchain by applying different theoretical models such as the 'Theory of Reasoned Action' (TRA), 'Technology Acceptance Model' (TAM), 'Innovation Diffusion Theory' (IDT), and the 'TOE' framework (Clohessy et al., 2019; Kuan and Chau, 2001; Ramanathan et al., 2017; Zhu et al., 2003). Some of these models (e.g., TRA, TAM) focus on predicting an individual's acceptance behaviour towards new technologies while others (e.g., IDT, TOE) investigate the organisational level of acceptance of emerging technologies (Gangwar et al., 2014).

Considering that the adoption of SCA is a strategic firm-level initiative, this research applied the TOE framework. The TOE framework, introduced by Tornatzky and Fleischer in 1990, considers technological, organisational and environmental dimensions that simultaneously impact innovation adoption at a firm level. First, the technological dimension refers to internal and external technologies relevant to a specific organisation and considers the complexity of new technology, compatibility with existing technologies, and perceived benefits. Second, the organisational dimension captures firm characteristics like culture and size (Teo et al., 2006a). Third, the environmental dimension entails the external firm environment, such as competitors, suppliers, and governmental regulations (Tornatzky and Fleischer, 1990).

The main reason for adopting TOE is that SCA systems require organisation-wide adoption across end-to-end supply chain operations; hence, an organisational adoption theory is suitable for this research. Moreover, TOE considers environmental factors, such as pressure from partners, along with technological and organisational factors to investigate firms' technology adoption decisions. SCA has not been widely adopted across industries yet, so it is plausible that a firm's external environment (e.g., suppliers) will have a critical role in the organisational adoption decisions. Another advantage of TOE over other models is its adaptability. The framework allows capturing different factors, a critical capability considering that each new technology might have unique characteristics and functionalities (Vilaseca-Requena et al., 2007).

3. Research Model and Hypotheses Development

This study proposes a unique research model based on the TOE framework and the literature findings. The first part of the model entails the determinants of SCA adoption, and the second part emphasises the implications of SCA adoption. Figure 1 depicts the research model and the relationships among the incorporated constructs.

Figure 1: Research model.

[Insert Figure 1 about here]

3.1 Technological Factors and SCA Adoption

Technological compatibility has been widely recognised in different studies as a crucial factor for innovation adoption (Wang et al., 2010). Compatibility has also been acknowledged as an essential factor in SCA, particularly considering the transition towards digitalisation of operations that aims to: (i) promote homogeneity in the execution of supply chain processes (Mettler et al., 2012); and (ii) enable visibility of resources' flows from suppliers to customers (Barbosa et al., 2018). To this end, from a technical viewpoint, common data structures along with interoperability and integration of information systems are major requisites to facilitate data sharing among diverse network actors and enable data analytics initiatives (Barbosa et al., 2017). Therefore, it is hypothesised:

H1: The perceived compatibility between SCA software and tools and existing business and technical structures positively impacts the adoption of SCA systems.

Data integrity (i.e., accurate and reliable data) is another factor that motivates companies to adopt innovation. Data integrity helps companies unveil data quality issues (e.g., inaccuracy, redundancy), thus further dictating the need to identify data types to be collected and pre-processing options to enable SCA for generating operational insights (Chae and Olson, 2013). As Wamba et al. (2015) emphasised, there is a need to ensure big data quality to assist managers in making informed decisions. From an analytics perspective, scalability is considered an a priori condition alongside the expansion of operations, horizontally (i.e., breadth of data) to cover multiple network echelons, and vertically (i.e., processing power and memory, storage capacity) to assure the feasibility of SCA. Thus, the following hypothesis can be derived:

H2: The perceived data integrity and scalability benefits positively impact the decision to adopt SCA systems.

In addition to data integrity, scalability and compatibility, SCA tools and software associate with several implementation challenges (Arya et al., 2017). Considering the huge amount of data generated across end-to-end supply chains, both at temporal and spatial dimensions, meticulous attention shall be focused on data privacy and security to leverage the potential of SCA (Barbosa et al., 2018). Companies are concerned regarding data confidentiality, as data breaches can impact corporate viability and reputation. Thus, concerns around security and privacy restrain SCA adoption (Markets and Markets, 2020). The following hypothesis is presented:

H3: The perceived security and privacy issues negatively impact the adoption of SCA systems.

Last but not least, capital-intensive innovations are less likely to be adopted (Tornatzky and Klein, 1982). The high initial cost of SCA adoption may lead to lower adoption intent despite the associated benefits (Barbosa et al., 2018). Companies prefer cheap, fast, and easy to install and use systems (Sahay and Ranjan, 2008). Thus, companies which perceive higher costs relative to benefits in an SCA system are less likely to adopt it. Based on these arguments, it is hypothesised:

H4: The perceived high cost of implementing SCA software and tools negatively impacts the adoption of SCA systems.

3.2 Organisational Factors and SCA Adoption

The readiness regarding the technological infrastructure and literate personnel on IT impacts the decision of companies to adopt new technologies (Oliveira and Martins, 2010; Wang et al., 2010). SCA require that firms have available both tangible and intangible internal resources. From a tangibles' viewpoint, data analysis requires the appropriate computational power and equipment; thus, investments in analytical technology systems are required (Arya et al., 2017). From an intangibles' perspective, data is the primary resource required to enable analytics (Barbosa et al., 2017). Firms also need to adopt data-mining techniques to gather internal and external data, e.g., from customers, suppliers, and warehouse management systems (Chae and Olson, 2013).

In addition, skills and capabilities to apply data analysis techniques and methods (e.g., mathematical programming, simulation, statistical analysis, machine learning algorithms) are required to handle data flows (Chae et al., 2014). For example, the lack of IT expertise is an inhibitor to B2B e-commerce adoption (Teo et al., 2006b), while other studies pinpointed that employees' knowledge and skills can positively impact IT adoption (Martins and Oliveira, 2009). Talent capture and a technical and managerial understanding of big data have been highlighted in several studies (Mikalef et al., 2018; Mikalef et al., 2020). Regarding SCA, it has been indicated through several studies that existing employees should be equipped with relevant technical and analytical skillsets to deliver digital analytics initiatives successfully (Deloitte, 2019). Furthermore, vulnerability challenges entail the need for security inspection expertise and equipment (Min et al., 2017).

Additionally, in terms of organisational readiness, the support received from top management for adopting innovations is a recognised condition for innovation implementation (Premkumar and Roberts, 1999). In this regard, top management needs to set the objectives and goals of business processes to determine the data analytics resources and requirements (Sahay and Ranjan, 2008). Wamba et al. (2015) also highlighted the need for top management support and involvement to leverage big data capabilities. Organisations need to develop an analytics culture, and C-level executives need to support and assimilate the integration of SCA initiatives (Bowers et al., 2017). To this end, investing in data-oriented processes can demonstrate leadership commitment towards SCA (Chae et al., 2014). Based on these arguments, it is hypothesised that:

H5: Organisational readiness positively impacts the adoption of SCA systems.

Organisation size has also been recognised as a fundamental determinant of an innovator's profile (Rogers, 2003). Firm size dictates the accessibility to required SCA capabilities and resources (Mettler et al., 2012), with small and medium enterprises (SMEs) typically not having the resources or knowledge to readily adopt newer technologies (Carcary et al., 2014). Kühn et al. (2019) also found that SMEs are reluctant to adopt emerging technologies and change their IT structures, processes, and work routines. The following hypothesis is presented related to organisational factors:

H6: Large organisations are more likely to adopt SCA systems.

3.3 Environmental Factors and SCA Adoption

Companies feel pressure to adopt new technologies in case their business partners recommend or request to do so (Kuan and Chau, 2001). Uncertainty in the operational environment, along with particular market volatility, dictate that supply chain actors need to implement analytics to generate insights over anticipated customer behaviours to enable organisational flexibility and match supply to demand (Srinivasan and Swink, 2018). Thus, high customer expectations are a crucial business consideration that motivates firms to adopt SCA systems. Therefore, we hypothesise that:

H7: Customer expectations positively impact the adoption of SCA systems.

Organisations are also dependent on their trading partners to design and implement a technology (Pan and Jang, 2008). Trading partners in SCA relate to the suppliers of software and hardware tools. Thus, trading partners' support is another influential external constituent that drives firms to adopt SCA. SCA entails that an end-to-end network of partners shares joint planning and performance management criteria and is willing to share data under any confidentiality measures (Chae et al., 2014). Considering the global presence of supply networks and the high coordination complexity among the involved actors, it is critical to streamline targets and operations. To this effect, traditional coordination approaches could impose delays; thus, modern supply chains need to ensure non-hierarchical coordination to enable data sharing among different organisational departments and analytics groups (Mettler et al., 2012). Furthermore, from a technology viewpoint, supply chain partners and, most importantly, the trading partners of the software and hardware tools need to ensure compatibility, coordination and interoperability of IT infrastructure to enable efficient data sharing (Chae et al., 2014). Hence, the following hypothesis is posited:

H8: Trading partners' support positively impacts the adoption of SCA systems.

Firms' decision to use SCA is also influenced by governmental regulations (Herden et al., 2020). The regulatory environment affects new technology adoption (Hsu et al., 2014). For example, the General Data Protection Regulation in the European Union and the European Economic Area made companies change their data behaviours. Companies encounter difficulties complying with policies and regulations due to the large amount of unstructured data (Kim et al., 2014). Unstructured data also challenges the adoption of an SCA system as companies have to ensure internal compliance, but they also have to consider the entire supply chain (Schwartz, 2020). Moreover, data protection laws are not the same everywhere. For example, regulations around data processing differ, which can cause many issues where there is a cross-border transfer of personal data (DHL, 2019). Financial support provided by governments can have a crucial role in fostering the adoption of new technologies in a given industry (Shi and Yan, 2016).

Lastly, about 205 national policy initiatives around the globe aim at enhancing data accessibility and sharing, hence highlighting the catalytic role of policy-making in supporting analytics initiatives, both at financial and regulatory fronts, particularly in international supply networks (OECD, 2019). Indicative policy initiatives focus on: (i) facilitating accessibility to public-sector data; (ii) supporting data sharing in the private sector; (iii) fostering the capacity of the society to perform data analytics; and (iv) developing national strategies for data management and analytics. Therefore, we hypothesise that:

H9: Harmonising policy and regulations, along with financial support from governments, can positively impact the adoption of SCA systems.

3.4 SCA Adoption Implications

Adopting IT systems can improve organisational performance and help a company achieve a competitive advantage (Bhatiasevi and Naglis, 2018; Gunasekaran et al., 2017). Several authors have also highlighted that SCA impacts an organisation's competitive edge (Bowers et al., 2017; Srinivasan and Swink, 2018; Tiwari et al., 2018). The effective use of SCA can improve the efficiency of internal and external processes (e.g., waste mitigation), reduce inventory costs (e.g., stockouts), reduce manmade errors, and enhance operational performance (e.g., supplier lead times, material availability planning errors, quality control) (Barbosa et al., 2018; Wamba and Akter, 2019; Wang et al., 2016a). These observations over the literature lead to the hypothesis:

H10: The SCA adoption positively affects organisational performance.

Empirical studies that tried to explore the impacts of BDA on competitive performance are relatively scarce, but a few studies show a positive overall association (Gupta and George, 2016; Mikalef et al., 2018). Regarding the competitive advantage, SCA enables companies to achieve transparency and visibility and collaborate closely with their suppliers (Arya et al., 2017; Min et al., 2017; Mubarik et al., 2019). Supply chain innovation can also be achieved by accessing timely and meaningful data (Shamout, 2019). Achieving resilience along the supply chain is another implication of SCA adoption (Brintrup et al., 2019; Zhao, 2019). In addition, SCA enables sustainability by capturing and offering the correct information for decision-making on sustainability issues and freeing up resources to enable employee-focused social practices' implementation (Shafig et al., 2019; Zhu et al., 2018). Thus, we hypothesise that:

H11: The SCA adoption positively affects the competitive edge.

4. Methodology

4.1 Sample

A survey tool was designed to test the proposed framework and hypotheses. Furthermore, primary data was collected from 217 supply chain professionals, senior managers, and mid-level managers with at least two years of experience in SCA. The survey participants represent manufacturing companies in the UK. A survey pre-testing was carried out with four scholars and four managers working as supply chain analysts in manufacturing companies but were not involved in the main survey. This process helped to evaluate the reliability and validity of the survey tool and assess possible completion times (Brandon-Jones and Kauppi, 2018). No significant changes were required to the questionnaire, beyond minor revisions (e.g., re-phrasing several questions), and the survey was launched.

Responses were collected by using SurveyMonkey Audience, provided by SurveyMonkey, which has a database with experts; thus, inclusion criteria were set to identify the right target audience (i.e., country: UK; industry sector: manufacturing; field of expertise: supply chain management, procurement, operations, logistics, SCA or related area). Based on these criteria, 300 potential respondents were identified. Then, a pre-screen question was added to the survey instrument asking participants whether they had SCA experience for at least two years; ultimately, 200 participants were identified as eligible and recruited in our study. Last but not least, based on our network in LinkedIn, a small proportion of identified experts, i.e., 17 out of 30 supply chain managers, were engaged. Thus, of the 330 potential respondents, 217 completed and usable questionnaires were collected, representing a 69% response rate. The link to the survey was available for three months, from December 2020 to February 2021; the profile of the respondents is provided in Table 3.

Table 3: Survey participants and their corporate role.

[Insert Table 3 about here]

Non-response bias was evaluated by comparing early and late respondents. Furthermore, ten items used in the questionnaire were randomly selected to compare the first and last thirty returned questionnaires. The findings did not show any significant variation between early and late responses; thus, this study's non-response bias is not considered an issue.

The participants were mainly from the following manufacturing sectors: industrial machinery and equipment (20%), food and kindred products (15%), electronics and other electric equipment (10%), transportation equipment (9%), and chemicals and allied products (9%) (Table 4). Most companies were large and medium-sized (Table 5) based on the number of employees, used as a standard criterion in previous studies (Gambi *et al.*, 2015). Company size was defined based on the OECD (2021) categorisation.

Table 4: Representative manufacturing sectors.

[Insert Table 4 about here]

Table 5: Representative manufacturing company size.

[Insert Table 5 about here]

4.2 Survey Design

A three-part questionnaire was designed, including: (i) demographic characteristics; (ii) evaluation of SCA adoption predictors; and (iii) evaluation of SCA adoption implications. Each construct was measured using a validated research instrument developed by previous studies (modified to fit the research context) and based on the literature review findings and the theoretical foundation (Cao and Zhang, 2011). A five-point Likert scale was used to overcome measurement errors (Knol et al., 2019). The Likert scale ranges from "strongly disagree" (i.e., 1) to "strongly agree" (i.e., 5). Table A1 in the Appendix describes the used survey items.

4.3 Measurements' Assessment

This research applied SmartPLS 3.0 to test our hypotheses through PLS path modelling. PLS was preferred as the aim was to predict the relationship between variables (Urbach and Ahleman, 2010), and both reflective and formative measurement scales can be used to analyse the model. Theoretical parsimony and less model complexity can be established using PLS (Wamba and Akter, 2019).

First, exploratory factor analysis, internal correlation analysis and internal consistency analysis were performed to examine the reliabilities, composite reliabilities, convergent validity (Table 6), and discriminant validity (Table 7). According to Sam and Chatwin (2018, p.3): "… *organizational readiness refers to how employees are prepared and willing to adopt big data analytics depending on the internal and external organizational factors*". The most widely recognised factors of readiness supported in the literature are top management, organisation size and availability of resources. Thus, initially, in this construct, we tried to capture the items based on previous studies individually, namely: (1) top management support; (2) organisational readiness; (3) skills; and (4) firm size. After collecting the data and conducting the exploratory analysis, the constructs of top management support, organisational readiness, and skills were not distinct as they were loaded onto the same factor, i.e., organisational readiness. Table A1 in the Appendix inserts the items loaded more than the recommended thresholds, i.e., 0.7 and 0.5 (Hair *et al.*, 2014). There is a good level of internal consistency as the Cronbach's alpha value for all constructs was more than 0.7. Results revealed that the Average Variance Extracted (AVE) for all constructs exceeded the minimum threshold value of 0.5, indicating that all latent variables have explained more than 50% of the variance in their observable measures. The composite reliabilities exceeded the recommended threshold value of 0.7 (Nunnally and Bernstein, 1994).

The next step was to measure the discriminant validity that shows if a concept is unique and unrelated to other measures (Bagozzi et al., 1991). Discriminant validity can be evaluated using the Fornell-Larcker criterion and the cross-loadings. The Fornell-Larcker criterion postulates that the correlation of a construct with its indicators (i.e., the square root of AVE) must be higher than the correlation between the construct and any other construct (Fornell and Lacker, 1981). The results showed that the root AVE values were greater than the corresponding off-diagonal correlations for all constructs, indicating sufficient discriminant validity (Barclay et al., 1995).

Table 6: Measurement model results – Convergent validity.

[Insert Table 6 about here]

Table 7: Measurement model results – Discriminant validity.

[Insert Table 7 about here]

Finally, we tested the full Variance Inflation Factor (VIF) values to assess multicollinearity. In the beginning, the FS construct was above 10 (e.g., Hair et al., 2014), so to mitigate the issue, we deleted certain items, e.g., the second item from the COST and TPS and the first item from the FS construct. Based on these changes, as shown in Table A1 in the Appendix, the FS for all items is less than the suggested threshold. Thus, multicollinearity among the predictor constructs is not an issue in the model. Then, the bootstrap method within PLS was used to test the significance of the structural relationships.

5. Findings

The significance of all paths of the structural model was also tested based on bootstrapping standard errors; t-statistics were also generated to assess the statistical significance of the path coefficients. Specifically, Table 8 illustrates the path coefficients, t-statistics, and significance (p-value). The constructs representing technological factors, namely: compatibility, diversity and scalability, security and privacy issues, and cost, were found to have no significant effect on SCA adoption, thus rejecting H1, H2, H3 and H4. The organisational factors represented by organisational readiness were significantly related to the intention to adopt SCA adoption; hence, H5 was supported, whereas the firm size does not seem to affect SCA adoption significantly. Furthermore, the environmental factors, namely customer expectations, trading partner support and policy and regulations, were significantly related to the adoption of SCA. Thus, H7, H8 and H9 were accepted. Last but not least, the results show that SCA adoption has a significant positive effect on organisational performance and competitive advantage. Therefore, H10 and H11 hypotheses are supported.

Table 8: Results of hypothesis testing.

[Insert Table 8 about here]

The variance explained (R2), effect size (F2) and predictive relevance (Q2) were used to evaluate the quality of the model. The R^2 values suggest that SCAA (62.98%), CA (34.50%), and OP (27.32%) adequately explain the model. Large amounts of variance (f^2 values) were explained in OP (0.382) and CA (0.533). Effect size was medium for OR (0.259), and f^2 can be classified as small for the rest of the constructs COST (0.04), CE (0.07), PR (0.02), SIP (0.06), TPS (0.02), and FS (0.03). In addition, the Q2 values for SCAA (0.4132), OP (0.1943), and CA (0.2180) indicate that the model has good predictive relevance since the values are more than 0.000 (Hair et al., 2014). The GoF value of the model exceeds the large cut-off point, and it is found to be 0.42, which indicates that the model has substantial explaining power. Moreover, the value of SRMR is 0.103, which is less than 0.201, the dULS value is 9.2, which is less than 13.127, and the dG value is 1.6, which is less than 6.602, thus indicating that the proposed model represents a good fit (Benitez et al., 2018).

6. Discussion and Conclusions

The study's main results can be summarised in two aspects: first, how different technological, organisational and environmental factors influence the adoption of SCA; and second, the impact of SCA adoption on organisational performance and competitive advantage.

The results demonstrate that the most significant factors that influence manufacturing companies' intention to adopt SCA are the readiness of the internal organisation and external factors, namely the providers of SCA tools and applications and business partners expectations. Notably, none of the investigated technological factors was found to influence manufacturing companies' intent to adopt SCA significantly. These findings are inconsistent with other studies which supported the need for significant investments in technological infrastructure and that SCA systems have to deal with data in different formats and huge amounts (e.g., Barbosa et al., 2017). For example, Nam et al. (2019) found that technological factors such as data infrastructure are the most critical in BDA adoption. Mikalef et al. (2019) also found that technological factors are more crucial in moderately uncertain environments, while in highly uncertain conditions, organisational factors such as skills are of greater importance.

This finding is also inconsistent with findings of prior IT innovation adoption studies (e.g., Awa et al., 2016), which suggested that technological factors such as data integrity, scalability, and security significantly influence innovation adoption. One explanation for the non-significance is that participants in this study were familiar and knowledgeable on how to well-match and easily integrate SCA into their environment. It has been supported that compatibility of an IT innovation and security concerns may have an effect during the post-adoption stage (Zhu et al., 2016); thus, future studies could examine the impact of these factors during the post-adoption stage of SCA.

In terms of cost determinants, it is found that mainly large manufacturing firms plan to adopt SCA because of customer expectations, policy requisites and regulations. Thus, organisations adopt SCA to promote their brand image and reputation and avoid falling behind the competition (Son and Benbasat, 2007), regardless of technological considerations, i.e., compatibility, data integrity and scalability, security and privacy issues and cost. Other scholars (Chen et al., 2015; Lautenbach et al., 2017; Maroufkhani et al., 2020) supported that BDA adoption could be driven by the corporate need to uphold a competitive position.

Regarding organisational factors, organisational readiness is found to have a significant influence. These findings suggest that manufacturing companies must have sufficient resources, e.g., skills, technical and financial readiness (Arya et al., 2017; Barbosa et al., 2018). There is also a need for top management support. Top management support can reduce resistance and help overcome barriers related to SCA initiatives so it can become "*an integral part of the fabric of the organization*" (Bowers et al., 2017). Mikalef et al. (2019) also emphasised the need to invest in resources and develop a top-down strategy to realise business value. A firm's size is also a critical adoption factor, in line with other studies that explored other technologies such as RFID and e-commerce (e.g., Hossain and Quaddus, 2011). However, this result is not aligned with Srinivasan and Swink (2018), who found that firm size is not related to analytics capability. Thus, our study supports that small companies lack the requisite resources and have limited capabilities to adopt SCA (Mettler et al., 2012).

In particular, we detected a positive direct effect of customer expectations, which posit another pressure affecting a firm's SCA adoption decision. Vendors or other partners have expectations and encourage manufacturing firms to adopt SCA systems (Chae et al., 2014). Our results align with IT adoption studies, e.g., Teo et al. (2009), who found that customer expectations significantly affect e-procurement adoption.

Similarly, trading partner support also produces a significant result. Thus, manufacturing companies are influenced by vendors' levels of support for co-creation and customisation. Previous literature findings suggested that third-party service providers can provide technical support that can lead to certain advantages, e.g., no need to maintain internal staff, ongoing training for the staff, and hiring new specialists required to implement SCA systems (Lundin, 2020). The results of this study indicate that policy and regulations are significant factors to SCA adoption. Previous studies have highlighted the importance of regulations to instil a sense of trust and eliminate governmental or legislative barriers that can hinder the adoption of technologies (Oliveira et al., 2014). The finding is also in line with Herden et al. (2020), who supported that government rules and regulations influence the decision to use SCA. However, Nam et al. (2019) found that government support has no significant effect in encouraging BDA use in Korea despite the government supporting companies with R&D for big data technology implementation.

Concerning the impact of SCA adoption on organisational performance, we observed that SCA adoption has a significant impact on both organisational performance and competitive advantage. This reflection is in line with previous studies that suggested that SCA systems enable companies to understand, transform, and shape data and differentiate their products, thus helping companies achieve competitive advantage (Sahay and Ranjan, 2008; Wang et al., 2016a). Moreover, SCA adoption may help manufacturing companies avoid overtime production, lost sales, and inventory overages (Srinivasan and Swink, 2018).

6.1 Theoretical Contributions

There are three main theoretical contributions of this research to the field of SCA. First, previous studies focused on other areas such as BDA or e-procurement adoption (e.g., Brandon-Jones and Kauppi, 2018) or aspects such as the capabilities needed to adopt SCA (e.g., Bonnes, 2014). This study is comprehensive as it is the first to identify most factors influencing the adoption of SCA holistically and in-depth. An integrated research model was developed to tackle the query about the factors that lead to SCA adoption. Thus, a practical, comprehensive framework and empirical evidence of SCA adoption in manufacturing companies were provided in this study, an unexplored area so far (Mubarik et al., 2019).

The second implication relates to the level of SCA adoption and the business partners' pressure. Our research shows that manufacturing companies adopt SCA through convincing power (e.g., financial incentives) or compulsory power (where the customers have higher bargaining power). Therefore, this study adds to the existing body of knowledge supporting that partners and customers influence the adoption of B2B e-commerce (Ocloo et al., 2020).

Thirdly, this study has found that SCA adoption improves organisational performance and competitive advantage and adds to the growing empirical evidence suggesting that SCA tools and applications enhance performance (Zhu et al., 2018) and lead to competitive advantage (Bowers et al., 2017). However, previous studies only examine the determinants of operational, social and financial performance (Chae et al., 2014; Shafiq et al., 2019) without showing the adoption impact on overall organisational performance or competitive advantage.

6.2 Managerial and Policy Implications

The results of this study have several implications for managers and policy-makers. First, it is evident from the results that mainly non-technological factors influence manufacturing companies to adopt SCA. Previous studies that explored the implementation of new IT systems highlighted the need to gradually implement any changes needed in operations and devise ways to minimise the resistance from employees and other stakeholders (Brown et al., 2002). Thus, prior to SCA adoption, factors such as organisational skills, capabilities, and trading partner's support need to be meticulously considered. To this effect, SCA systems can be adopted and used effectively and efficiently, i.e., how companies will integrate SCA to fit their organisational culture, structure, and strategic goals. Second, the findings of this study indicate that SCA providers need to satisfy customers' requirements entirely and ensure top management's support to enable a collaborative engagement between SCA providers and customers. The top management has to ensure and build the proper infrastructure required to facilitate the implementation of SCA. Manufacturing companies are dependent on SCA vendors and need to involve them at an early stage in the implementation phase to enable SCA adoption. At the same time, to improve performance and achieve a competitive advantage, firms should monitor these vendors and draft service-level agreements that allow flexibility to change vendors in case of inability to respond to their needs, e.g., commitment to full consultation and transparency. Third, as competition is "*between supply chains*" (Christopher, 1998), more and more organisations are increasingly adopting SCA to minimise supply chain costs and secure competitive advantage. Thus, companies have to assess their needs in training programmes and technical consulting (through customers or vendors) and determine the compatibility with the existing supply chain network's systems and processes. The assessment of extant and required support on BDA adoption can further assist companies in formulating and implementing an appropriate digital supply chain strategy to sustain growth and competitiveness (Ho et al., 2022).

Furthermore, the SCA trading service providers can further develop their resources and processes (i.e., minimise the barriers and challenges) and enhance service capabilities to accelerate SCA adoption. Regarding policy, it is noted that creating favourable legislative and regulatory schemes will positively influence the use of SCA systems. In this regard, regulations that simplify and facilitate data integration, address data privacy and management issues, and support training activities (Kazancoglu et al., 2021) are necessary. In addition, different schemes that can help solve the cost and payment barriers and encourage SCA adoption could be catalytic.

6.3 Limitations and Future Research

Although several contributions to extant research in the area of SCA and technology acceptance more broadly were made, there are certain limitations in this study. First, the sample of this study entails manufacturing companies in the UK which means that the results might be different in other countries. Thus, this study should be applied to diversified national contexts to improve the generalisability of the results.

Moreover, this study has not explored the potential interaction between industry type and SCA adoption. It is interesting to investigate if there are differences between industries regarding the determinants for SCA adoption. Our model considered various determinants, but other variables such as relative advantage may be potential determinants of SCA adoption. Future research may incorporate other technological, organisational, and environmental factors. Finally, this study only focused on the adoption decision of SCA and not on its implementation.

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Table 1: Theories applied to the study of supply chain analytics.

Study	Theory and Study Contribution	Type of Study
Chae and Olson (2013)	<u>Dynamic Capabilities</u> Proposes a theory-driven and practical framework for understanding how SCA can support firms.	Theoretical
Chae et al. (2014)	<u>Resource-Based View Theory</u> Explores the implications of advanced analytics and manufacturing data accuracy on operational performance.	Empirical (partial least squares/structured equation modelling)
Souza (2014)	Describes the application of analytics techniques in supply chain management.	Theoretical
Lee (2016)	Demonstrates the usefulness of visual analytics on business decision-making, particularly with regard to manufacturing cost.	Empirical (visual analytics of primary data)
Arya et al. (2017)	Explores the use of analytics in the military spare parts supply chain and logistics.	Theoretical
Barbosa et al. (2018)	<u>Resource-based View/Dynamic Capabilities View</u> Investigates how analytics has been investigated on supply chain management studies, e.g., which processes are involved.	Theoretical
Barbosa et al. (2017)	<u>Network Theory</u> Identifies the most central actors in this area	Theoretical
Bowers et al. (2017)	Discusses the need to develop SCA as an internal capability to generate actionable insights in a responsive manner.	Empirical (survey and interviews)
Herden (2017)	Investigates the role of types of Data Science in SCA for better informed decision-making processes.	Theoretical
Srinivasan and Swink (2018)	<u>Organisational Information Processing Theory</u> Examines factors associated with a firm's development of an overall analytics capability for operational decision-making.	Empirical (survey/hierarchical regression)
Tiwari et al. (2018)	Explores the big data analytics research and application in supply chain management.	Theoretical
Zhu et al. (2018)	<u>Organizational Information Processing Theory</u> Investigates how SCA capabilities support operational supply chain transparency.	Empirical (survey and unrelated regression)
Brintrup et al. (2019)	Investigates the use of data analytics in predicting supplier disruptions.	Empirical (case study)
Wamba and Akter (2019)	<u>Resource-Based View/Dynamic Capabilities View</u> Develops a multi-dimensional, hierarchical SCA capability model.	Empirical (survey and partial least squares-based structural equation modelling)
Mubarik et al. (2019)	Examines the impact of big data SCA on supply chain performance	Empirical (survey and covariance based structural equation modelling)
Shafiq et al. (2019)	<u>Stakeholder Theory/Resource-Based View</u> Investigates the role of SCA capability and customer pressure for ethical conduct towards the adoption of socially responsible practices by suppliers.	Empirical (survey and covariance based structural equation modelling)

Study	Theory and Study Contribution	Type of Study
Shamout (2019)	Knowledge-Based View Examines the effectiveness of SCA in enhancing firm's innovation and robustness capability in the Arabian context.	Empirical (survey and variance-based structural equation modelling)
Zhao (2019)	Provides an overview of the applications of analytics in supply chain management.	Empirical (case study and model development)
Herden et al. (2020)	Explores the barriers that logistics and supply chain management organisations experience in employing supply chain analytics	Empirical (mixed method: Grounded Theory and Q-Methodology)

Table 2: Implications of supply chain analytics.

Implications	Authors
Operational improvement	Barbosa et al. (2018); Bowers et al. (2017); Chae and Olson (2013); Chae et al. (2014); Mubarik et al. (2019); Sahay and Ranjan (2008); Shafig et al. (2019); Srinivasan and Swink (2018); Tiwari et al. (2018); Wang et al. (2016a); Wamba and Akter (2019); Zhao (2019)
Supply chain efficiency	Arya et al. (2017); Bowers et al. (2017); Mubarik et al. (2019); Shafig et al. (2019); Srinivasan and Swink (2018); Tiwari et al. (2018); Wamba and Akter (2019); Wang et al. (2016a); Zhao (2019)
Customer service performance	Arya et al. (2017); Bowers et al. (2017); Srinivasan and Swink (2018); Zhao (2019)
Supply chain innovation	Shamout (2019)
Collaboration	Arya et al. (2017); Mubarik et al. (2019); Wamba and Akter (2019)
Resilience	Bowers et al. (2017); Brintrup et al. (2019); Min et al. (2017); Mubarik et al. (2019); Tiwari et al. (2018); Wamba and Akter (2019); Wang et al. (2016a); Zhao (2019)
Transparency	Arya et al. (2017); Chae et al. (2014); Min et al. (2017); Mubarik et al. (2019); Sahay and Ranjan (2008); Srinivasan and Swink (2018); Tiwari et al. (2018); Wang et al. (2016a); Zhu et al. (2018)
Sustainability	Shafig et al. (2019); Wang et al. (2016a); Zhu et al. (2018)

Table 3: Survey participants and their corporate role.

Company Role	No. of Participants	Sample Share
Supply chain manager	27	12%
Supply chain analyst	18	8%
Operations manager	18	8%
Manager	16	7%
Supply chain administrator	16	7%
Purchasing manager	14	6%
Senior director of supply chain digitalisation	13	6%
Head of supply chain and logistics	9	4%
Chief executive officer	9	4%
Sales representative	9	4%
Supervisor	9	4%
Logistics manager	8	4%
Director	8	4%
IT manager	7	3%
Chief information officer	6	3%
Buyer	6	3%
Senior demand and supply planner	5	2%
Supply chain quality assurance manager	5	2%
Procurement manager	4	2%
Supply chain project manager	4	2%
Senior purchasing manager	3	1%
Supply clerks	3	1%
Total	**217**	**100%**

Table 4: Representative manufacturing sectors.

Manufacturing Sector	No. of Representatives	Sample Share
Industrial machinery and equipment	43	20%
Food and kindred products	33	15%
Electronic and other electric equipment	22	10%
Transportation equipment	20	9%
Chemicals and allied products	20	9%
Primary metal industries	16	7%
Fabricated metal products	15	7%
Pharmaceutical	12	6%
Textile mill products	11	6%
Rubber and miscellaneous plastic products	10	4%
Petroleum and coal products	9	4%
Cosmetic industry	6	3%
Total	**217**	**100%**

Table 5: Representative manufacturing company size.

Company Size	No. of Representatives	Sample Share
Small (10 to 49 employees)	52	24%
Medium-sized (50 to 249 employees)	65	30%
Large (>250 employees)	100	46%
Total	**217**	**100%**

Table 6: Measurement model results – Convergent validity.

Constructs	AVE	CR	Cronbach's alpha
CA	0.656	0.905	0.869
COST	0.885	0.958	0.935
CE	0.793	0.938	0.915
COM	0.714	0.909	0.872
DIS	0.659	0.885	0.828
FS	0.969	0.985	0.984
OP	0.724	0.887	0.81
OR	0.609	0.903	0.837
PR	0.693	0.871	0.779
SCAA	0.692	0.87	0.774
SPI	0.757	0.903	0.839
TPS	0.792	0.938	0.912

Table 7: Measurement model results – Discriminant validity.

Constructs	CA	COST	CE	DIS	FS	OP	OR	PR	SCAA	SPI	TPS
CA	0.8102										
COST	0.1530	0.9324									
CE	0.4939	0.1400	0.9244								
DIS	0.6143	0.1101	0.4219	0.8120							
FS	0.2669	-0.0326	0.3058	0.2500	0.9845						
OP	0.7890	0.0901	0.3821	0.5814	0.1839	0.8514					
OR	0.6279	0.0569	0.6227	0.5129	0.3964	0.5454	0.7786				
PR	0.3471	0.4029	0.3796	0.3170	0.1128	0.3110	0.2726	0.8333			
SCAA	0.5889	0.0691	0.6043	0.4290	0.3549	0.5248	0.7412	0.3591	0.8320		
SPI	0.4934	0.1661	0.3482	0.5924	0.2111	0.4328	0.4722	0.2550	0.4332	0.8703	
TPS	0.1989	0.3507	0.3243	0.1152	0.1408	0.1433	0.2301	0.4285	0.3154	0.1827	0.8899

Table 8: Results of hypothesis testing.

Hypotheses	Path	Path Coefficient	t-statistics	p-value	Decision (effect)
H1	COMàSCAA	0.0698	0.9088	0.3639	Rejected
H2	DISà SCAA	-0.0434	0.5351	0.5928	Rejected
H3	SPIà SCAA	0.0663	1.0413	0.2983	Rejected
H4	COSTàSCAA	-0.0743	1.2982	0.1948	Rejected
H5	ORàSCAA	0.4649	5.5053	0.0000***	**Accepted**
H6	FSàSCAA	0.0708	1.4926	0.1362	Rejected
H7	CEàSCAA	0.2368	3.1000	0.0020*	**Accepted**
H8	TPSàSCAA	0.1059	2.1397	0.0329*	**Accepted**
H9	PRàSCAA	0.1015	2.0558	0.0403*	**Accepted**
H10	SCAAàOP	0.5259	9.1277	0.0000***	**Accepted**
H11	SCAAàCA	0.5900	11.2739	0.0000***	**Accepted**

Notes: * p<0.05; *** p<0.001.

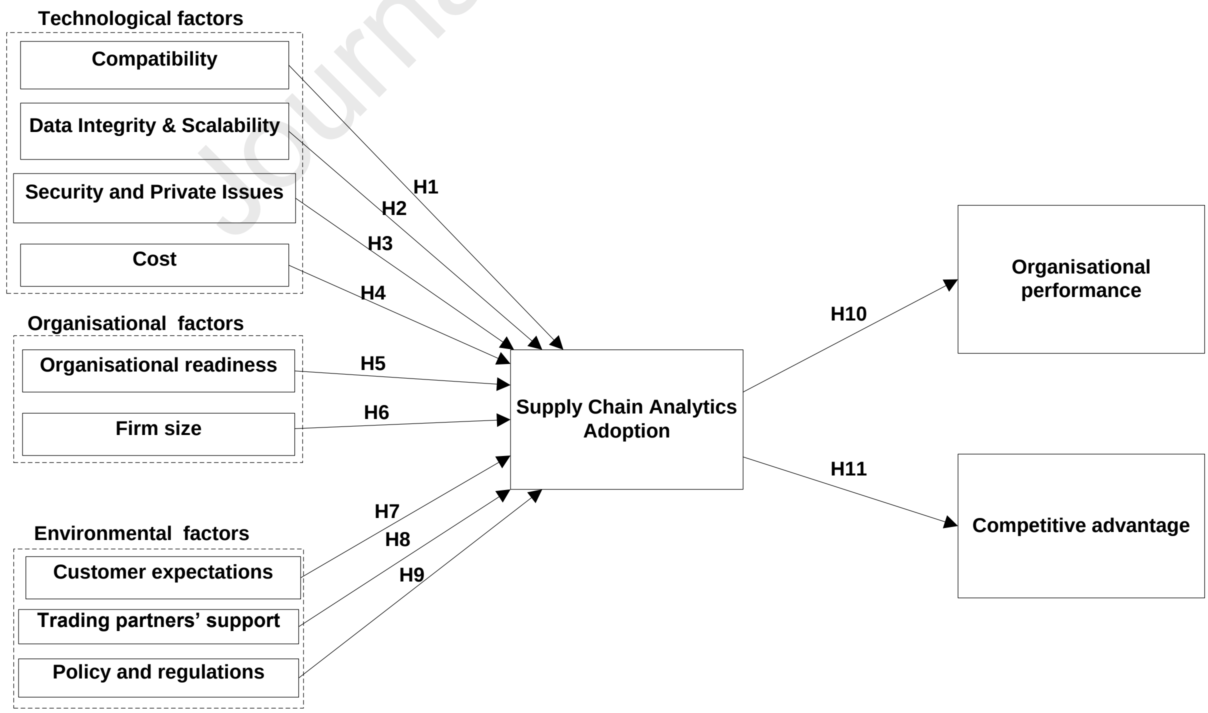

Figure 1: Research model.

Appendix I

Table A1. Items used to measure each survey construct and loadings.

Construct		Items	Loadings	VIF
COM	Compatibility (COM), adapted from Oliveira *et al.* (2014)	The use of SCA systems fits the work style of the company.	0.8587	2.2421
		The use of SCA systems is fully compatible with current business operations.	0.8645	2.3177
		Using SCA systems is compatible with the company's corporate culture and value system.	0.7956	1.8222
		The utilised SCA systems are compatible with existing hardware and software applications in the company.	0.8604	2.0354
DIS	Data Integrity and Scalability (DIS), adapted from Cruz-Jesus et al. (2019)	The utilised SCA systems are compatible with existing hardware and software applications in the company.	0.8254	2.0815
		Data quality issues are relevant to my organisation when implementing SCA systems.	0.7543	1.7384
		Data interoperability issues are relevant to my organisation when implementing SCA systems.	0.8336	1.835
		SCA systems are supported by data quality and data integration tools.	0.8323	1.9093
		Customer data needs to be integrated in SCA systems and checked for quality.	0.8254	Deleted
SPI	Security and Privacy Issues (SPI), adapted from Oliveira *et al.* (2014)	My organization is concerned with data security in SCA systems.	0.8825	2.4942
		My organization is concerned about customers' data security in SCA systems.	0.9016	2.6522
		My organization enacts procedures to protect the information shared in SCA systems against e.g. modification or disclosure.	0.8250	1.5915
COST	Cost (COST), adapted from Oliveira *et al.* (2014)	The investment on adopting SCA systems is far greater than the emanating benefits.	0.9311	2.9925
		The cost of maintenance and support of SCA systems is substantial.	0.9467	Deleted
		The amount of money and time need to be invested in training employees to use SCA systems is substantial.	0.9456	2.9925
OR	Organizational readiness (OR), adapted from Alshamaila *et al.* (2013) and Lai *et al.* (2018)	My company has the human capabilities and capacity on using SCA systems to support operations.	0.7682	1.8679
		My company has no difficulties in accessing all the necessary resources (e.g., funding, people, time) to adopt SCA technologies.	0.7208	1.6842
		My company employees are knowledgeable and skilful about SCA systems.	0.7869	1.7796
		My company supports on-going personnel training schemes on SCA systems.	0.7695	1.7428
		The company management considers SCA systems important and supports its use.	0.8360	2.4922

Construct		Items	Loadings	VIF
		The management is willing to communicate with staff and participate in the implementation process of SCA systems.	0.7971	2.1624
FS	Firm Size (FS), adapted from Wang *et al.* (2016b)	The capital value of my company is high compared to the industry, in general.	0.9673	8.7569
		The annual revenue of my company is high compared to the industry, in general.	0.9800	Deleted
		The number of employees in my company is high compared to the industry, in general.	0.9892	8.7569
CE	Customer Expectations (CE), adapted from Hao *et al.* (2020)	Business partners recommended that our firm should adopt SCA systems.	0.8375	1.9042
		My company's customers are requesting the use of SCA systems for doing business with them.	0.9034	2.4358
		My company's relationship with customers would suffer if we do not adopt SCA systems.	0.8771	2.1606
		My company's customers may consider it as drawback if we do not implement SCA systems.	0.9410	Deleted
TPS	Trading Partners' Support (TPS), adapted from Premkumar and Roberts (1999)	Third party service providers provide technical support for the effective use of SCA systems.	0.8735	2.2953
		There are agencies that provide training on SCA systems.	0.9018	Deleted
		Technology vendors provide incentives for adoption, but they do not ensure compatibility, and interoperability of IT infrastructure.	0.9044	2.6341
		Technology vendors offer free training sessions but without a comprehensive manner on how structure and deploy SCA systems.	0.8799	2.3287
PR	Policy and Regulations (PR), adapted from Lai *et al.* (2018)	There is legal protection in the use of SCA systems, but companies have difficulty in complying with policies and regulations due to the large amount of unstructured data.	0.8678	1.7322
		Legislation and regulations are sufficient to guarantee the use of SCA systems.	0.8384	1.8003
		Financial incentives to promote the adoption of SCA systems are provided.	0.7896	1.4509
SCAA	SCA Adoption (SCAA), adapted from Amini (2014)	My company is currently evaluating the usage of SCA systems.	0.8063	1.5700
		My company has evaluated and planned the adoption of SCA systems.	0.8830	2.4067
		My company has already adopted SCA systems.	0.7974	1.753
OP	Operational Performance (OP), adapted from Hao *et al.* (2020)	SCA systems adoption increases the rate of timely delivery of products and services.	0.8632	1.9686
		SCA systems adoption increases efficiency of internal and external processes (e.g., inventory, waste mitigation, overtime production).	0.8546	1.9053
		SCA systems adoption shortens the work processes and task handling time.	0.8360	1.5862
CA	Competitive Advantage (CA), adapted	SCA systems adoption differentiates the company from its competitors (e.g., innovation, sustainability).	0.8277	2.1263

Construct		Items	Loadings	VIF
	from Brintrup *et al.* (2019); ; Chae *et al.* (2014); Shamout (2019) ; Wamba and Akter (2019)	SCA systems adoption strengthens buyer-supplier relationships.	0.8057	2.3263
		SCA systems adoption increases information sharing thus increases transparency and resilience.	0.7808	2.1034
		SCA systems adoption helps our firm to quickly introduce new products into the market.	0.7936	1.817
		SCA systems adoption increases the flexibility which is the ability to effectively adapt or respond to change (unexpected events).	0.8415	2.1517

Highlights

- Firms' adoption of Supply Chain Analytics (SCA) is tepid due to diverse challenges.
- A TOE-based research model is developed to assess the SCA adoption determinants.
- Primary data was collected from 217 individuals working in UK manufacturing companies.
- Firm characteristics, partners' and customers' expectations influence SCA adoption.
- Statistical analysis show that SCA enhances firm performance and competitiveness.