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Digitalizing Procurement: The Impact of Data Analytics on Supply Chain Performance

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Abstract

This study investigates digitalization as a performance driver in supply chains, especially the role of data analytics in the digitalization of procurement. Data analytics capabilities are the firm's abilities to exploit external and internal data in its business processes. Digital procurement capability is the ability of the firm to realize and utilize various e-procurement processes in order to improve supply chain performance. Using structural equation modeling, empirical survey data is analyzed to test the relationships between firm internal and external data analytics capabilities, digital procurement capabilities, and supply chain performance. The study confirms positive and significant relationships among digital procurement capabilities, data analytics capabilities, and supply chain performance. Digital procurement capabilities mediate the positive relationship between external data analytics capabilities and supply chain performance. Thus, external analytics capabilities that increase the firm's understanding of its markets, suppliers, and operating environment are found to co-evolve with digital procurement capabilities, whereas analytics capabilities focusing on internal operational efficiency contribute less to digital procurement capabilities but have an impact on supply chain performance. Therefore, investing in analytics capabilities should improve firms' supply chain performance, whereas in order to improve their digital procurement capabilities firms should strengthen their competences in external analytics.

Keywords: Purchasing and supply chain management, digitalization, information systems, data analytics, e-procurement, operational capabilities

1 Introduction

For companies competing in the global market environment, the operational business processes that constitute the firms' supply chains are characterized by excessive amounts of data and information exchange. To improve their competitive position, companies must be able to effectively use and convert available data into information useful for decision making and coordination in purchasing and supply chain management (SCM). SCM focuses on optimizing goods and material flows by sharing and analyzing information about the supply chain activities in internal and external business transactions (Chen & Paulraj, 2004). Turbulence in the firms' business environments increases volatility and increased risk of failure in supply chains, forcing companies to seek ways to increase the agility and structural flexibility of the supply chain (Christopher and Holweg, 2011; 2017). Thus, a major focus in SCM is the digitalization of real-time information sharing between systems in the supply chains (Dinter, 2012; O'Dwyer & Renner, 2011; Calatayd, Mangan, and Martin, 2019). The adoption of new technologies and solutions within the supply chain increases the availability of data from internal and external sources. To exploit digitalization effectively organizations must resolve the practical challenges to strengthen their data analytics capabilities, and consequent research gaps can be identified in the SCM domain. In this, relations between data analytics capabilities, maturity of digital procurement processes, and performance of the business processes to understand impacts of IOT to the supply chain management are worth to further examined in which empirical studies has potential to identify and to establish related concepts (Frederico et al., 2019).

From theoretical perspective, the dynamic capability view frame activities which are needed to deal with digitalization of the procurement processed and achieving new performance into supply chains. The dynamic capability framework recognizes sensing, seizing and

reconfiguration as key capacity drivers by which a firm can develop its resiliency against environmental turmoil (Teece, 2007). The performance impacts of dynamic capabilities of the organization materialize in three different forms: as measurable performance compared to competitors, knowledge transfer, and flexibility (Côte-Real, Oliveira and Ruivo, 2017). Furthermore, the supply chain management requires organizational capabilities amongst other organizational resources which are important sources of competitive advantage by the Resource-Based View of the firm (RBV) at the operations strategy level (Barney, 1991). RBV is one of the theories used in SCM in which many of the basic concepts and frameworks are implicitly based on the assumptions of RBV (Halldorsson, Kotzab, Mikkola, and Skjøtt-Larsen, 2007). Building on these views, pre-existing research has shown a direct linkage between the organizational capability to conquer digitalization challenges and the overall performance of the firm which can be measured in terms of both the process efficiencies and the dynamic capabilities (Jacobides and Hitt, 2005; Akter et al., 2016; Teece, 2017). The role of technology skills and analytics capabilities regarding environment has found critical for SCM performance recent studies whereas the role organizational capabilities by the RBV has diminished in the era of digitalization (Bag et al., 2020; Braganza et al., 2017). The performance in the SCM context depend on the sensing capabilities including scanning, scenario working and knowledge creation by experts which targets to increase awareness over strategic alternatives and rationality of decisions (Foerstl et al., 2020; Haarhaus & Liening, 2020). The previous is valid process in case of trend-like long term shifts of industry, e.g. digitalization, where SCM capability creation can occur through knowledge transfer reconfiguring existing skills with new capabilities (Conti et al., 2020). To sum the capability creation perspective, technology adoption, sensing capability and SCM performance are interlinked features of the organization which outlines the theoretical landscape to which this study contributes.

Studies explaining impacts of digitalization in the SCM context have shown that gaps exist in theory regarding interaction between technology maturity, capabilities to understand environment, and effective reconfiguration of the supply chains (Bag et al., 2020). To address gap, this study targets to the questions regarding linkage of organizational awareness on role of big data utilization and implementation digital procurement activities which provide support for earlier hypothesized indirect effects of analytics capabilities and supply chains activities (Zhu et al., 2018; Frederico et al., 2019). Relating to previous, this study particularly increase understating on influence of organization analytics capabilities to procurement processes which enables further develop competency model of supply chain management covering maturity of digital processes, role of human resources, and performance of business processes of companies (Yadegaridehkordi et al., 2018; Bals et al., 2019; Viet et al., 2020). The discussion in this study also targets assess interaction between organizational and dynamic capabilities which is shown dyadic in certain environments (Schriber & Löwstedt, 2020). By the selected structure, the article also further develops framework which explain interaction between increased capabilities to utilize process, customer and market information in order to redefine relationships with supplier network (Birkel and Hartmann, 2020; Gawankar, Gunasekaran and Kamble, 2020).

Approaches utilizing data analytics to coordinate supply chains are a critical area of development, since today's supply chains entail large volumes of different types of data about the firm and its operations (Trkman et al., 2014). The extensive use of supply chain analytics (SCA) is relatively novel in purchasing and supply chain practice (Chae et al., 2014a). Business analytics is one of the many developments responding to the need to manage the massive amounts of data enabled by the growth of digital technologies in supply chains (Kwon et al., 2016). Large volumes of data in supply chains is generated from various sources and/or applications through transactions and operations, and this data is expanding (Holsapple et al.,

2014; O'Dwyer & Renner, 2011). For example, the emergence of sensor data and Internet of Things (IoT) solutions have also provided novel opportunities in traditional supply chains (Opresnik & Taisch, 2015; Wang et al., 2014, Tortorella et al. 2019), especially when such technologies provide visibility to customers' operations, thus making their needs easier to anticipate (Holmström et al., 2010; Parry et al., 2016). In addition, the increased availability of different forms of data have prompted the need to investigate the prospects of Big Data analytics and IoT in the supply chains (Aryal et al., 2018). Big Data differs from traditional data sources in that it is high-volume, often external and unstructured, which requires new analytical techniques (O'Dwyer & Renner, 2011). The data that accumulate from IoT sensors and systems can be more structured but are voluminous and require similar, advanced analytics approaches that can manage large masses of data (Opresnik & Taisch, 2015). To address the need for better exploitation of data, this study examines how internal and external data analytics capabilities are linked to the digital procurement capabilities and supply chain performance.

The challenge to the current electronic processes and applications for supply chains is that they alone do not fully support Big Data analytics and the integration of data from different sources in the supply chain. To become disruptive, these technologies need to be adopted at the supply chain process analytics level and, more broadly, at the strategic and tactical levels in supply chain planning and design (Aryal et al., 2018). In a 2011 study, more than 80 percent of top managers (CIOs and CEOs) reported that investments in business analytics intelligence and insight were their highest priority when improving the competitiveness of their organization (IBM Corporation, 2011). Although a steep growth in research in this area has been reported through systematic reviews (Aryal et al. 2018; Birkel and Hartmann, 2019), research focusing on supply chain analytics and capabilities is scant. A recent systematic review identified 102 research articles that explored the intersection of IoT and SCM, yet only four of them were empirical surveys (Birkel and Hartmann, 2019). Because IoT and Big Data enable, but do not

guarantee, improved supply chain success, further research is needed. Empirical research needs to focus on the role of data analytics capabilities and digital procurement capabilities in supply chains, particularly on the effect of data analytics on supply chain and business performance.

This study investigates the relationship between data analytics capabilities, digital procurement capabilities, and supply chain performance. A survey instrument is developed to collect responses from supply chain managers on the adoption of different digital procurement processes and supply chain systems in their firm, as well as their usage of internal and external data analytics practices (predictive and market intelligence). This data on adoption and usage is linked with measures of supply chain performance and business success. Based on the current analysis, the study finds that business analytics practices and digital procurement capabilities positively influence supply chain performance and business success.

2 Digitalization of Purchasing and Supply Chains

This section first outlines the contextual and theoretical landscape for the study, and then proceeds on a more detailed treatment of the research constructs to develop the research model and build the hypotheses based on pre-existing research. The first subsection reviews and explains the concept of digitalization; the business expectations of digitalization are discussed from the perspective of supply chain management and purchasing. For the current purposes of the current study, digitalization is framed as the building and adoption of the organizational resources and processes to take advantage of data and analytics; thus the study takes the resource based view as its theoretical foundation and focuses on the role of data analytics capabilities in realizing the performance potential in digitalization. The section then moves on to discuss the different capabilities (digital procurement, internal and external analytics) and establish the relationships to be tested in the hypotheses.

2.1 Digital transformation and business expectations

Although *digitalization* (sometimes also ‘digitization’) has been a buzz word in academia and among business practitioners for several years, a consolidated definition for the concept has not been broadly adopted by both academics and practitioners. To clarify this concept, this section discusses the definition, characteristics, and major business expectations concerning digitalization in the context of SCM.

Digitalization, in this study, refers to the adoption of a broad set of technologies and practices that through the smarter use of data, information technology, and automation are expected not only to improve the operational efficiency, speed, and quality of business processes, but also to enable entirely new business activities. Thus, digitalization in the supply chain refers to the adoption of such processes and systems that allow companies to manage supply chain processes and operations. Further ahead in the use of digital technologies lies a vision of the ‘self-thinking supply chain’ where the firms in the supply chain are digitally connected through cloud-based IoT architecture that allows real-time connectivity and the use of artificial intelligence to monitor the supply chain performance (Catalayd et al., 2019).

From a business perspective, the solutions promised by digitalization include activities that (i) automate human resource-intensive tasks, (ii) create meaningful information from data, or (iii) redefine relationships among members of supply chains (Dehning, Richardson and Zmud, 2003). Herein, the resources needed to progress digitalization among the organizations can be categorized as (i) tangible technological resources, (ii) new human resources, and (iii) intangible organizational practices. The technological resources include direct investments to so-called ‘big data resources’, i.e. the technology infrastructure that enables aggregation of data from the environment and the extraction of valuable information for the various purposes of both strategic management and operational control (Gandomi and Haider, 2015). Beyond the

obviously high costs and external constraints associated with technology and data availability, the managerial challenges in digitalization include reaching the required capability levels in terms of development cycles, strategic agility, and performance optimization of the processes considering products and services (Akter et al., 2016).

A major underlying theme in digitalization is the objective to gain information about changes in the environment of the organization, including markets, customer behavior, and competitive landscape. The organization must be able to identify, have access to and collect the relevant data, combine and refine it, implement data analytics capabilities in order to transform the data into useful and actionable information, and interpret this information appropriately in its decision-making. To achieve this the top management must foster the *absorptive capabilities* of the firm; ensuring availability of the necessary skills calls for proactive education of personnel, promotion of a positive mind-set, and communication of the pivotal needs for renewal (Ravichandran, 2018; Warner and Wäger, 2019).

The capabilities to promptly alter business processes and interactions among supply chain actors provide value gains for the firm but require developing both analytical skills and novel approaches to optimize or automate production (Trkman et al., 2010; Vial, 2019). Most performance impacts that firms gain from utilizing digitalized processes relate to the improved quality of decision making, which relies on descriptive, predictive and prescriptive analyses creating deeper understanding of the environment and its patterns (Sivarajah et al., 2017; Ghasemaghaei, Ebrahimi and Hassanein, 2018). On the other hand, prerequisites for the performance gains from such information intensive processes require sophisticated plans for connectivity, compatibility, and modularity of the data resources (Akter et al., 2016).

The current discussion on industry perspectives on digitalization leads to the following important reflections. First, continuous assessment of the role of analytics in the organization

and criticism towards data is necessary, because the data is incomplete and can be biased (Jones, 2019). Second, digital processes are not a silver-bullet for performance improvements; for instance, the highly interactive nature of the big data approaches requires cross-organizational capability development (Günther et al., 2017). Third, the digitalization of business processes is not merely a technical challenge; it is an organizational task where the goal is to overcome several technical and attitudinal obstacles in order to enhance flexibility and ability of the firm to adapt with its environment (Sivarajah et al., 2017). Thus, the top management should be able to support emergence of digital maturity of the workforce, to enable experimentation of the strategies and to provide tools to optimise supply chains using the digital tools (Côte-Real et al., 2019; Warner and Wäger, 2019). Due to this prominent nature of the described organizational capabilities in implementing the digital transformation at the level of the firm and its supply chain, the study adopts the capability-based view as the theoretical lens for the current analysis.

2.2 Digital procurement as an organizational capability

The resource-based view divides the organizational capabilities to leverage resources into three types: (i) operational capabilities and (ii) first- and (iii) second-order dynamic capabilities (Collis, 1994). According to Collis (1994), capabilities are distinguished from other organizational activities as a combination of the following characteristics: (i) capabilities are highly patterned and founded on organizational routines (i.e., repeatable yet possibly partially tacit), (ii) guided by managerial processes, and typically, (iii) require costly investments to be developed and sustained. Winter (2003) defined *operational capabilities* as processes that enable firms to earn revenue in the short term. Operational capabilities introduce no change to the firm and thus, are considered ‘zero-level’ capabilities (Collis, 1994; Winter, 2003). *Dynamic capabilities* are defined as those that extend, modify, or create the operational capabilities (Winter, 2003), and as organizational and strategic routines that generate market

change by gaining, integrating, reconfiguring, and releasing the firm's internal and external resources (Eisenhardt and Martin, 2000). Both Collis (1994) and Winter (2003) distinguish two levels of dynamic capability. First-order dynamic capabilities are processes that involve some change beyond the zero-level allowing the firm to adjust and adapt its operational processes, and are highly patterned and routine, such as product development and searches for new customer segments (Winter, 2003). Collis (1994) called these capabilities dynamic improvements. Second-order dynamic capabilities allow the firm to develop new resources and to deploy them as a competitive advantage (Collis, 1994).

As explained above, digitalization in the current study refers to the adoption and increasing use of the digital technologies (cf., Srai and Lorentz, 2019, p. 79), systems, and practices by which organizations exploit data and automation to improve operational efficiency, redesign existing processes, and enable entirely new activities. The potential uses and performance implications of digitalization are broad and influence all three levels of capabilities discussed above. Supply chain processes are operational capabilities, partly internal (within companies) and partly collaborative (among companies within a supply network). Focusing on the supply management context, first-order dynamic supply chain capabilities allow firms to improve the processes of the supply networks, for instance, by identifying new suppliers, developing new ways of processing data and orders, and identifying inefficiencies in the supply process. For example, Aslam et al. (2020) identify three distinct dynamic supply chain capabilities; market sensing, supply chain agility, and supply chain adaptability. In this context, second-order capabilities enable entirely new forms and processes, or even new business models based on a novel supply solution.

Digitalization in the supply chain level refers to the implementation of the above means in supply management processes to manage data related to internal and external operations. This

data needs to be analyzed and interpreted to serve the supply management tasks of a firm, to support decision-making and become actionable in the strategic, tactical, and operative levels. Digital procurement capabilities therefore represent the firm's ability to leverage information technology resources in its supply management activities. The use of internet-based technology pervades all major components of the purchasing processes and is called e-procurement (Presutti, 2003); e-procurement processes use the digital solutions in the component level. Thus, the adoption and the utilization rate of the e-procurement systems and -processes reflect the organizational maturity in exploiting digital technologies as a part of its purchasing function, as well as the institutionalization of the digital procurement processes in the firm.

2.3 The impact of digital procurement on supply chain performance

Both the IOT and the Big data are concepts of digitalization phenomena referring system of interconnected devices, platforms and humans where measurement data is converted into context related knowledge to be utilized by the business management (Lee and Lee, 2015). The digitalized business activities (e.g. supply chain management) relies on platform covering (1) devices to acquire data from real world, (2) network to transfer data from devices and to users, (3) cloud platform to store data, and to enable application development, and (4) service layer for interacting with the user (Čolaković and Hadžialić, 2018; Birkel and Hartmann, 2020). In addition, the predictive analytics as part of the digitalized supply chain management requires the IoT, the clouds, and the big data as resource for the data-based decision making and management of activities (Frank et al., 2019). Recent studies show that Big Data analytic capabilities improve knowledge, dynamic capabilities, process performance, and overall competitiveness at the firm level. At this level, the effects are amplified along with the increased environmental dynamics (Chen, Preston, and Swink, 2015; Côte-Real, Oliveira, and Ruivo, 2017). The benefits emerging from data-driven decision making related to Big Data also occur at the supply chain management level; these can be observed as improvements in

supply chain processes, logistics performance, enhanced inventory control, and overall cost of the procurement function (Gawankar, Gunasekaran, and Kamble, 2020). However, such firm-level gains from data-driven decision making require established knowledge conversion within the organization and fluid information flow across the functions; these elements are only available if the analytics capabilities are tightly aligned with the business strategy (Aryal et al., 2018; Akter et al., 2016; Côte-Real, Oliveira, and Ruivo, 2017). In organizational purchasing, digitalization is expected to provide various competitive strengths and benefits for firms through the automation of business processes and the more effective use of data. The effective use of information technology in procurement contributes to the overall performance of the supply chain as procurement includes strategic, tactical, and operational processes in a supply chain (cf. Van Weele, 2009). The role of digital platforms is critical in the management of procurement activities and developing partnerships, which generate gains in company performance (Rai *et al.*, 2006). Relating to previous, E-procurement can be defined as a concept that links and integrates business processes and systems with automation within purchasing and supply management to improve an organization's competitiveness (Alvarez-Rodriguez et al., 2014). According to Kalakota and Robinson (2001), the benefits of e-procurement and supply chain digitalization can be achieved from increased supply chain process efficiency, faster cycle times, lower purchasing costs, closer integration of procurement function, better organized information reporting, and reduced unauthorized buying.

The major components of the procurement process, the common e-procurement processes and digital applications used in procurement are presented in Figure 1. The entire purchasing process has to be considered in the implementation of e-procurement systems (Deise et al., 2000; Presutti, 2003). The supply chain processes that are illustrated in the top layer of Figure 1 are adapted from the generic procurement process model by Van Weele (2009) and the common e-procurement systems below from IAPWG (2006). Here, e-sourcing system supports

the specification phase, e-tendering system supports the selection phase, and e-ordering and web-based ERP are used to perform the process of creating and approving procurement requisitions and to place purchase orders (IAPWG, 2006). supported by increasingly fragmented IT solutions and separate purchasing support solutions implemented to support operational purchasing (e.g., ordering, order tracking, delivery, and return management) and tactical sourcing to support a process for initiating procurement projects, documenting procurement requirements, tendering documentation, and supplier management (Rai and Hornyak, 2013). Both operational purchasing and sourcing activities have focused research on the company's supply chains (Hult and Chabowski, 2008). Different procurement systems create integrated information management by providing procurement professionals with easy access to integrated, consistent, and accurate information (Gattiker and Goodhue, 2004). Integrated processes and data analytics play an important role in the operation and development of this entity.

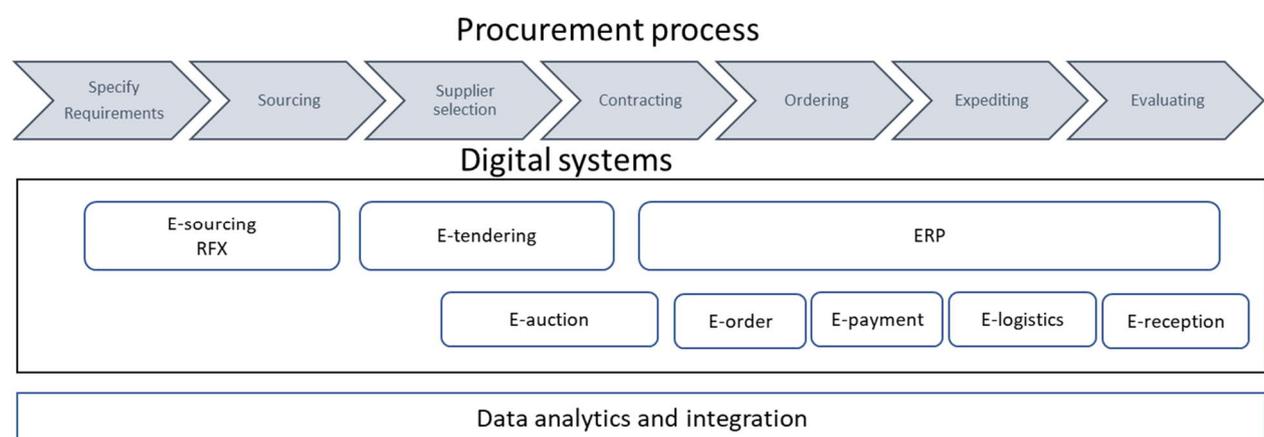


Figure 1. The procurement process: major components and digital systems for e-procurement.

Developed applications are available across the entire procurement process. For example, the source-to-pay and deliver-to-pay processes are rather standard in many industries and can be run using different applications. These applications include e-sourcing, order and delivery

tracking systems, billing systems, and enterprise resource planning (ERP) systems that combine several operations management applications. E-sourcing denotes the process of identifying new suppliers for particular categories of purchasing requirements by using web-based technology. Furthermore e-tendering is the process through which a firm sends the request for information about specifications and pricing to the potential suppliers and receives the suppliers' responses via the e-tendering tool that an e-sourcing solution contains (De Boer et al., 2002). These processes give suppliers the opportunity to provide information and bid against each other, and the winner is the lowest bidder, while other criteria also can be taken into account (Smart, 2010). Thus, rather than focusing on specific applications, comprehensive digital transformation of the supply chain requires that the management promotes both internal coordination and control, management of external resources, and generation of supply market knowledge (Srai and Lorentz, 2019).

The purchasing process is a critical element in managing the supply chain since it directly affects the supply chain performance of a company (Chang et al., 2004). According to earlier research, the adoption and use of electronic processes and applications can result in several types of benefits that improve supply chain performance. E-procurement streamlines the management of the purchase-to-pay process, increase process efficiency and optimization within the supply chain, and decrease risks related to procurement (Kim & Shunk, 2004; Purchase & Dooley, 2010; Ronchi et al. 2010; Lenka et al., 2016;). There is evidence that e-procurement systems are able to increase supply chain performance by increasing transparency (Puschmann & Alt, 2005). Digitized processes also reduce administrative and transaction costs (Eadie et al., 2007; Ronchi et al., 2010). More broadly, further process-related benefits in the digital supply chain may include flexible, faster, and agile processes (Garrido et al., 2008; Christopher and Holweg, 2011).

Digitalization offers opportunities for improving functionality and ensuring higher reliability rates (Porter & Heppelmann, 2014). At a more specific level, the uses and forms of digitalization depend on where in the SCM process they are implemented. In the procurement process, digital procurement capabilities can generate significant impacts on the improvement of process efficiency and optimization within the supply chain (Purchase & Dooley, 2010; Lenka et al., 2016). Digital procurement capabilities reflect the maturity and rate of use of the digital procurement processes in the firm – it is not the availability of digital tools that realizes the benefits but their consistent and frequent utilization. Thus, the following hypothesis is proposed:

H1a: Digital procurement capabilities positively influence supply chain performance.

2.4 Effect of supply chain performance on business success

The supply chain performance drives business success mainly through the coherency of the strategy and the efficiency of operations. The strategy aspect is related to the clarity of the roles between the different entities in the overall business ecosystem that support the managers in shaping both organizations toward an effective form. The second aspect—operations—considers both the supplier relationship and the efficiency of the processes within a firm. To gain superior business performance, the firms must be aware of their positioning in the ecosystem. Here, the positive impact of the coherent strategy on business performance relates to a balanced set of competitive priorities and the capability to apply resources in order to create a sustained competitive advantage (Kroes and Ghosh, 2010). An adequate selection of activities for the organization seems to lead to a reduction of lead times in production, in customer orders, and in delivery, which all have positive externalities measured by customer retention rates (Kenyon et al., 2016). However, the supply chain performance-driven benefits may not always be realized as business success, particularly in the case of complex products or relationships

(Huo et al., 2016; Swink et al., 2007). Recent studies have also shown that a combination of low product complexity and high market complexity are markers for potentially lucrative targets for investments with regard to business process digitalization (Ataseven & Nair 2017; Wong et al. 2015;).

The framework for measuring supply chain performance encompasses strategic, tactical, and operational levels (Gunasekaran et al., 2004) Furthermore, both financial and qualitative indicators have been identified as important in measuring supply chain performance. Since there is a large number of different indicators for measuring supply chain performance (Gunasekaran et al., 2004), we have limited the measurement in this study to cover existing measurement constructs. In this study, we have applied both operational and tactical performance items in supply chain performance, including the flexibility, resource efficiency, integration, costs, speed, delivery reliability, and visibility of the supply chain (Boyer and McDermott, 1999; Beamon, 1999; Williams 2013). Since the goal of digitalization is to build visibility in supply chains, it is important to also consider this as part of performance. According to Williams et al. (2013), supply chain visibility is one outcome of external integration and describes access to high-quality information that explains various factors of demand and supply.

In summary, improving supply chain relationships through information technology has provided benefits in operational performance, visibility, transaction costs, delivery times, and better inventory turnover (Ataseven & Nair 2017; Frohlich, 2002; Paulraj & Chen, 2006). In light of the previous, we set the hypothesis as follows:

H1b: Supply chain performance positively influences business performance.

2.5 Effect of data analytics utilization on supply chain performance

A large amount of data in the purchasing and supply chain is produced from various applications which create potential for management to identify risks and trends in sourcing markets and inform possibilities to improve productivity of the firm (Wang et al., 2016). SCM data analytics combines data from various sources (e.g., processes, applications, sensors, and platforms) from internal and external business environments and refines the data for problem solving, predicting, and decision-making. To exploit this heterogeneous set of data, companies need to develop analytical capabilities and data processing approaches the SCM field, because digitalization of SCM concerns the quality and accessibility of information (Berente & Vandenbosch, 2009). Trkman et al. (2010, p. 318) define business analytics in the SCM context as the “application of various advanced analytic techniques to data to answer questions or solve problems”. They point out that, rather than being a technology, analytics refers to the combined use of different approaches, tools and procedures in order to acquire and analyze information, and to predict the outcomes of different solutions to SCM problems (Trkman et al. 2010). For instance, SCM data science tries to solve substantive problems in SCM, predict outcomes, and improve quality by employing both quantitative and qualitative data sources and analysis methods in global trading (Faller and Fawcett, 2013).

Many studies have reported the impact of data and analytical capabilities on operational efficiency performance (Chae et al. 2014a, 2014b; Trkman et al., 2010). Digital automation through sensors and remote monitoring have showed to have a significant positive association with supply chain performance (Tortorella et al. 2019). Yet, previous research is clear that information systems do not improve organizational performance automatically and the data alone is not enough to contribute to the performance because the effect of data analytics is twofold in the supply chains and operations (Markus, 2004). First, applications for running separate business processes are needed for automating and integrating data flows which enable

organizations to respond to changes in the market quickly. Second, various competences, processes, and organizational leadership are critical enablers for realizing the potential of the digital tools. Automated and integrated processes also need proper utilization and analytics of data in order to extract value from the electronic processes and systems (e.g., Acito & Khatari, 2014). To accomplish this, it is essential that they have access to current data that usually are stored in operational databases (Negnevitsky, 2011). Thus, we set the second hypotheses as follows:

H2a: Internal data analytics capabilities positively influence supply chain performance.

H2b: Internal data analytics capabilities positively influence digital procurement capabilities.

Advanced SCA considers not only internal but also external sources of data. SCA can support decision makers by leveraging supply chain capabilities, understanding of supply markets, and assessing risks in supply chains, where organizations can better describe and predict dynamics of markets in order to fulfil the operations requirements competitively (Wang et al., 2014). Supply market analysis includes gathering, classification, and analysis of data related with, the purchasing of goods and services, logistics chains, supply network structures, and ecosystem descriptions, which utilizes structured and quantitative forms of historical data, but is also extended to unstructured, qualitative data, and real-time analysis (Holsapple et al., 2014; O'Dwyer & Renner, 2011; Van Weele, 2009). The effects of external data analytics on the supply chain performance address both the strategic and operational levels. In the strategic level, the SCA capability helps business management to perceive dynamics in micro and macro environments in order to improve strategic fit (Akter et al., 2016; Wamba et al., 2017). Maintaining strategic fit requires capabilities to monitor demand trends regularly over time using both numeric and textual data sources (Yang, See-To and Papagiannidis, 2019). At the

operational level, the SCA has impact on process optimization, capabilities to predict capacity use, awareness considering critical contact points between employees and improved possibilities to experimentation of competing processes constructs (Côte-Real et al., 2019). These capabilities are associated with digital transformation of the business in general and technical platform capabilities which are recognized as drivers e-business process capabilities (Zhu et al., 2015). The influence of the SCA into adoption of the e-procurement processes emerges from internal and external reason. Internally, use of external data requires digitalized processes and integrated tools to gain benefits which have spill over-effects across the business functions (Nasiri et al., 2020). Indeed, extensive use of external data sources requires inter-organizational harmonization of the processes and shared platforms which create pressures to firms for renewals in procurement functions (Chang et al., 2019). Therefore, it is posited that:

H3a: External data analytics capabilities positively influence supply chain performance.

H3b: External data analytics capabilities positively influence digital procurement capabilities.

2.6 Summary of the conceptual framework

The study focuses on the internal and external data analytics capabilities, digital procurement capability and their influence on supply chain performance. We will also investigate the relationship between data analytics capabilities and digital procurement capabilities mediating role of digital procurement capability between data analytics and supply chain performance. Internal data analytics includes the techniques or tools of supply chain analytics used to solve the integration of internal supply chain processes, and external data analytics refers to the combining of external data from suppliers (Wang et al., 2016). Furthermore, the relationship between supply chain performance (e.g., Boyer and McDermott, 1999, Beamon, 1999,

Williams 2013) and overall business performance is tested (e.g., Germain et al., 1996). Figure 2 presents the conceptual framework of the study. The framework combines the hypotheses and main relationships between concepts described earlier in the study. Arrows in the figure show the assumed cause-and-effect relationships between concepts. The items used to measure the concepts are presented in Appendix 1.

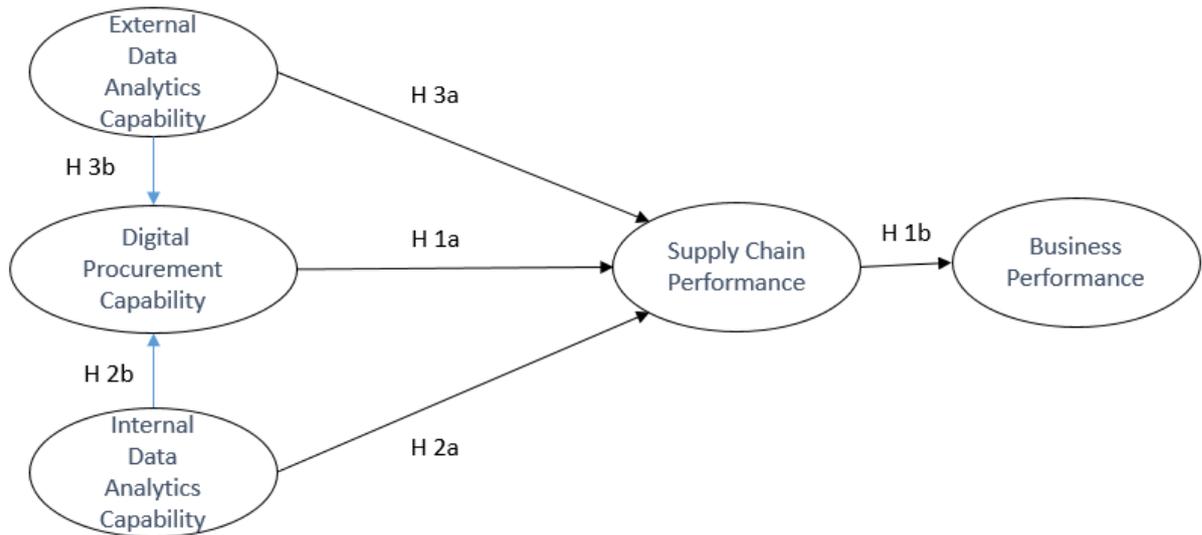


Figure 2. Conceptual model of the study

3 Research methodology

This study is based on a survey conducted in Finnish manufacturing and service companies and focus on their external downstream supply chain operations. Downstream supply chain operations were selected as a research target because there is still relatively little empirical support between procurement processes and data analytics. Finland was chosen because of being one of the top-performing countries in terms of the adoption of digital business processes (Koch, 2017). According to the IMD World Digital Competitiveness Ranking (IMD, 2019), Finland’s ICT competitiveness is the seventh best in the world. The Finnish manufacturing

industry is highly dependent on imports and global supply chains (Statistics Finland, 2018) which makes Finnish supply chains an interesting sample.

The sample was extracted from manufacturing and service supply chain actors of Finnish biorefinery companies as part of a large Finnish forest industry cluster digitization development program. The sample was determined together with the experts of the forest industry program. The forest industry currently generates about one-fifth of Finland's export revenues and is a major employer in the country. The commercial Amadeus database was used to collect information about companies in addition to the survey. The survey instrument was carefully tested before sending it with a group of pilot respondents because we wanted to ensure that the concepts specifically related to digitization were in line with those used in the industry.

More than 500 large and medium-sized companies were selected for the sample, representing all regions in Finland. Companies were first contacted by telephone to identify the most suitable informant in relation to digitalization and supply chain management. From those companies outreached, 348 respondents agreed to participate in the survey, and a weblink to the questionnaire was emailed to them. A total of 101 answers were received (101/348), representing a response rate of 29%. The survey employed an online questionnaire using the Webropol system.

The survey respondents represented different manufacturing and service industries. The respondents presented different work profiles: 34% were from top-management, 40% from middle management, and 26% were experts. The respondents' functions in their organizations were divided as follows: Sales 14.9%; Production 15.8%; Purchasing and supply chain 16.9%; Logistics 3%; ICT 9.9%; R&D 5%; Business development 20.8%; and Other (e.g. Finance, Maintenance) 13.8%.

The group containing Machinery, Equipment, Metal, and Electronics was the largest, in terms of the number of companies, at 37%. The next largest groups were Industrial Services, with share of 20% and ICT, with a share of 19%. Thereafter were Bio, Paper, and Chemical (9 %). The other industries (15%) includes respondents e.g. from Energy, Construction, Process and Public sectors. The average operating revenue of the responding companies was 633 M€

The developed survey instrument included firm background information. Various constructs informed the measurement items. The survey instrument was pre-tested with a group of specialists before being sent to the respondents. Survey items were identified from the literature and through cooperation with industry practitioners. The items and associated references are detailed in Appendix 1. Participants responded to the questions on a five-point Likert scale, where 5 indicated total agreement and 1 indicated total disagreement; responses are thus their subjective evaluations of the organization they represent. For a broader understanding, the survey also included open questions. These questions were not mandatory, and the respondent could bypass individual questions at their own discretion. For this reason, the number of responses to individual questions varied somewhat.

The analysis of the research model for testing the hypothesis was accomplished by the PLS-path modelling approach in order to reach robust results because some level of non-normality of distribution and collinearity of the observed variables occurs in the data, and the sample size was rather low (Hair et al., 2019; Hair et al., 2014; Henseler et al. 2014). Complexity of the research model by the tested paths advocates also use of the PLS-estimator for the structural model. The non-normality issues of the data can be solved also in the covariance-based structural equation modelling which leads to significantly higher sample size requirements for reaching reliable results (Flora and Curran, 2004; Olsson et al., 2000). We applied SmartPLS 3.0 software package for data analysis (Ringle, Wende and Becker, 2015).

3.1 Survey instrument

The survey instrument operationalises the most relevant theoretical concepts for this study. Regarding dynamic capability theory, sensing capability is measured using Internal and External Analytics Capability constructs. Digital Procurement Capability corresponds technology adoption level in the downstream activities which describes a dimension of organizational capabilities in the RBV theory. Finally, SCM and Business performance constructs provides a measure to probe level of rationality of the SCM.

Internal Analytics Capability (IntAnalytics) measured the respondent's expectation for his or her firm's capability of using data analytics to improve internal processes. The construct is related to the velocity perspective of the big data challenge in which competitiveness is grounded on the capability to react rapidly to observed anomalies (Johnson, Friend and Lee, 2017; Srinivasan and Swink, 2018). The construct included three dimensions which that cover the prediction of product quality, prediction of internal process reliability, and overall capability to utilize data gathered from IoT systems. The construct included four items.

External Analytics (ExtAnalytics) probes the respondent's expectation for his or her firm's general agility to utilize data to increase awareness of the competitive environment. This concept is closely related to the volume and variety features of the data exploitation (Johnson, Friend and Lee, 2017; Srinivasan and Swink, 2018; Aydiner *et al.*, 2019). The construct included four items representing the directed dimensions market intelligence, overall utilization of big data and utilization of customer and supplier information.

Digital Procurement Capability measures in the survey instrument followed the standard description of purchasing processes phases (see e.g. Van Weele, 1998) and their electronic

forms. In general, the digitalized purchasing processes follow standards such as Universal Business Language (UBL). Electronic processes were selected for the survey to provide concrete insight into the studied phenomena.

To measure the performance implications of digitalization, two measurement constructs, supply chain performance (SCPerform) and business performance (BPerform), were included in the survey instrument. Supply chain performance (adapted from Boyer and McDermott, 1999, Beamon, 1999, Williams 2013) measured operational and tactical performance items in supply chain performance, including the flexibility, resource efficiency, integration, costs, speed, reliability, and transparency of the supply chain. Business performance (adapted from McLaren *et al.*, 2002) included items about the company's business success in terms of indicators such as profit, net income, and return on investment (ROI).

3.2 Validity and reliability of the measurement model

In order to assess the common method bias, we conducted the full collinearity test which is comprehensive procedure for the simultaneous assessment of both vertical and lateral collinearity (Kock, 2015). In the test the variance inflation factors (VIFs) are generated for all latent variables in a model. The occurrence of a VIF greater than 3.3 is proposed as an indication that a model may be contaminated by common method bias. Based on the VIFs obtained for the latent variables in the model the model includes no latent variables with VIF greater than 3.3 and therefore we may assume that no common method bias exist in the dataset.

The measurement model was validated pertaining its 1) internal consistency reliability; 2) convergent validity of the factor structure; and 3) discriminant validity (Hair et al., 2019; Gefen & Straub 2005; Henseler et al., 2009). Construct reliability (CR) analysis was applied to evaluate the measurement reliability and average variance extracted (AVE) for assessing variance captured from latent constructs (e.g., Fornell & Larcker, 1981). The critical value for

CR coefficient is at $CR > 0.50$ which indicate acceptable reliability if the overall model validity is adequate (Kline, 2011; Little et al., 1999). The measurements for reliabilities in Table 1 manifest good reliability level for all of the latent variables, where CRs vary from high 0.818 to a very high 0.914. To validate the factor structure, we analyzed i) significance and ii) weight of factor loadings and ii) cross loadings between latent factors. For the measurement model, all loadings were found to be significant ($p < 0.001$) and sufficient, where weights vary from 0.603 to 0.878. The AVE indicates acceptable convergent validity acceptable for all latent factors, where all of the concepts reached critical value of $AVE > 0.50$ (Fornell & Larcker, 1981). In the final phase, the discriminant validity of the model was estimated to ensure empirical uniqueness of each latent construct when the variance captured is not represented by others (Hair, Sarstedt and Ringle, 2019). We applied 1) cross loadings of the measurement items, 2) the square root of AVE (Fornell-Larcker criterion), and heterotrait-monotrait ratio of correlations (HTMT) for that purpose (Cepeda-Carrion, Cegarra-Navarro and Cillo, 2019; Hair, Sarstedt and Ringle, 2019; Gefen & Straub, 2005; Henseler et al., 2009). To previous, the Fornell-Larcker criterion assesses level of shared variance between constructs whereas HTMT contrasts indicator correlations between constructs in the model (Hair, Sarstedt and Ringle, 2019). As conclusion, we find that all the measurement items presented high loadings to the latent factors, and cross loadings remained at sufficient level, less than 0.338. Discriminant validity of the measurement model was also interpreted good. Fornell-Larcker criterion shows that the square roots of AVE are significantly higher than any of the correlations between the latent factors. Also, the HTMT ratios do not exceed the critical limits of .85 for conceptually different constructs varying from .112 to .389 (Hair, Sarstedt and Ringle, 2019).

Table 1 Measurement reliabilities

	Loading	t-value	p-value	Mean	SD	CR	AVE	
Digital Procurement Capability (DPCap)							0,914	0,640
DPCap1	0,725	10,994	****	2.257	1.535			
DPCap2	0,655	9,249	****	3.766	1.492			
DPCap3	0,832	23,596	****	2.788	1.562			
DPCap4	0,835	21,054	****	2.599	1.603			
DPCap5	0,868	23,975	****	3.060	1.596			
DPCap6	0,862	26,525	****	3.195	1.617			
Internal Analytics (IntAnalytics)							0,818	0,532
IntAnalytics1	0,621	3,833	****	3.830	1.025			
IntAnalytics2	0,840	7,701	****	3.325	1.128			
IntAnalytics3	0,742	4,857	****	3.140	1.225			
IntAnalytics4	0,698	4,651	****	3.183	1.215			
External Analytics (ExtAnalytics)							0,825	0,545
ExtAnalytics1	0,838	13,082	****	3.006	1.027			
ExtAnalytics2	0,804	8,958	****	3.082	1.024			
ExtAnalytics3	0,685	5,618	****	2.448	1.128			
ExtAnalytics4	0,603	4,125	****	3.235	1.162			
Supply Chain performance (SCPerform)							0,911	0,631
SCPerform1	0,781	18,014	****	3.241	0.938			
SCPerform2	0,664	8,502	****	3.323	0.908			
SCPerform3	0,832	23,831	****	3.128	0.868			
SCPerform4	0,841	18,656	****	3.248	0.978			
SCPerform5	0,853	19,833	****	3.223	0.862			
SCPerform6	0,781	14,281	****	3.285	0.849			
Business performance (BPerform)							0,903	0,757
BPerform1	0,859	6,782	****	3.447	0.872			
BPerform2	0,872	7,063	****	3.248	0.849			
BPerform3	0,878	7,864	****	3.323	0.891			
n) Not significant, *) Statistically significant at $p < 0.1$, **) Statistically significant at $p < 0.05$, ***) Statistically significant at $p < 0.01$, ****) Statistically significant at $p < 0.001$								

3.3 Partial Least Square Path Model

In the analysis of the main effects in the model, defined by hypotheses 1–4 (Table 2), the bootstrap sample size was $n = 101$, which is equal to the original sample. The resampling of the data was repeated 5000 times (basic bootstrapping) in the analysis, which is adequate for estimating the parameters in the model (Henseler et al., 2009; Kline, 2011). The quality of the

structural model was tested and validated through the following steps: (1) collinearity issues and overall fit, (2) explanatory power, and (3) path significances.

We assessed the collinearity and the model fit to the data in order to validate the structural model, which provides information on potential misspecification problems. The variance inflation factor (VIF) of the latent constructs did not indicate collinearity issues where the values (VIF = 1.000–1.164) remain clearly below a critical value of 5. Because of the hypothesis testing objective of the article, we needed to assess the overall fit of the structural model. For that purpose, we used the standardized root mean square residual (SRMR, critical value < 0.08) and root mean square residual covariance (RMStheta, critical value > 0.12) to specify the estimation error and misspecification of the model (Cepeda-Carrion, Cegarra-Navarro and Cillo, 2019; Hair et al., 2014; Henseler et al., 2014). Here, the model fit of $SRMR = 0.087$ and $RMStheta = 0.166$ indicates that serious misspecification of the structural model does not occur. In-sample explanatory power of the model can be assessed by the proportion of the variance explained of an endogenous variable (R^2) which is an indicator for the variance captured into the latent constructs, The R^2 for the latent variables in the path model were $DPCap = 0.141$, $SCPerform = 0.197$, and $BPerform = 0.048$ indicating sufficient level of explanatory power, regardless of the relatively low sample, because the true phenomenon in the focus is remarkably complex, including the multiple influences outside the tested model (Abelson, 1985; Prentice & Miller, 1992). Furthermore, predictive relevance measured by Q^2 for each endogenous construct were positive, $DPCap = 0.141$, $SCPerform = 0.197$, and $BPerform = 0.048$, indicating sufficient level of in-sample explanatory power and out-of-sample of prediction of the model over the phenomenon, and from the aspect of generalizability of the results (Hair, Sarstedt and Ringle, 2019).

The tested path model (see Table 2) shows that the digital procurement capabilities has a significant influence on the supply chain performance confirming *Hypothesis 1a*. We also found that the supply chain performance has a statistically significant influence on the business performance, confirming assumptions presented in *Hypothesis 1b* which support findings of previous literature. The internal analytics had a significant influence on the supply chain performance, which supports *Hypothesis 2a*. However, we did not found statistically significant influence between the organizations capability to utilize internal data (i.e. internal analytics) and the digital procurement capabilities which lead us to reject *Hypothesis 2b*. By data, the rate of utilizing the external market-related data (i.e. external analytics) did not have statistically significant influence the supply chain performance which lead us also to reject *Hypothesis 3a*. The external analytics has however significant influence on digital procurement capabilities which supports *Hypothesis 3b*. Post-hoc tests considering indirect effects were performed for the model in order to confirm the overall validity of the model structure. The procedure is necessary because the PLS (Partial Least Square) does not provide well-established global fit measures. The test confirms the overall structure of the research model. To conclude, the results indicate that analytical capabilities which increase organizational awareness on efficiency of the processes do not serve development of the digital procurement capabilities. On the other hand, the market analytic capabilities which provide understanding considering the state of the operating environment seem to co-evolve with digitalization of the procurement activities.

Table 2 The structural model to test the main hypothesis and the post-hoc tests

Hypothesis	Effect	Path	β	t-statistics	p-values
Main effects in the research model					
<i>H1a</i>	Direct	DPCap → SCPerform	0.285	2.762	0.006***
<i>H1b</i>	Direct	SCPerform → BPerform	0.219	2.264	0.024**
<i>H2a</i>	Direct	IntAnalytics → SCPerform	0.251	2.417	0.016***
<i>H2b</i>	Direct	IntAnalytics → DPCap	0.101	0.782	0.434 ⁿ
<i>H3a</i>	Direct	ExtAnalytics → SCPerform	0.059	0.441	0.660 ⁿ
<i>H3b</i>	Direct	ExtAnalytics → DPCap	0.334	3.717	0.000****
Post-hoc tests					
	Indirect	DPCap → BPerform	0.034	0.941	0.347 ⁿ
	Indirect	ExtAnalytics → BPerform	0.061	1.582	0.114 ⁿ
	Indirect	IntAnalytics → BPerform	0.063	1.544	0.123 ⁿ
n) Not significant, *) Statistically significant at $p < 0.1$, **) Statistically significant at $p < 0.05$, ***) Statistically significant at $p < 0.01$, ****) Statistically significant at $p < 0.001$					

4 Discussion

Building on the resource-based perspective on organizational processes, the study examined firms' capabilities to exploit digital tools in their supply management processes and to leverage the adopted resources in value creation. In particular, the study explored the role of internal and external data analytics capabilities as crucial complementarities to technological resources. The importance of data analytics in procurement and supply chains emerges from the increasing amount of available data; making sense of this data and utilizing it is becoming a fundamental capability for competitive supply chains. When the data from different systems, platforms, and sources in the supply network is combined, even including the customers' activities, new opportunities and data-based service innovations may take place (Holmström et al., 2010; Opresnik & Taisch, 2015; Parry et al., 2016).

The motivation behind the research, and the focus on internal and external data analytics, develops from the view that organizational capabilities are complementarities for the technological resources and assets firms acquire, and hence can play critical role in the digitalization of the supply chain – including the procurement process. Moreover, existing studies often focus on the adoption of assets and resources as proxies of the capabilities,

because these are easier to measure (e.g., Chae et al., 2014a; 2014b). RBV posits that sustainable competitive advantage is rendered from complex configurations of organizational resources; whereas technological assets are tradable and imitable and thus provide temporary competitive advantage, knowledge and skills are institutionalized and embedded in the processes and routines of the firm; combining such non-tradable and inimitable heterogeneous resources can turn temporary resource advantages to long-term competitive advantage. This creates research gaps concerning the resource complementarities, as investments on technology alone do not explain the sustained competitive advantage firms may gain from digitalizing their supply chain.

The results pinpoint the importance of data analytics capabilities in the digitalizing supply chain operations environment. Interestingly, the results indicate that external data analytics capabilities, such as using big data, reinforce the firm's digital procurement capability. Whereas the rate of utilizing external market-related data (i.e. external data analytics capability) did not have statistically significant influence the supply chain performance, the external analytics capability has significant influence on digital procurement capabilities. The findings show support for the indirect (mediation) effect of external data analytics on supply chain performance via digital procurement capability. The external data analytics capabilities, which provide understanding considering state of the operating environment, seem to co-evolve with digitalization of the procurement activities. This finding supports the call for new analytical techniques related to big data also in the field procurement (O'Dwyer & Renner, 2011).

In contrast, internal data analytics capabilities contribute to supply chain performance directly. This is in line with the study by Tortorella et al. (2019) who found that process technologies have a significant positive association with supply chain performance. However, statistically significant influence between the organizations' capability to utilize internal data (i.e., internal

data analytics capability) and digital procurement capabilities was not found. This implies that that analytical capabilities which increase organizational awareness of the efficiency of internal processes do not serve as drivers for the development of the digital procurement capabilities.

The contribution of the study to the research on digitalization in supply chains is twofold. First, the study finds that as the adoption and use of information systems has an impact on the operational performance of the supply chain and, further, the broader business success of industrial companies. While previous studies have operationalized different constructs in their models, the overall research conclusions are aligned; electronic supply chain processes influence operational performance (Chae et al. 2014a, Chae et al. 2014b; Garrido et al. 2008; Trkman et al. 2010) and transaction cost (Eadie et al. 2007). The framework of Chae et al. (2014a) conceptualizes SC analytics as a set of complementarities for the dedicated IT-enabled resources: data management, SC planning, and performance planning. In RBV, complementarities are organizational resources required for a particular asset to be effective, such as analytics. The studies by Chae et al. (2014a; 2014b) focus on the production planning side of supply chain management processes (i.e., downstream); their analyses confirm mediated relationships among SC analytics and operational supply chain performance but no support for the direct impact. The current study adds emphasis on the procurement side (i.e., upstream) and confirms the direct impact between internal analytics capabilities and SC performance. While Chae et al. (2014a; 2014b) investigate internal analytics for production management purposes, the current study also considers external data analytics capabilities and discovers the mediated effect: external analytics capabilities influence supply chain performance through the digital capabilities of the procurement function.

Second, in addition to confirming the impact of e-procurement processes on the supply chain performance of companies, the findings demonstrated the indirect effect of the utilization of

external data analytics. External business analytics practices that are linked with increased awareness of supply markets and improved supply chain capabilities procurement processes influence the SC performance through the digital procurement capability (Wang et al., 2014).

Results show that the connection between internal data analytics capabilities and supply chain performance is more evident than with external data analytics capabilities. One reason for this could be that external data is often unstructured and rarely integrated to the systems and thus not directly applicable to the processes than internal data which is often structured and linked to the operational systems and processes. As discussed earlier, capabilities are founded on organizational routines that are highly patterned, guided by managerial processes, and require effort to develop and maintain. Operational capabilities focus on earning revenue without introducing changes, whereas first and second order dynamic capabilities are patterned activities that introduce change (Collis, 1994; Winter, 2003). While internal data analytics capabilities correspond with the idea of zero-order operational capabilities, External data analytics capabilities correspond with the idea of first-level dynamic capabilities (Winter, 2003) or 'dynamic improvements' (Collis, 1994), i.e., patterned activities that introduce some changes beyond the zero-level and allow the firm to adjust its capabilities. As the procurement activities are often unstructured and complex and contain already different types of data, big data analytics techniques and especially external data analytics capabilities have great potential to enhance digital procurement capabilities of companies.

To recap, these findings supports the existing literature, which says that information systems alone do not necessarily improve an organization's performance (Markus, 2004). Therefore, the results align with the basic assumptions of RBV in pinpointing the role of organizational capabilities or competences as important complementarities to technological resources. The information sharing processes and analytical capabilities of supply chain processes are key

components in creating supply chain performance, and it can be assumed that by developing integration between them, supply chain digitization can be accelerated. In upstream supply chain processes, the development of information exchange technology may not have been as rapid as in downstream processes, but it is important to note that the connection of upstream electronic processes to data analysis affects the performance of the entire supply chain. Companies that integrate both upstream and downstream supply chain processes in a unified manner improve the ability of both suppliers and customers to leverage data sharing and integration throughout the supply chain. The results are also consistent with a previous study in which sharing data upstream and downstream improved supply chain performance as whole (Sezen, 2008). Achieving the full benefits of SCM digitization should be understood not only as automatization of processes but also in the context of leveraging awareness in both upstream and downstream operations. Digital SC description also requires automation of data collection from both suppliers and customers side so that the view of the business environment is not skewed.

5 Conclusions and Limitations

5.1 Conclusions

Effective exploitation of the opportunities emerging from digitalization in the SCM domain requires solving questions related with technical capabilities, cross-organizational processes, and capability to absorb available information as well. The key challenges in the given context are related with vast amount of data from internal and external sources generated from new technologies and solutions within the supply chain. To explain the dynamics in the SCM level, the dynamic capability framework and RBV provides theoretical landscape which enable discussion regarding roles of sensing, seizing and reconfiguration capabilities, and ordinary organizational capabilities to build resilient SC (Teece, 2007; Halldorsson, Kotzab, Mikkola,

and Skjøtt-Larsen, 2007). The study addressed gaps in the in theory considering interaction between technology adoption in organization, knowledge creation, and effectiveness of the SCM which are observed from aspects of big data utilization and implementation digital procurement activities and performance implications (Bag et al., 2020; Zhu et al., 2018; Frederico et al., 2019).

This study investigated digitalization in the supply management process by examining the role of digital procurement capabilities and data analytics, using external and internal data, to increase supply chain performance. To clarify theoretical implications of the study, the following four contributions that can be drawn from the conclusions based on the findings.

Conclusion 1, implementation of digital procurement processes positively and directly influences supply chain performance. The current study focused on digital procurement capabilities that reflect both the organizational maturity in adopting e-procurement technology and the institutionalization of the e-procurement processes, and results confirm their direct relationship with supply chain performance. This support earlier research that has reported the positive impacts of adopting e-procurement systems to supply chain performance (Eadie et al., 2007; Kim & Shunk, 2004; Lenka et al., 2016; Purchase & Dooley, 2010; Puschmann & Alt, 2005; Ronchi et al. 2010). *Conclusion 2, analytics capabilities improve competitiveness of the firm in the domain of procurement and SCM, but internal and external data analytics have serve different purposes in the digitalization of SCM.* This study contributes recent literature showing importance to understand viewing angle of data sources for SCM because overall effects are valued different way depending whether the data describe internal or external performance (Foerstl et al., 2020; Haarhaus & Liening, 2020). *Conclusion 3, internal data analytics capabilities have a direct positive impact on supply chain performance directly.* This is in line with the study by Tortorella et al. (2019) who found that process technologies have a significant positive association with supply chain performance. However, statistically

significant influence between the organizations' capability to utilize internal data (i.e., internal data analytics capability) and digital procurement capabilities was not found. This implies that that analytical capabilities which increase organizational awareness of the efficiency of internal processes do not serve as drivers for the development of the digital procurement capabilities which add arguments on debate regarding causal relationships between dynamic and organizational capabilities (Schriber & Löwstedt, 2020). *Conclusion 4, external data analytics capabilities have a positive direct impact on digital procurement capabilities; the positive impact of external data analytics on SC performance is mediated by the digital procurement capability.* The results indicate that external data analytics capabilities, such as using big data, reinforce the firm's digital procurement capability. Whereas the rate of utilizing external market-related data (i.e. external data analytics capability) did not have statistically significant influence the supply chain performance, the external analytics capability has significant influence on digital procurement capabilities. The conclusion support earlier arguments regarding shift of balance to emphasize role of dynamic instead of organizational capabilities in case of digitalized SCM (Bag et al., 2020; Braganza et al., 2017).

5.2 Managerial implications

From the managerial point of view, the findings highlight the importance of gaining knowledge from gathered data and digitalized processes. Managers must focus on data utilization strategies to improve the operational performance expected from the digitalization of supply chain activities. In particular, managers need to consider exploiting data through new creative approaches as part of digital procurement operations. To conclude, from an operative perspective, supply chain digitalization calls for adequate data utilization plans at the top management level as well in order to outperform conventional processes. Since supply chain information is scattered in many places in companies, it is important to develop the capability to find the right sources of information, obtain this information automatically to support data

analytics, and be able to utilize this information in decision making. A prerequisite for utilizing both external and internal data is that the information must be in a form that can be combined. In companies, attention must therefore be paid to improving the reliability of information content, as it is a prerequisite for utilizing information. This study showed particular potential for combining information related to the procurement process and external analytics. For example, such a development area could be in terms of supplier market information, where the market would provide good information on changes in the supplier field to support sourcing decisions.

5.3 Limitations

This study provides empirical evidence from the sample that consists of respondents from the representatives of the international industrial companies operating in Finland. This may affect the results. Although a large proportion of these companies operate globally, companies from another geographic population could have differing skill sets and resources in internal and external SCA. The sample size and response rate are sufficient for the statistical analysis; however, the sample focused on companies in the industrial process sector and therefore does not contain companies representing all industrial sectors. For this reason, further research on the role of external and internal data analytics capabilities and digital procurement capability is encouraged to validate the relationships with larger samples covering multiple industries.

The maturity of data analytics utilization is, assumedly, still in the early stages of development, and therefore new constructs and research items will be developed for studying data analytics in the supply chain. The current analysis concentrated on digital procurement capabilities the purchasing process. However, the crucial role of external data analytics discovered in the study suggests that the broader framework of demand and supply process integration (Jüttner, Christopher, and Baker, 2007) is the next context to investigate digital transformation in supply

chain management. For instance, interesting avenues are to study the role of platforms and data integration since the transfer and aggregation of data between different platforms in supply chains seem to be an important driver of competitiveness in supply chains. In addition, explorative research is needed on the possibilities of new emerging technologies based on artificial intelligence in the automatization of sourcing processes.

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Appendix 1 – Survey instrument

Digital Procurement Capability (adapted from UBL, van Weele 2009)

Consider the capability of your company to realize the following e-procurement processes?

(1 = not implemented at all; 5 = fully implemented)

DPCap1	<i>e-Bidding (The buyer requests an offer from the seller)</i>
DPCap2	<i>e-Billing</i>
DPCap3	<i>e-RFP (Request for proposal)</i>
DPCap4	<i>e-Order change</i>
DPCap5	<i>e-Order</i>
DPCap6	<i>e-Order confirmation</i>

Data analytics capabilities

How much do you use the following analytics methods? (1 = very little, 5 = very much)

Internal Process Analytics

IntAnalytics1	<i>We use internal data (e.g. orders, deliveries) to support production planning</i>	Sources: (Chen, Preston and Swink, 2015; Gupta and George, 2016)
IntAnalytics2	<i>We use internal data to predict and prevent product failures</i>	
IntAnalytics3	<i>We use internal data to predict machine failures</i>	
IntAnalytics4	<i>We collect data from equipments and sensors and utilize it in processes and services</i>	

External Analytics

ExtAnalytics1	<i>We use external customer information (e.g. market research) to support planning</i>	Sources: (Tallon and Pinsonneault, 2011; Tallon et al., 2016; Côte-Real, Oliveira and Ruivo, 2017; Johnson, Friend and Lee, 2017)
ExtAnalytics2	<i>We use external information (e.g. price information) to support planning</i>	
ExtAnalytics3	<i>We use Big Data (external and internal) in business decisions</i>	
ExtAnalytics4	<i>We use external supplier information (e.g. vendor location information, credit information) for evaluating supplier risks</i>	

Supply Chain Performance (adapted from Boyer and McDermott, 1999, Beamon, 1999, Williams 2013)

How well your company has succeeded in achieving its goals improve supply chain management (1 = very poor, 5 = very good)

SCPerform1	<i>Increase flexibility</i>
SCPerform2	<i>Increase resource efficiency</i>
SCPerform3	<i>Decrease costs in supply chain</i>
SCPerform4	<i>Reduce delivery time</i>
SCPerform5	<i>Increase delivery reliability</i>
SCPerform6	<i>Increase visibility</i>

Business Performance (adapted from McLaren et al., 2002)

How would you rate the success of your company in the following areas over the last three years compared to companies in the same industry? (1 = very poor, 5 = very successful)

BPerform1	<i>Profit</i>
BPerform2	<i>Net income</i>
BPerform3	<i>Return on investment (ROI)</i>