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1. The fourth industrial revolution (Industry 4.0): technologies disruption on operations and supply chain management

1.1 Context

During the last five years, journals in robotics, electronics, computer science and production engineering have devoted significant attention to Industry 4.0 and related subjects, including additive manufacturing/3D printing, intelligent manufacturing and big data (Lee et al., 2014; Xi et al., 2015; Pfeiffer et al., 2016; Mosterman and Zander, 2016; Chen and Zhang, 2015; Jia et al., 2016). A systematic literature review on Industry 4.0 or on some of its specific technologies (e.g. additive manufacturing) is provided by Liao et al. (2017), Strozzi et al. (2017) and Khorram Niaki and Nonino (2017) among others. Although prominent scholars have acknowledged the relevance of Industry 4.0 for management in general, as well as for Operations and Production Management (O&PM) specifically (Brennan et al., 2015; Fawcett and Waller, 2014; Holmström and Romme, 2012; Melnyk et al., 2018), relatively little consideration has been given to these topics by mainstream O&PM journals, especially on Industry 4.0 technologies’ disruption on operations and supply chain management. A few prominent exceptions are represented by the recent attempts to shed lights on: the link between Industry 4.0 and lean manufacturing (Buer et al., 2018; Tortorella and Fettermann, 2018); the link between Internet of Things (IoT) and supply chain management (Ben-Daya et al., 2017); the impact of additive manufacturing on supply chain processes and performances (Liu et al., 2014; Oettmeier and Hofmann, 2016; Li et al., 2017); and the short-term supply chain scheduling in smart factories (Ivanov et al., 2016). While in the past there were very few pilot Industry 4.0 projects, the number of applications has significantly increased, both in terms of demonstration and “real” factories hence give rise to more empirical studies. Demonstration factories include Factory 2050 at the University of Sheffield (UK), Demonstration Factory at Aachen University (Germany), TRUMPF Group Factory in Chicago (USA) and SmartFactoryKL in Kaiserslautern (Germany), whilst “real” factories are at Audi’s Ingolstadt factory (Core77, 2016), Arla Foods (ARC, 2016), Siemens’ Amberg plant (Siemens, 2016) and Bosch’s Feuerbach plant in Stuttgart (Automotive World, 2016). A recent survey conducted by PwC on more than 2,000 companies from 26 countries showed an overall adoption rate of Industry 4.0 concepts (e.g. digitization and integration) of 33 percent, and forecasted that it will reach 72 percent by 2020 (PwC, 2015). This growth will be further fostered by the funding and innovation plans launched by several countries leading this industrial revolution, e.g., Manufacturing USA in the USA, Industrie du Futur in France, Industrie 4.0 in Germany, Industria 4.0 in Italy, Made in China 2025, Made Smarter UK. It is argued that different industrial sectors have different pace of adopting Industry 4.0. For instance, the aerospace sector has sometimes been characterized as “too low volume for extensive automation” however Industry 4.0 principles have been investigated by several aerospace companies, technologies have been developed to improve productivity where the upfront cost of automation cannot be justified, one example of this is the aerospace parts manufacturer Meggitt PLC’s project, M4. Here, the fourth industrial revolution (Industry 4.0) refers to the “confluence of technologies ranging from a variety of digital technologies (e.g. 3D printing, IoT, advanced robotics) to new materials (e.g. bio or nano-based) to new processes (e.g. data driven production, Artificial Intelligence, synthetic biology)” (OECD, 2016). These technologies have the potential to revolutionize operations and supply chain management (Brennan et al., 2015; Holmström et al., 2016; Rüßmann et al., 2015; Fawcett and Waller, 2014; Waller and Fawcett, 2013). Industry 4.0 is not merely about integrating...
technologies, but it is about the whole concept of how future customer demands, resources and
data are shared, owned, used, regenerated, exploited, organized and recycled to make
a product or deliver a service, faster, cheaper, more efficiently and more sustainably (Spath,
2013). As such, Industry 4.0 requires a rethinking and shift in mindset of how products are
manufactured and services are produced, distributed/supplied, sold and used in the supply
chain; thus, it will drive significant structural theoretical evolution and revolution for
operations and supply chain management. Whilst classical theories such as resource based
view, institutional theory, chaos theory, systems theory, stakeholder theory, transaction
economic cost theory, evolutionary theory to name a few may need reshaping, the issues of
trust will become prominent in such a disruptive digital environment, driving major
evolution of technological singularity in the transformation process, where blockchain may
play a central role with IoT and Artificial Intelligence (AI) (Carter and Koh, 2018).

2. Introduction
So far, all the industrial revolutions that took place in the past two centuries is promoted
by altering production mode enabled by a specific emerging technology at that time
(Liao et al., 2017). The arrival of steam engine promoted the first industrial revolution; the
application of electricity led to the second revolution, and the widespread use of information
technology and electronics products support the third revolution (Liao et al., 2017). The recent
popularization of the IoT and cyber-physical system (CPS) (Khaitan and McCalley, 2014) has
attracted the attention of both enterprise and academics. Leveraging those two emerging
technologies is promising to enable the higher level of connection between information,
products and people (Ibarra et al., 2018), thereby making contributions to the current production
mode. This phenomenon is considered as the fourth industrial revolution, also known as
industry 4.0, which is about to bring about an extensive range of innovation from a variety of
digital technologies (Lu, 2017), advanced materials (Schumacher et al., 2016), innovative
products (Pereira and Romero, 2017), to new manufacturing processes (Wagner et al., 2017).

Industry 4.0 is an emerging concept deriving from technological advancement and disruptive
developments in the industrial sector worldwide in the past few years (Dallasega et al., 2017).
It defines a methodology applying emerging technologies to revolutionize the current production
that transits from machine dominant manufacturing to digital manufacturing (Oztemel and
Gursey, 2018). Some consider it as the integration of technologies such as CPS, IoT, Big Data and
Cloud manufacturing (Pereira and Romero, 2017). However, there is a discourse arguing that
industry 4.0 is not only regarding integrating technologies but concerning the whole concept of
how to acquire, share, use, organize data and resource to make the product/service deliver faster,
cheaper, more effective and more sustainable (Piccarozzi et al., 2018).

As the interest in the Industry 4.0 research is growing rapidly, these studies do not limit
their focus on industry 4.0 itself, but seek to find the relationship between industry 4.0 and
other topics. For instance, Piccarozzi et al. (2018) try to link industry 4.0 with management
studies; Dallasega et al. (2018) investigate industry 4.0 in the context of the supply chain.
Müller et al. (2018) and Kamble et al. (2018) explore the relationship between industry 4.0 and
sustainable development.

This position paper intends to summarize the major topics in the current research
regarding Industry 4.0 and charts key thematic future research directions and paradigms.
In the following section, the paradigms and principles of industry 4.0 are concluded. Five
technologies that are widely discussed in the current research are identified and the
outcomes of industry 4.0 are discussed at the end of this position paper.

3. Paradigms in industry 4.0
According to Weyer et al. (2015), industry 4.0 can be subdivided into three paradigms: the
smart product, the smart machine and the augmented operator. This conclusion of the major
paradigm of industry 4.0 is also agreed by Longo et al. (2017) and Mrugalska and Wyrwicka (2017). The first paradigm is the smart products, it refers to objects and machines that are equipped with sensors and microchips, controlled by software, and connected to the internet (Lu, 2017; Kamble et al., 2018). Smart products can store the operational data and requirements independently, and further, the product can inform the machine-related manufacturing information, for instance, when to produce, where to produce, or what parameter should be adopted to complete the product manufacturing. In this case, smart product shifts the role of the workpiece in a system from passive to an active part (Loskyll et al., 2012).

The second paradigm is the Smart Machine. It refers to a device equipped with machine-to-machine and/or cognitive computing technologies (i.e. AI and machine learning (ML)). Through leveraging these technologies, machines can reason, problem-solve, make decision ad eventually take action. Smart machine brought decentralized self-organization, thus replacing the previous traditional production hierarchy (Mrugalska and Wyrwicka, 2017). In such innovative system, the use of open networks and semantic descriptions allow the communication among the autonomic components (Oztemel and Gursev, 2018), while the local control intelligence communicate with other devices, production modules and products, thereby, contributing to the improvement of flexibility and modularity of the production line (Pereira and Romero, 2017).

The third paradigm of industry 4.0 is the augmented operator. This concept emphasizes the technological support of the worker in the production system with higher flexibility and modularity (Weyer et al., 2015). Mrugalska and Wyrwicka (2017) state that augmented operator addresses the knowledge automation in the system, therefore making them the most flexible and adaptive part in the production system. Workers in such production system are likely to encounter with varieties of tasks including specification, monitoring and verification of production strategy. Meanwhile, they may have to annually intervene in the self-organized production system. Under the support of mobile, context-sensitive user interfaces and user-focused assistance system (Gorecky et al., 2014), such workers play the role of strategic decision-makers and flexible problem-solvers in the circumstance of increasing technical complexity (Mrugalska and Wyrwicka, 2017).

4. Design principles in industry 4.0
Based on the three paradigms mentioned above, some researchers further conclude six principles that should be considered when designing the implementation of industry 4.0 (Oztemel and Gursev, 2018). Those principles include interoperability, virtualization, decentralization, real-time capability, service orientation and modularity (Lu, 2017, Oztemel and Gursev, 2018). Kamble et al. (2018) conduct a systematic literature review to develop a framework of sustainable industry 4.0 and further justify the role of these principles on industry 4.0 implementation.

First, interoperability is the first principle for industry 4.0. Interoperability refers to the ability of two systems to communicate with and understand each other and use the functions of one another (Hermann et al., 2016; Lu, 2017). It addresses the capability of data exchanging and information and knowledge sharing among systems (Lu, 2017). It is assumed that interoperability is the key advantages of industry 4.0 as it ensures the connection and communication among products, machines and humans (Mrugalska and Wyrwicka, 2017) throughout the diversified autonomous procedure (Lu, 2017).

Further, Lu (2017) proposes a framework of interoperability of industry 4.0 and concludes four levels of interoperability in industry 4.0, including operational, systematic, technical and semantic interoperability. The author gives specific explanations for each level of interoperability. Operational interoperability indicates the concepts, standards, languages and relationships within the system. Systematic interoperability describes
the methodologies, standards and models; technical interoperability illustrates tools and platforms for technical development, and the semantic interoperability ensures the exchanged information is well understood among different groups.

Qin et al. (2016) confirmed that interoperability constructs a trusted environment in a manufacturing system, in which information is accurately and swiftly shared among partners (Kamble et al., 2018), therefore resulting in a cost-saving operation with higher productivity (Lu, 2017).

Virtualization is used for process monitoring and machine-to-machine communication. It indicates that devices have the capability of monitoring the physical process. The sensor data is linked to virtual plant models and simulation models, thus constructing the virtual copy of physical objects (Mrugalska and Wyrwicka, 2017). Meanwhile, each device can be virtualized and become a part of the plant model. The virtual model can simulate various scenarios based on the monitored data. Once the potential risks or failures are detected in the virtual models, operators are informed and they can take the preemptive action (Kamble et al., 2018), thus reducing the actual error rate and smoothing the inter-company operations (Brettel et al., 2014).

Third, decentralization denotes that companies, operation staff, and even devices are able to make independent decision rather than depending on the centralized decision-making. It can be achieved with the use of embedded computer, which provides the operation staff or devices the capability of individual control and independent decision-making (Marques et al., 2017). As the development of customization and product variety, the flexible production line is expected to be extensively adopted. Overall control of the production line is less advisable. However, the embedded control system can empower each device or the unit of the device to make independent decisions, thus making the decision-making efficient and offering more flexibility (Kamble et al., 2018).

Fourth, real-time capability refers to the immediacy of data collection and analysis, and the real-time of data transmission. Smart factory requires continuous real-time data monitoring and analyzing, to detect the errors timely and satisfy the new demand. The collection of real-time data relies on big data technology (Kamble et al., 2018). The huge amount of data regarding machines, equipment, and products are collected from factories, and data regarding customers are collected from multiple sources such as social media or outlets. The analysis of those real-time data may alter the ways of decision-making and pose an impact on the profitability of the companies implementing industry 4.0.

Fifth, service orientation required that devices are capable of satisfying the needs of users through the internet of service. As all the entities in the production system are interconnected, and therefore, the concept of the product will extend from the product itself to product-service (Lasi et al., 2014). Service orientation indicates that product should be considering the users’ practical needs, such as user-friendly or convenience for maintenance, at the very beginning of product design. Moreover, through service orientation, corporate can achieve flexibility and agility and thus to have a quick response to the market change (Kamble et al., 2018).

Sixth, modularity refers to the device or the components of a device is produced following standards. Therefore, they can be assembled, replaced and expanded as needed in the modular production system (Qin et al., 2016). In this case, modularity provides smart factories with the capability of adapting capacity at a lower cost to cope with seasonal fluctuation and changes in production needs (Mrugalska and Wyrwicka, 2017).

5. Technologies in industry 4.0

Lu (2017) defines industry 4.0 as an integrated, adapted, optimized, service-oriented and interoperable manufacturing process in which algorithms, big data and high technologies are included. Technologies are considered as the very heart of industry 4.0 as the
interconnection in the industry 4.0 is supported by the adoption of software, sensor, processor and communication technologies (Bahrin et al., 2016). Five technologies are frequently discussed in the literature: IoT, big data analytics, cloud, 3D printing and robotic systems (Piccarozzi et al., 2018; Kamble et al. 2018), where technologies such as AI, ML, digital twin and 5G are emerging.

Internet of Things (IoT)

The IoT is an emerging industrial ecosystem. It facilitates the combination of intelligent machines, advanced predictive analytics and machine-human collaboration, aiming at promoting productivity, efficiency and reliability (Kamble et al., 2018). In industry 4.0, IoT can support the smart factory. It can lead to the creation of virtual networks to support the smart factory (Xu et al., 2018); meanwhile, it provides the factory with the ability to collect real-time data and transmit the data swiftly (Yang et al., 2017). Therefore, it enables the remote operation of manufacturing activities and affects collaboration among stakeholders (Yang et al., 2017). IoT can benefit the integration and coordination of product and information flow (Tao et al., 2014), and enable the decentralization of decision-making, interconnected devised can perform automatic analytics and decision-making, thus improving the responsiveness to the environment change (Wang et al., 2014).

Big data analytics

Manufacturing companies have realized that data analytics capabilities are imperative for their competitive advantage in the era of digitization. Therefore, they devote themselves to improving skills for algorithms development and data interpretation (Lee et al., 2017). Big data analytics and technologies can promote data collection from multiple sources, and the ability of comprehensive data analysis and real-time decision making based on the data analysis results (Bahrin et al., 2016). It has been widely adopted in manufacturing to monitor the process. Also, big data is used for failure detection, thus supporting new capabilities such as predictive analytics (Lee et al., 2017). Data quality and qualified data analysis capabilities are key to achieve the desired outcomes of big data analytics (Kamble et al., 2018). Therefore, leveraging the intelligence in big data to improve agility will require new challenges, for example how to ensure the data consistency and confidentiality in a long and complex supply chain (Kamble et al., 2018).

Cloud

Cloud computing is a computing technology. Cloud computing centers can store and compute a huge amount of data, therefore promoting the manufacturing and production and further bringing organizations higher performance and lower cost (Mitra et al., 2017). Cloud computing is supported by virtualization technology, as it provides cloud computing with resource pooling, resource sharing, dynamic allocation, flexible extension and other capabilities (Xu et al., 2018). Xu et al. (2018) also address the usefulness of cloud computing in facilitating efficient data exchange and sharing. Through cloud computing, data can be stored in either private cloud or public cloud servers, and thus cloud computing can promote complex decision-making (Xu et al., 2018).

Cloud-based manufacturing is key to the success Industry 4.0 implementation. It enables the modularization and service-orientation in the field of manufacturing (Xu et al., 2018), where system orchestration and sharing of service and components are essential considerations and are affected by modularization and service-orientation (Xu et al., 2018). Branger and Pang (2015) assumed that cloud manufacturing is expected to be the next paradigm in manufacturing in Industry 4.0.
3D printing

3D printing relies on additive manufacturing (as opposed to subtractive manufacturing). Final products in 3D printing are built up with successive layers of materials (Oztemel and Gursey, 2018), thus avoiding the component assembly in the production process. Additive manufacturing techniques can make contributions to Industry 4.0 in terms of offering organizations construction advantages, as it allows to produce small batches of customized products with complex and lightweight design (Kamble et al., 2018). Chen and Lin (2017) state that the exploitation of 3D technology can optimize smart manufacturing and lean manufacturing. However, there are technical challenges in the use of 3D printing, namely, limited accuracy and productivity, and limited available material (Chen and Lin, 2017). Because of the technical challenges, additive manufacturing (3D printing) is still in the initial stage. However, once the challenges have been solved, it is expected to see wider adoption of this technology in Industry 4.0 (Kamble et al., 2018).

Robotic systems

However, robotics has been used for production in many manufacturing industries, the modern robotics systems are more flexible, autonomous and smart and are able to communicate and cooperate with one another and even have learning ability (Kamble et al., 2018), leading to the next generation of robotic systems, namely, cobot (collaborative robots). Pei et al. (2017) state that the modern robotics can perform well in most of the processes in the smart factory, for instance, Mueller et al. (2017) proposed that it is feasible to use programmable dual-arm robots to efficiently distribute and allocate materials in the assembly line. Therefore, the application of modern robots can provide the factory with cost advantages and a wide range of capabilities (Pei et al., 2017). To ensure the safe operation of the robotics system, a device named safety eye is equipped. Once the device has detected any disturbance in the operation, it will stop the robot and will not reactivate the robot before the operators remove the objects that disturb the operation (Kamble et al., 2018).

6. Outcomes of industry 4.0

Considering industry 4.0 can revolutionize the products and manufacturing system in terms of operation, product, design, production processes and services across the supply chain, it is expected that implementing industry 4.0 can positively impact the industry, markets and multiple participants (Dallasega et al., 2017). Pereira and Romero (2017) conclude six areas on which industry 4.0 may exert influence. Those areas include: industry, products and service, business model and market, economy, work environment and skills development. Kamble et al. (2018) further link industry 4.0 with sustainable development and argued that industry 4.0 can generate sustainable outcomes in terms of environmental, social and economic.

Industry 4.0 has brought manufacturing industry new decentralized and digitalized production patterns, in which the production elements are highly autonomous, and therefore they can trigger actions and respond to the environment change independently (Pereira and Romero, 2017). Industry 4.0 also promote the integration of products and processes, thus transforming the production pattern from mass production to mass customization (Lu, 2017). Additionally, production processes and operations are significantly affected by the emergence of smart factories and emerging technologies, such as IoT, 3D printing and robotic systems. In this case, Industry 4.0 can improve the flexibility in operations and efficiency in resource allocation (Pereira and Romero, 2017). Dallasega et al. (2018) state that Industry 4.0 will not only affect the productivity in the manufacturing industry but also influence the entire supply chain from product development and manufacturing process to the product distribution. Products and services are also affected by industry 4.0. The principle of modularisation makes
the products modular and configurable, and as a result, products and services are more
customized to satisfy specific customer needs (Jazdi, 2014).

Industry 4.0 has brought a number of new disruptive technologies that have altered the
approaches of delivering products or services, hence affecting the traditional business
models and encouraging the new business models (Pereira and Romero, 2017). For instance,
system integration and complexity in industry 4.0 will result in the emergence of more
complex and digital market models, in which the barriers between information and physical
structure are reduced (Ibarra et al., 2018).

Industry 4.0 is transforming jobs and required skills, which have impacts on the working
environment and skills development. With more robots and smart machines is involved in
the daily operation, the physical and virtual world are fusing together, thus launching
transformation in the working environment. For example, as human-machine interfere
requires the communication among smart machines, smart products and employees,
ergonomic issues should be considered in the future system should stress the workers and
their importance in the system (Pereira and Romero, 2017). For skills development, as in the
context of industry 4.0, interdisciplinary thinking and qualified skills in the social and
technical field are required. These new competencies should be included in the employee
training and education (Pereira and Romero, 2017), to make workers and managers well
prepared for this new industrial paradigm.

Moreover, Kamble et al. (2018) state that Industry 4.0 can lead to sustainable development.
With the support of cloud computing and big data analytics, organizations can achieve cost
reduction and lean production, thus realising the economic sustainability; Employing
technologies such as sensing, detection and tracing analysis can help to mitigate the problem
of industrial waste disposal, which facilitates the environmental sustainability; technologies
(risk maps or wearable technologies) for improving the safety of employees in hazardous work
areas helps to ensure the process safety and promote the social sustainability.

7. Methodological approaches adopted by Industry 4.0 research

Industry 4.0 literature is characterized by a prevalence of conceptual papers. Piccarozzi et al.
(2018) found for instance in their systematic review on Industry 4.0 in management studies
54 percent of conceptual papers, mainly literature reviews and developments of models/
frameworks. As far as empirical papers are concerned, qualitative methods (mainly case studies)
and quantitative methods (surveys) are almost equally adopted (25 vs 21 percent, respectively).

An agreed definition and operationalization of the Industry 4.0 construct is missing
(Culot et al., 2018). While some authors have indeed sought to develop maturity models and
readiness indexes, which identify incremental levels of Industry 4.0 implementation (for a
review see Mittal et al., 2018), Industry 4.0 literature still relies on different operationalizations
of the concept. As an example, the bunch of technologies considered as Industry 4.0 varies
significantly from one paper to the other. This poses serious limitations to theory building and
research comparability.

Finally, Industry 4.0 papers belong to a wide set of disciplinary domains. Muhuri et al.
(2019) identified in their bibliometric analysis of Industry 4.0 the top 10 subject areas in the
Scopus database. At the first place there is Engineering (65 percent), followed by
Computer Science (45 percent), Business, Management and Accounting (16 percent) and
Decision Sciences (14 percent). While these disciplines were the most important ones also in
the previous investigation conducted by Liao et al. (2017), their relative importance has
significantly changed (Engineering was at the second place after Computer Science; Business,
Management and Accounting and Decision Sciences were significantly less frequent). Besides this wide set of disciplines involved, there is however a limited number of
interdisciplinary papers.
8. Suggestions for future Industry 4.0 research – methodological approach

As we pointed out in this position paper, Industry 4.0 research so far is still characterized by a prevalence of conceptual papers in the operations and production field. However, paradigms, design principles and technologies prevalent to industry 4.0 have been examined. Whilst this might be partially justified by the novelty of the topic and the consequent limited adoption by companies (the Industry 4.0 concept was indeed introduced at the Hannover Fair in 2011), the scientific research cannot overlook the contact with the industrial world. One of the main challenges for future Industry 4.0 research is therefore to carry out more empirical investigations as well as large-scale data analysis. For this reason, we decided not to accept any conceptual contribution in our special issue (even though we received some high-quality conceptual papers). Alongside the traditional empirical methods (i.e. case study and survey), other exploratory methodologies – such as Delphi studies or focus groups – could bring significant insights given the interdisciplinary and “futuristic” nature of the topic.

A further potential methodological limitation of current Industry 4.0 research is the absence of agreed definitions and operationalizations of the main constructs. Without these operationalizations, there is a risk that the significant relationships observed are just due to the specific definitions considered and are not reproducible in other studies. A second significant challenge for future Industry 4.0 research is therefore to define the main Industry 4.0 constructs (e.g. Industry 4.0 adoption, Industry 4.0 maturity, Industry 4.0 readiness) and empirically validate them. This challenge will not be easy since both the technological landscape and the application fields of Industry 4.0 are rapidly evolving. Researchers should however find a way to define a common set of constructs to support further theory building and theory testing efforts.

The issue pointed out above is particularly significant in quantitative research, which is usually based on closed-ended questions or secondary data (requiring a precise operationalization of the measured constructs). The almost equal representation of qualitative and quantitative research might in this sense signal a potential issue. We therefore think that qualitative theory building papers should be particularly welcome in this stage, to develop a set of constructs and relationships to be tested on larger samples in a later stage.

Finally, Industry 4.0 is a highly interdisciplinary topic, involving a wide set of knowledge domains (e.g. automatic controls, robotics, sensors, computer science, and management) and actors (e.g. researchers, companies, technology providers, policy makers, schools). The successful transition toward Industry 4.0 requires indeed a joint effort of the above-mentioned actors to create a successful ecosystem (Xu et al., 2018). Interdisciplinary research should therefore be significantly encouraged at all levels. First, Industry 4.0 researchers should for instance try to aim in their paper more at the policy makers and the managers. Research should indeed support the different authorities to take better decision to support the digital transformation. Second, authors from different disciplines or affiliations (universities, applied research centers, companies, technology providers, governments and regulatory bodies) should try to systematically integrate the different perspectives and point of views. Finally, the reviewing and editorial board of journals might also be broadened/hybridized by involving experts from the industrial and the policy making worlds.

9. Conclusion

The purpose of this position paper is to summarize the major topics of recent research on industry 4.0. First, three paradigms and six principles of industry 4.0 are identified, and five technologies that are frequently discussed in industry 4.0 are concluded. The outcomes and impacts of industry 4.0 are discussed at the end. In addition, the methodological approaches in industry 4.0 research has been discussed, and future research directions and paradigms of industry 4.0 methodological approach have been proposed.
Although industry 4.0 has been widely discussed from multiple perspectives, as technology advancement still takes place constantly, thus continuously shaping the industry and organizations, there are abundant research opportunities in this topic. Meanwhile, with the increasingly in-depth understanding of industry 4.0, there are more research potentials to combine industry 4.0 with other research fields, to further investigate the industry 4.0 with a wider scope.

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Note
1. The sum of percentages exceeds 100 percent since some papers are categorized by Scopus in more than one category.

References


Further reading


Exploring blockchain implementation in the supply chain
Learning from pioneers and RFID research

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Abstract
Purpose – There is great interest in blockchain in the supply chain yet there is little empirical research to support the consideration of the technology. Ferdows (2018) calls for research aimed at learning from pioneers in the field and Gartner points out that the interest in blockchain holds similarities to the interest surrounding RFID 15 years ago. As a result, there may be opportunities to leverage insights from RFID research to inform the consideration of blockchain. The purpose of this paper is to explore how the Reyes et al. (2016) framework for the implementation of RFID may inform the consideration of blockchain in the supply chain.

Design/methodology/approach – A two-stage approach is used to explore RFID implementation considerations from the Reyes et al. (2016) RFID implementation framework, using an initial exploration of managers interested in blockchain using a focus group and a survey and to more in depth explore three case companies pioneering blockchain.

Findings – Several RFID implementation considerations can inform the consideration of blockchain but there are also differences in considering blockchain. A framework is developed that details considerations found to be relevant by implementation stage.

Originality/value – This paper adds to the limited amount of empirical research on blockchain in the supply chain and advances research beyond the consideration of use cases into the exploration of actual implementation of blockchain in the supply chain. The decision framework developed both leverages and nuances findings from RFID research and can inform managerial decision making. It also adds to research a multi-stage approach to implementation and uncovers rich opportunity to further learn from pioneers.

Keywords RFID, Research, Framework, Implementation, Blockchain, Supply chain technology

Paper type Research paper

1. Introduction
Blockchain is said to be a ground-breaking innovative platform (Abeyratne and Monfared, 2016) that is set to transform supply chain activities (Carter and Koh, 2018; Ksherti, 2018) and blockchain reached the top of Gartner’s hype cycle a while ago (Bociek et al., 2017). Dobrovnik et al. (2018) state that there is very little empirical research on blockchain in the supply chain. And Treiblmaier (2018) states that most publications are practitioner-oriented and that while publications predict a huge impact of the technology, these predictions are not grounded in existing theory and little is done to warn against unrealistic expectations. It is perhaps not surprising therefore that in a study of blockchain use cases Verhoeven et al. (2018) found indications that there may be a lack in mindfulness of blockchain technology implementation and that there may be a degree of “a solution looking for a problem” surrounding blockchain use cases.

Given the limited amount of empirical research on blockchain in the supply chain and given the high expectations and interest in the technology it is relevant to empirically explore the consideration and implementation of blockchain in the supply chain. Ferdows (2018) in his most recent IJOPM paper called for more research into blockchain. Additionally, he encouraged more case study research stating that we can learn from pioneers in this area just like we did from Toyota on lean. In this paper we hope to respond
to this call directly. However, because there may only be a few pioneers to date, it seems relevant to also explore what factors companies and managers that are interested in blockchain in the supply chain, but that are not necessarily yet pioneers, are using when considering blockchain in the supply chain.

In addition to learning from pioneers and interested companies, learning from research on existing technology is another way to add to the limited research. Dwight Klappich from Gartner in a recent interview with supply chain quarterly points specifically at the parallel between blockchain and RFID technology and calls for effort to avoid relearning lessons of the past:

There is hype around how blockchain is going to solve world hunger, create world peace. No technology can live up to all that hype. It relates to what we saw around RFID in 2004-2005. It was a technology with clear potential and opportunity but the hype became so overzealous. I remember being at an event where it was claimed that soon we would have refrigerators with RFID readers that would auto-replenish. I don’t think we have that yet today, we did not replace the barcode, we still have work to do on RFID and there is still more potential for its roll out. (June 4, 2018)

Considering this parallel there may be valid lessons from research into RFID implementation that can inform the development of an understanding of blockchain implementation in the supply chain. Leveraging the rich body of research on RFID implementation may help accelerate and nuance the learning about blockchain in the supply chain and in this respect the Reyes et al. (2016) framework for the implementation of RFID in the supply chain may be informative and helpful. In particular because recent studies point at similarity in supply chain functionality between RFID and blockchain. Both technologies support visibility and traceability throughout the supply chain (Saberi et al., 2018; van Hoek, 2019a, b) making them more similar than other technologies such as ERP or robotics that offer distinctly different functionalities. Additionally, recent papers have indicated that RFID and blockchain could complement each other well when adopted in concert with blockchain (Biswas et al., 2017; Chen et al., 2017; Galvez et al., 2018; Saberi et al., 2018; Toyoda et al., 2017). Tseng et al. (2018), for example, suggest the use of RFID for data capture and blockchain for the authentication and dissemination of these data throughout the supply chain.

In summary, there is great interest in blockchain as a newer technology in the supply chain, in both research and industry. Given the lack of empirical exploration of blockchain implementation in the supply chain and because of the similarities with RFID technology, there may be opportunities to use the existing framework for the implementation of RFID from Reyes et al. (2016) to inform consideration of blockchain in the supply chain. This may also help avoid needing to relearn lesson in research and industry. We therefore pose the following research question:

**RQ1.** How can the Reyes et al. (2016) framework for the implementation of RFID in the supply chain inform the consideration of blockchain in the supply chain?

The remainder of this paper is structured as follows: the next section will review literature on the blockchain implementation in the supply chain, further consider why RFID literature may be a relevant source of lessons learned and review RFID literature for implementation considerations. An overview of implementation drivers, barriers and benefits of RFID is generated and the comprehensive implementation framework from Reyes et al. (2016) is used to frame lessons learned about implementation considerations. This provides the basis for a two-part empirical exploration of blockchain in the supply chain. The first part in a broad quantitative exploration of implementation considerations using a focus group and a survey. The second part is a more qualitative set of rare and rich multiple case studies of companies that are pioneering and actually implementing blockchain in the supply chain. Based upon the cross-method comparison of findings we adapt the Reyes et al. (2016) RFID implementation framework to inform the consideration of blockchain in the supply chain and are able to develop a decision framework for considering blockchain in the supply chain.
2. Literature review – blockchain in the supply chain and factors from RFID literature to consider
Given the wide interest in blockchain in the supply chain (Mena et al., 2018; van Hoek et al., 2019; Dobrovnik et al., 2018) stress the relevance of more detailed consideration of blockchain in the supply chain:

Despite the claim that blockchain will revolutionise business and redefine logistics, existing research so far is limited concerning frameworks that categorise blockchain application potentials and their implications. In particular, academic literature […] to date has not sufficiently distinguished between blockchain adoption (“what to adopt”) and the identification of the right business opportunity (“where to start”).

Regarding “where to start,” companies may perceive barriers to the implementation of blockchain in the supply chain. Even if only perceived by managers interested in blockchain, these are still of relevance as perceived ease of use of blockchain in the supply chain has been found to influence intention to implement (Kamble et al., 2018). Based upon a conceptual exploration, Saberi et al. (2018) point at intra-organizational, inter-organization and system related barriers. Intra-organization barriers include financial constraints, lack of managerial commitment and lack of knowledge and expertise. Inter-organization barriers include challenges with information disclosure policy between supply chain partners and problems in collaborating, communicating and coordinating in the supply chain. Cole et al. (2019) state that blockchain can impact the relationship between supply chain parties and, more specifically, Wang et al. (2019) point at the need to build a blockchain ecosystem by involving the right supply chain partners and establishing a governance model. Finally, Saberi et al. (2018) and Wang et al. (2019) point at system related barriers including security concerns, system reliability issues and the need to integrate blockchain with existing supply chain technology.

In response to Dobrovnik et al.’s (2018) question “what to adopt,” Ksherti (2018) and Verhoeven et al. (2018) found a number of different use cases in the public domain ranging from sourcing applications upstream in the supply chain to shipping applications further downstream in the supply chain. A review of the literature indicated that blockchain can be applied in different sections of supply chains, varying from sourcing, manufacturing, warehousing, transportation and logistics (Conoscenti et al., 2016; van Hoek, 2019a, b). These existing studies of high-level use cases and early pilots focus on early stages of implementation and Wang et al. (2019) call for research into scaling implementation across the supply chain.

2.1 Parallels between RFID and blockchain
There are at least three reasons for specifically considering lessons learned from RFID research when considering blockchain in the supply chain. These are: similarities in hype as pointed out by Gartner and focus in research, similarity in functionality and use cases that is stronger than with other supply chain technologies and a growing call for considering combined applications of RFID and blockchain in the supply chain making it relevant to consider lessons learned about RFID implementation.

2.1.1 Similarity in hype and research focus. In 2003, after the US Department of Defense (DOD) and several major retailers around the world announced plans for large scale RFID implementation throughout their supply chains, there was a lot of interest in the technology. Predictions of an RFID revolution in the supply chain were common (Srivastava, 2004) and a fair amount of myth about the potential of RFID was created (Reyes and Jaska, 2007). One of them was that RFID was going to replace barcodes (Thiesse et al., 2011). As Gartner pointed
out, blockchain is receiving similar attention today as RFID did 15 years ago. Because RFID has been around longer, fortunately, a healthy body of research as been able to be developed, empirically investigating true implementation, benefits and challenges of implementing RFID in the supply chain (Vijayaraman and Osyk, 2006; Li et al., 2010).

With RFID technology we may have gone through precisely what Treiblmaier (2018) is warning for when pointing at the risk of unrealistic expectations for blockchain. Treiblmaier’s research also reveals a similarity with RFID research when it comes to questions asked. He explores how economic theories such as the resource-based view of the firm and transaction cost economics could inform blockchain decision making. This is a question that Cannon et al. (2008) already answered for RFID, considering the same theories.

2.1.2 Similarity in functionality and use case. Recent studies point at similarity in supply chain functionality between RFID and blockchain. Both technologies support visibility and traceability throughout the supply chain (Saberi et al., 2018; van Hoek et al., 2019) making them more similar than other technologies such as ERP or robotics that offer distinctly different functionalities. Additionally, unlike other widely studied supply chain technologies such as ERP or robotics, RFID and blockchain are also used primarily in a cross company supply chain setting, across supply chain tiers, instead of inside a company and in one segment of the supply chain.

2.1.3 Combined implementation reinforcing relevance of RFID lessons learned. Recent papers have indicated that RFID and blockchain could complement each other well when adopted in concert in a joint supply chain implementation (Biswas et al., 2017; Chen et al., 2017; Galvez et al., 2018; Saberi et al., 2018; Toyoda et al., 2017). In the study and development of numerous different supply chains, from food to fishing to wine production to governance of the drugs supply chain authors have pointed at the value of combining RFID and blockchain. Tseng et al. (2018), for example, suggest the use of RFID for data capture and blockchain for the authentication and dissemination of these data throughout the supply chain. In making this connection, blockchain can enable faster dissemination of RFID data across multiple tiers in the supply chain simultaneously. This is functionality that RFID technology can do not achieve by itself.

2.2 Lessons learned about the implementation of RFID in the supply chain

In one of the more recent studies of the implementation of RFID in the supply chain Reyes et al. (2016) offer both a critical review of RFID implementation and develop a framework for understanding implementation. The framework is shown in Figure 1 and it may provide a

![Figure 1. Model for implementing RFID in the supply chain](source: Revised from Reyes et al. (2016))
framework that can be used for the study of blockchain in the supply chain. Reyes et al. (2016) build upon a rich body of research on RFID in the supply chain and several solid literature reviews (Lim et al., 2013; Ngai et al., 2008; Sarac et al., 2010).

The Reyes et al. (2016) framework for the empirical study of RFID implementation in the supply chain is comprehensive and considers implementation dynamics and degrees of implementation over time, without assuming overnight implementation. Nor does it imply that RFID makes existing technologies obsolete. The framework realistically considers barriers as well as performance and economic benefits and provides a clear overview of key considerations and their interrelations. Thus, the framework can be used to realistically, without hype, inform senior management about implementation considerations. The framework as displayed in Figure 1 includes a few added considerations within the main constructs based upon our review of existing literature as shown in the Appendix.

Reyes et al. (2016) break drivers for RFID implementation into internal and external drivers. Internal drivers that are commonly referenced in literature include operating costs reductions, improved visibility and tracking and reductions in out of stocks. The most commonly referenced external driver is customer pressure. A third driver of RFID implementation in the Reyes et al. (2016) framework is leadership commitment. This area is broken into top management and middle-level management commitment. But only top management commitment was found to be a significant driver of implementation (Reyes et al., 2016). The importance of top management commitment is obvious (van Hoek et al., 2010), particularly in emerging technologies. It can drive focus, investment and resourcing. But middle management is key for the implementation of new technology, process and capability (van Hoek et al., 2014). Reyes and Jaska (2007) specify several types of managers who should be involved in the effective implementation of RFID. Perhaps this reflects middle-management engagement more than just commitment.

There are four barriers to RFID implementation included in the Reyes et al. (2016) framework – cost issues, lack of understanding, technical issues and privacy issues. Based upon the review of literature, we reframed the cost barrier to “cost and financial issues.” Items that were missing from the cost issue factor in Reyes et al. (2016) are that the cost of maintaining the system may be high (Li et al., 2010) and that there may be a lack of funds (Vijayaraman and Osyk, 2006). Frequently referenced cost issues are the costs of tags and readers and the ROI on the investment being too low and uncertain (Smart et al., 2010). Within lack of understanding, the item “lack of understanding about RFID technology and its implementation in the supply chain” is frequently referenced, followed by “resistance from employees.” The latter is argued to be driven by a fear of jobs being automated away (Hou and Huang, 2006; Bhattacharyya, 2012). Technical issues most frequently referenced are system reliability issues and lack of standards (Chuang and Shaw, 2007) The lack of a business case to benchmark against and to justify costs vs benefits is referenced as a barrier in several studies (Prater et al., 2005; Chuang and Shaw, 2007).

Implementation of RFID was measured with a qualitative scale ranging from not considering, to considering, piloting and implementing (Vijayaraman and Osyk, 2006; Reyes et al., 2016). Additional measures used include implementation paths (Lee et al., 2008), scale and scope of implementation (Roh et al., 2009), and areas of supply chain implementation (Zelbst et al., 2012). Benefits of RFID studied include costs and productivity improvements (Shin and Eksioglu, 2014), customer service (Sarac et al., 2010), improved asset management (Tzeng et al., 2008) and communication between channel partners (Lim et al., 2013), improved inventory efficiency (Shin and Eksioglu, 2014), reduced inventory shrinkage (Rekik et al., 2008), improved visibility and tracking (Prater et al., 2005) and speed and inventory flow (Ferrer et al., 2010).

3. Method
We use multiple methods that can complement each other and build upon each other toward a richer empirical exploration. This study is structured into two stages, initial exploration
using a focus group and a survey and further exploration using a multiple case study method. Initially, implementation considerations were explored in a focus group with managers interested in blockchain in the supply chain. This served the purpose of beginning to identify relevant implementation considerations suggested in RFID research for considering blockchain in the supply chain. Next, the exploration is continued using a high-level survey of 99 managers. The survey serves the purpose of beginning to evaluate the relevance of considerations statistically. The use of this initial exploration using a survey is in line with Goldsby and Zinn’s (2018) call for more multi-method research, combining qualitative and quantitative research when studying complex phenomena. They suggest that survey research can be used to frame, rather than to statistically generalize a problem, perhaps counter to common uses of multi-method and survey research, in that way returning to its descriptive roots. The use of a survey in this stage of research and with this objective is obviously different from the more conventional survey research focused on robust statistical generalization. However, our research explores a terrain where there is very little empirical research and industry experience and practice in existence today. As a result, we feel that it is more appropriate to use the survey to broadly explore and provide input to the deeper exploration in case studies. Put differently, the current state of research may not yet make robust statistical generalization appropriate, nor may there be the sample of companies that are implementing blockchain available to survey at this point.

The next stage in our research involved conducting multiple case studies of companies that are actually piloting and pioneering blockchain in their supply chains. The case studies provide an opportunity to learn from innovators such as called for by Ferdows (2018). Table I further outlines how the methods and research stages complement and supplement each other in our research design.

### 3.1 Initial exploration using focus group and survey

A focus group was organized with EMBA alumni, bringing together executives for a highly interactive worksession on blockchain in the supply chain. In order to provide a basis for the

<table>
<thead>
<tr>
<th></th>
<th>Focus group</th>
<th>Survey</th>
<th>Case studies</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Primary contribution to the goal of</strong></td>
<td>Simplicity</td>
<td>Initial generalization about key consideration</td>
<td>Accuracy</td>
</tr>
<tr>
<td><strong>Secondary contribution to the goal of</strong></td>
<td>Accuracy</td>
<td>Accuracy</td>
<td>Simplicity</td>
</tr>
<tr>
<td><strong>Least performing on Set up</strong></td>
<td>Generalization</td>
<td>Simplicity</td>
<td>Generalization</td>
</tr>
<tr>
<td></td>
<td>Discussion amongst interested executives facilitated by author</td>
<td>Survey of interested executives using items generated in focus group</td>
<td>Deep dive study of case companies</td>
</tr>
<tr>
<td><strong>Objective-contribution</strong></td>
<td>Learning from interested companies</td>
<td>Learning from interested companies</td>
<td>Learning from pioneers</td>
</tr>
<tr>
<td></td>
<td>Exploring considerations at high level</td>
<td>Exploring engagement specifically (found key in focus group) with early statistical analysis</td>
<td>Exploring considerations and implementation factors holistically</td>
</tr>
<tr>
<td></td>
<td>Identify relevant considerations descriptively</td>
<td>Begin to evaluate relevant considerations identified in focus group descriptively</td>
<td>Dive deeper into relevant considerations identified in focus group and survey</td>
</tr>
</tbody>
</table>

| Geographical scope | USA | Europe and USA | Companies in Europe and USA |

**Table I.** Overview of research methods used
discussion participants were asked to complete a questionnaire in advance of the meeting and aggregated findings were used during the session to drive discussion. The questionnaire used items from RFID literature (see Appendix 1). Across the 58 participants a number of industries were represented. There was a concentration of retailers (14 participants) and consumer products companies (12 participants). Additionally, professional and financial services (12 participants) and logistics services (4 participants) were prominently represented. Participant experience ranged from manager to vice president.

In order to further the exploration of implementation considerations and the validity of items from RFID literature for blockchain, we conducted a survey among supply chain professionals in both the USA and Europe. Data were collected online from 330 conference attendees during a supply chain conference in Finland, 20 university research center participants in the USA and 220 supply chain executive contacts in the professional network of the author. Because we set out to study considerations of interested companies specifically, not a random sample of companies we intentionally used a convenience sample. Additionally, because blockchain is a newer technology there may not yet be that many companies with interest and experience to make it possible to survey a random sample.

A total of 99 responses were received in a six weeks period, leading to a response rate of 17.37 percent. This represents a response rate higher than that in most papers referenced in the literature review and well above, for example, Li et al. (2010), who received 49 respondents from an unspecified sample size of several hundred. Non-response bias was assessed by comparing responses for the first 20 percent of respondents to the last 20 percent of respondents. No statistically significant differences were found in these tests. Table II provides demographic information of the survey respondents. There are a wide variety of industries represented in the sample, which enhances the generalizability of the findings. In addition, the size of the firms is fairly evenly distributed across the brackets listed.

3.2 Further exploration using case studies

Three case studies of companies piloting blockchain in the supply chain were found and studied. Table III offers details on these companies. The companies represent different industries and positions in the supply chain (e.g. logistics providers, consumer product manufacturers and retailers), geographies (North America and Europe), and blockchain applications (international shipping and tracking, tracing of ingredients and creating transparency of the environmental footprint of supplies used). This serves as a basis for broader exploration, which is appropriate at this early stage of knowledge development.

While the inclusion of three case studies may represent a smaller number of companies than in some other blockchain studies, it should be taken into consideration that these are case studies that go beyond the use case stage and publicly available data used in existing research. They study pioneers well into their implementation process and this represent empirical scope beyond existing research. We should acknowledge also that there are not that many pioneers that are this far along into the implementation process.

<table>
<thead>
<tr>
<th>Industry</th>
<th>Logistics and transportation – 20%</th>
<th>Other manufacturing – 15%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Energy, Oil and Gas – 11%</td>
<td>CPG and FMCG – 11%</td>
</tr>
<tr>
<td></td>
<td>Healthcare and medical technology – 10%</td>
<td>Construction – 8%</td>
</tr>
<tr>
<td></td>
<td>Technology and high tech – 6%</td>
<td>Media and entertainment – 4%</td>
</tr>
<tr>
<td></td>
<td>Financial services and insurance – 4%</td>
<td>Retail – 3%</td>
</tr>
<tr>
<td></td>
<td>Wholesale – 2%</td>
<td>Hospitality – 2%</td>
</tr>
<tr>
<td>Revenue size</td>
<td>&lt; $500m – 18%</td>
<td>&gt; $500m–$1bn – 22%</td>
</tr>
<tr>
<td></td>
<td>&gt; $1bn–$20bn – 39%</td>
<td>&gt; $20bn – 21%</td>
</tr>
</tbody>
</table>

Table II. Respondent’s demographics
The case studies were conducted through multiple interviews with multiple informants representing different levels in the company (executive and manager), as well as different functional domains (IT and supply chain). Additionally, we interviewed informants at different levels and forms of involvement in the pilots, including project team members and sponsoring executives. We also included an external consultant involved in case companies 1 and 3 to get an outside perspective from an expert who is involved in the pilots. Internal company reports and videos were also used as sources. Table IV offers further detail on the case study process used leveraging screens for rigorous case study research from Barratt et al. (2011) and Beverland and Lindgreen (2010).

<table>
<thead>
<tr>
<th>Case Study 1</th>
<th>Case Study 2</th>
<th>Case Study 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry</td>
<td>Logistics services</td>
<td>Food and beverage products</td>
</tr>
<tr>
<td>Location</td>
<td>North America</td>
<td>Europe</td>
</tr>
<tr>
<td>Focus of pilot</td>
<td>International shipping lanes</td>
<td>Tracking and tracing of ingredients and environmental footprint upstream in the supply chain</td>
</tr>
<tr>
<td>Number of informants</td>
<td>4 (multiple calls with each)</td>
<td>2 (multiple meetings with each)</td>
</tr>
<tr>
<td>Level of informants</td>
<td>Senior supply chain and IT executives and project team members</td>
<td>Senior (global supply chain leadership team) and project team member</td>
</tr>
<tr>
<td>Function of informants</td>
<td>Supply chain, commerce, IT and external consultant</td>
<td>IT and supply chain</td>
</tr>
<tr>
<td>Additional sources</td>
<td>Project documentation, consultant documents and templates used</td>
<td>Project documentation and internal video of project team online work meetings testing the blockchain, also used to communicate internally</td>
</tr>
</tbody>
</table>

Table III. Case study details

The screens for rigorous case study research and how they are covered in this research include:

- **Number of cases**: Case studies from different continents and industries to enable both broad explorations, as well as to be able to reflect upon findings across different operating environments.
- **Explicit justification of case method**: Justified based upon the limited amount of research and practice in place today; there are very few known applications to be studied and this study aims to begin to explore blockchain applications in the supply chain in this infancy stage.
- **Data sources**: Observation, files, documents and video, in depth discussion.
- **Reliability**: Multiple informants and multiple interviews and data sources help reduce risk of bias.
- **Interview and coding process**: Author populated the case study item table and cross-referenced findings from one conversation to the next. Drafted findings were also shared back with the case companies for verification, correction, addition and validation.
- **Number of coders**: Author in multiple steps, from in-company documents to discussing and testing findings with company representatives to reviewing drafted cases study reports. Pattern matching through cross-case comparison.
- **Internal validity**: Multiple case studies in different continents and industries.
- **External validity**: The blockchain pilot of the case companies.
- **Unit of analysis**: The blockchain pilot of the case companies.
- **Theory vs phenomenon focus**: Study is grounded in existing RFID literature aiming explicitly to leverage learning from prior research into this new technology domain.
- **Data analysis**: Within and cross-case analysis.
4. Findings from the initial exploration
In order to explore the relevance of considerations from RFID literature for blockchain implementation, participants in the focus group were first asked to rate relevance of items from RFID research using a seven-point Likert scale, ranging from 1 "not at all" to 7 "to a very large degree." Figures 2 and 3 show average scores ranked from high to low, and these tables were used to drive discussion during the focus group.

Regarding drivers, pressure from customers ranks low. This may indicate a difference from RFID, which initially had pressure from customers surrounding its implementation. The top-ranking drivers surround transparency and visibility drivers and a substantial portion of the workshop discussion surrounded this theme. One participant indicated how blockchain can build upon RFID capability:

With blockchain you can make RFID data available throughout the supply chain and this accelerates its impact and grows the transparency that it helps create.

The drive to fix processes is also an interesting item. In the words of one participant:

If we can have greater transparency throughout the supply chain faster, we can begin to identify processes that need improving – such as in case of responding to food safety issues.

The importance of this driver may indicate that managers are turning their attention beyond initial use case considerations to what improved transparency can help them achieve. In the words of one participant:

Blockchain can offer new functionality and supply chain capability, and this is interesting.

Figure 2. Drivers for blockchain implementation in the supply chain
While blockchain consideration may be less driven by customer demand or mandate, interested companies and managers do explicitly consider supply chain objectives, just as Ksherti (2018) suggested they should.

Regarding barriers, interestingly enough, security, data integrity and technical issues with hardware and software rank toward the bottom of the list. Participants had lots of questions and recognized a need to develop greater understanding of how to integrate blockchain into their supply chain processes, as well as the benefits, the costs and the ROI of doing so. In the words of one participant:

> It is not hard or expensive to start a blockchain pilot. But, beyond the initial technical proof of concept and the initial pilot, the question becomes how to scale throughout the supply chain and what will the cost and the ROI of that be — we don’t know enough about that yet.

This limited understanding today reinforces the relevance of including the focus group exploration; pioneers may not have this lack of understanding, yet many interested managers and companies are asking lots of questions. The consideration being given is positive because it reinforces the relevance of our research and the value of aiming to learn from pioneers.

It was clear from the discussions during the workshop that the concerns are far less about the technology and a lot more about how to adopt and roll the technology out well. This is positive because in their study of use cases Verhoeven et al. (2018) found that the
technology is sometimes picked first, and the problem is applied to a blockchain solution afterwards. This risk may be decreasing.

Participants did indicate that engagement and leadership commitment in blockchain is a key consideration for them today:

There is so much interest in blockchain today around the company and this is really driving a willingness to get started and pilot.

Executives are interested in blockchain and are asking their teams what we are doing with blockchain in our supply chain – this is driving consideration and focus on pilots and use cases. It makes it easier to make the business case, set up a team and include blockchain on the technology roadmap.

These considerations were not included in the focus group discussion document and it seemed relevant therefore to use the high-level survey to further study engagement as a consideration identified to be of great relevance.

Whereas the focus group explored drivers and barriers of blockchain implementation, we used the survey to explore the other key factors impacting implementation; leadership commitment and engagement as also identified as a key consideration in the focus groups. Because of the lack of supply chain-wide implementation of blockchain, we chose to ask respondents to indicate if they were piloting blockchain in their supply chain or not. Next, we asked respondents to indicate the degree of engagement in blockchain using a seven-point Likert scale ranging from −3 (not at all) to +3 (very much so).

Table V shows one-way ANOVA analysis comparing average scores for respondents that are piloting vs respondents that are not piloting blockchain in their supply chain. All of the differences between those averages were found to be significant ($p < 0.01$). As a result, our exploration indicates that executive engagement does matter for the implementation of blockchain in the supply chain, as was the case with the implementation of RFID in the supply chain. This engagement breaks out into both executive and operational management engagement. Additionally, this engagement should be leveraged to develop a strategy for the implementation of blockchain, a business case, a roadmap and a programmatic approach that is staffed with a team. Table VI presents correlation coefficients between these items. The large coefficients imply that there may be opportunities for multi-item scale development in the future as research progresses beyond initial exploration stages. We will revisit this in the future research suggestions.

The findings from the focus group and the survey indicate that implementation factors and considerations suggested in RFID literature are relevant for the consideration of blockchain in the supply chain. In the next section, case study findings will be presented to further explore implementation factors and considerations.

5. Findings from case studies
5.1 Case Study 1
Case Company 1 is a logistics service provider that is piloting blockchain in an international shipping lane. The international flow of goods involves hundreds of documents – customs forms, shipping logs and other records. The company hoped that blockchain could make these documents available sooner and easier. The blockchain pilot is customer facing and tracks shipments through an international shipping lane. The small scale and scope were very intentional. As a consultant involved in the pilot described:

If you keep a use case focused, you can move fast and learn fast. What is key during the process is that you keep watching for scope creep and the natural tendency of project team members to start solving more and more things during the process. You need to keep a long backlog of issues for phase 2, otherwise you can quickly get bogged down in complexity.
Table V.
Comparison of engagement scores between companies that are and that are not piloting blockchain in the supply chain, one-way ANOVA

<table>
<thead>
<tr>
<th>Question</th>
<th>Not Piloting Blockchain</th>
<th>Piloting Blockchain</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>To what degree is there recognition in your company for the potential of</td>
<td>-0.94</td>
<td>1.47</td>
<td>0.000</td>
</tr>
<tr>
<td>blockchain in the supply chain?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>To what degree is there executive engagement in your company in</td>
<td>-1.16</td>
<td>1.09</td>
<td>0.000</td>
</tr>
<tr>
<td>blockchain in the supply chain?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>To what degree is there operational management engagement in your</td>
<td>-1.49</td>
<td>0.97</td>
<td>0.000</td>
</tr>
<tr>
<td>company in blockchain in the supply chain?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>To what degree does your company have a strategy in place for blockchain</td>
<td>-1.81</td>
<td>0.38</td>
<td>0.000</td>
</tr>
<tr>
<td>in the supply chain?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>To what degree does your company have an accepted business case in</td>
<td>-1.64</td>
<td>1.12</td>
<td>0.000</td>
</tr>
<tr>
<td>place for blockchain in the supply chain?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>To what degree does your company have a program in place for blockchain</td>
<td>-2.02</td>
<td>0.53</td>
<td>0.000</td>
</tr>
<tr>
<td>in the supply chain?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>To what degree does your company have a roadmap in place for blockchain</td>
<td>-1.92</td>
<td>0.41</td>
<td>0.000</td>
</tr>
<tr>
<td>in the supply chain?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>To what degree does your company have a dedicated team in place for</td>
<td>-1.95</td>
<td>0.35</td>
<td>0.000</td>
</tr>
<tr>
<td>blockchain in the supply chain?</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The pilot started when both chief executive officer (CEO) and the chief commercial officer expressed an interest in blockchain and inquired internally as to what was being done with blockchain. This led to the commercial team volunteering for a pilot. Counter to common practice, the company did not go through a business case development process. The interest of the CEO and anticipation from the commercial leadership team that innovating in blockchain could provide meaningful attention and potential differentiation in the marketplace was sufficient bases for launching a pilot. As the supply chain team member on the project team described:

It was pretty simple to get going. Leadership was interested, the pilot was inexpensive, and we saw real potential to stand out in the marketplace with blockchain innovation and drive revenue based upon that. Furthermore, the chief information officer (CIO) stated:

There were also other benefits we anticipated including improved transparency of the flow of goods, reduced administrative burdens, resulting in increased speed in the flow of goods.

Regarding barriers and obstacles, some differences with RFID implementation were found, at least at this pilot stage. Costs concerns are lower because no major investments in hardware were needed and coding requirements were limited. Leveraging insights from an external consultant also made the pilot faster and more doable. A lack of understanding about blockchain was more of a driver behind the pilot and less of a barrier:

We were really hoping to learn fast and experiment to develop lessons learned. (CIO)

Technical issues were fewer than with RFID, at least in the pilot stage. Beyond the pilot stage, however, the blockchain needs to be scaled across more parties and computing powers need to increase. Additionally, data entry is manual and results in possible integrity and accuracy issues. So, unlike RFID, there is less of a system reliability and privacy issue with blockchain pilots, but interoperability between different systems and blockchains and integrity of data may create barriers.

It is too early in the pilot project to fully evaluate the benefits achieved from the pilot. However, similar to RFID not replacing the barcode, blockchain is also not replacing existing technology. In fact, it uses existing EDI links and RFID data as inputs to its dataset:

We are not replacing technology. We are getting more out of it and creating a neutral platform where we can pull data together to get a more visibility. (Supply Chain manager involved in the pilot)

Integrating systems creates more information availability earlier in the process so that documentation can be handled with fewer errors. The benefits are faster flow through, fewer hold ups for the shipper and improved asset utilization.

5.2 Case Study 2
Case Company 2 is food and beverage company. Its pilot centered around tracking the environmental impact of ingredients from upstream suppliers through the supply chain.

<table>
<thead>
<tr>
<th></th>
<th>Recognition of potential</th>
<th>Executive engagement</th>
<th>Operational engagement</th>
<th>Strategy in place</th>
<th>Accepted business case</th>
<th>Program in place</th>
<th>Roadmap in place</th>
</tr>
</thead>
<tbody>
<tr>
<td>Executive engagement</td>
<td>0.776</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operational engagement</td>
<td>0.738</td>
<td>0.812</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Strategy in place</td>
<td>0.663</td>
<td>0.741</td>
<td>0.745</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Accepted business case</td>
<td>0.698</td>
<td>0.709</td>
<td>0.741</td>
<td>0.736</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Program in place</td>
<td>0.692</td>
<td>0.728</td>
<td>0.787</td>
<td>0.903</td>
<td>0.822</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Roadmap in place</td>
<td>0.717</td>
<td>0.760</td>
<td>0.773</td>
<td>0.880</td>
<td>0.807</td>
<td>0.915</td>
<td></td>
</tr>
<tr>
<td>Dedicated team in place</td>
<td>0.645</td>
<td>0.701</td>
<td>0.744</td>
<td>0.857</td>
<td>0.765</td>
<td>0.929</td>
<td>0.849</td>
</tr>
</tbody>
</table>

Table VI. Pearson correlation coefficients between engagement items all significant at 0.01 level, two tailed
Linking energy and water consumption information from suppliers to shipments, consumer can scan the barcode on a product on the shelf and see the environmental impact of the ingredients used in that product.

The pilot started after the IT team had communicated about blockchain technology to company leadership in a standing brief about new technologies. This was followed by an internal session with leadership from various functions exploring potential use cases for blockchain. As an outcome of this session, there were requests to the IT team to start pilots. The chief procurement officer (CPO) and the procurement team were among the first and most engaged, and its use case was selected for a pilot:

It really helped that both the CIO and the CPO wanted to do this pilot, and it helped that there was a procurement manager who was also really willing to commit. (IT manager on the project team)

The limited investment needed in the pilot was provided by the CIO and the CPO, and an external consultant also absorbed some of the costs for the development work. The consultant provided external expertise and resources, as well as some investment.

Case Company 2 also found that the use case and teaming are key:

It is not about the technology. That is the easy part. It is about finding a relevant process and a group of stakeholders internally and externally who are willing to engage. We had great engagement from the procurement leadership and from procurement management on the project team. We had an external partner willing to invest, and we found a supplier that was willing to pilot – that is what it took to get going. (IT project team member)

Case Company 2 also leveraged existing technologies, such as barcodes, in its pilot. The scale and scope of the pilot was kept very focused on one type of ingredient and a limited set of the supply line, in order to be able to develop the pilot fast.

The benefits achieved in the pilot are new levels of visibility into the energy and water consumption throughout the supply chain. Consumers can scan the barcode on a product and see its upstream environmental impact. The focus for case Company 2 is less on speed, cost and inventory reduction and more about developing new capabilities to achieve the company’s sustainability objectives and respond to consumer demands.

5.3 Case Study 3
Case Company 3 is piloting blockchain as a technology that can track product from the retail shelf back to the producer. What is different from the focus on RFID is that the use case is less focused on on-shelf availability and product inventory. Instead, the focus is on the ability to track product quality or safety issues upstream to the producer. The benefit is the ability to address issues at the source quickly without needing to shut down the entire supply chain. Traditionally, when there is an incident of salmonella in lettuce, for example, the entire supply chain is shut down. All lettuce is removed from the shelves and it takes days if not weeks to find the source of the problem before the supply line can be reopened. In the traditional process there is significant waste, all producers are impacted by the shut down (not just the producer that caused the issue) and consumers are faced with product unavailability and fear.

The intended use of case Company 3’s blockchain pilot is to not have to shut down the entire supply chain for days or weeks. Instead, they can address the concern with the producer right away by tracing the product back to the producer within seconds, not days or weeks. This has tremendous customer service benefits, financial benefits and sustainability benefits; less waste, minimal supply chain disruption and limited impact on product availability and on non-troublesome suppliers. As a supply chain manager describes:

The ability to target product issues without needing to shut down the entire supply chain holds big consumer value; better product on the shelf in an economical manner.
The pilot focused on establishing proof of concept. By working with one farmer and one product group, across several pilot efforts proof of concept was established. The company was able to start piloting quickly by keeping the pilot scope small and by engaging just a few interested supply chain partners. Obviously, this means that scaling beyond the pilot may require more work and a greater effort. As the CIO puts it:

If the technology works that is great but if you have proof of concept you have not yet rolled it out to the supply chain – that will require a lot more than a working technology.

5.4 Cross-case comparison and interpretation of findings

Table VII summarizes findings using the factors from the Reyes et al. (2016) framework.

5.4.1 Drivers. In all three case companies, the consideration of blockchain in the supply chain is driven by customer and market considerations. Whether being innovative in the eyes of customers for case Company 1, creating new customer visibility for case Company 2 or greater product safety for consumers in case Company 3 all use cases prominently feature the customer. The customer however, is featured in a different way than in many RFID implementations. Customer-mandated implementation drove more RFID implementation than it does with blockchain. And internal consideration of blockchain represents more critical drivers. Whether it be the desire to improve sustainability in case Company 2, reduce administrative burdens in case company or improve traceability in case Company 3, all case companies have clear internal interests that are driving them to consider blockchain in the supply chain. This does not, however, mean that implementation is only driven by internal considerations. As is the case with RFID, blockchain is very much considered across supply chain tiers and multiple companies.

5.4.2 Leadership commitment. Case companies indicate that blockchain implementation can begin quickly with selected senior and middle/operational management engagement. This is in contrast to RFID implementation, which requires greater upfront technology and equipment investment. The case companies intentionally scoped their pilots narrowly to allow for a quick start and rapid learning. In addition to the engagement of a few senior executive sponsors and operational management peers, engagement of a few supply chain players (supplier, farmer, shipper) is also key to start a pilot.

5.4.3 Barriers. With the narrow and targeted scoping of blockchain pilots, case companies are able to begin implementation quickly. It also reduces the need for a business case because funding requirements are limited, and a pilot can provide a rich opportunity to learn and reduce lack of understanding about the technology. Interestingly, in all three case companies, technical and privacy issues were not perceived as a barrier in the pilot stage. Additionally, like with RFID technology, blockchain technology does not typically replace existing technology (despite popular claims about this). Instead, case companies use data feeds from existing technologies (RFID in case Company 1 and bar codes in case Companies 2 and 3).

Implementation – All three case companies were still uncertain of their ability to scale the implementation across the supply chain. Case Company 1 noted a lack of standards, case Company 2 cited limits on supplier acceptance if multiple forms of data entry are required for blockchain, and case Company 3 stressed that moving beyond proof of concept may require more time and effort.

5.4.4 Benefits. While case companies have achieved proof of concept in their pilots, the benefits considered as part of the use case are not fully experienced in the pilot setting. However, it is clear that there is substantial overlap with RFID benefits in areas such as visibility, tracking and improved communication throughout the supply chain. This may lead to cost reductions, productivity and inventory benefits, but the case companies are more focused on improving service and disseminating data more quickly.
<table>
<thead>
<tr>
<th>Items from literature</th>
<th>Case study 1</th>
<th>Case study 2</th>
<th>Case study 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Drivers</strong></td>
<td>Improving transparency and reducing administrative burdens enabling the</td>
<td>Commitment to sustainability and an interest in learning and experimenting with</td>
<td>Improving ability to trace sources of product safety issues upstream much faster</td>
</tr>
<tr>
<td>Internal drivers</td>
<td>speeding up of the supply chain. Fewer drivers than suggested in literature for</td>
<td>technology as part of larger supply chain digitization ambitions</td>
<td>and effectively</td>
</tr>
<tr>
<td>RFID and external</td>
<td>were more important</td>
<td></td>
<td></td>
</tr>
<tr>
<td>External drivers</td>
<td>Key factors: Interest in using blockchain to be seen as innovative and to</td>
<td>While tracking and tracing and supply chain transparency also is a driver in</td>
<td>Potential consumer benefit critical driver behind pilot</td>
</tr>
<tr>
<td></td>
<td>differentiate the company in the market. This is different from drivers found in RFID;</td>
<td>RFID, the use of that is different here. The focus is on creating environmental</td>
<td></td>
</tr>
<tr>
<td></td>
<td>it is less driven by big customer pull and more by supplier push</td>
<td>impact visibility throughout the supply chain</td>
<td></td>
</tr>
<tr>
<td>Top management</td>
<td>CEO and Chief Commercial Officer interest drove early efforts and made it</td>
<td>CIO and CPO engagement made funding and staffing easy</td>
<td>Supply chain and IT leadership driving but pilot was also featured in</td>
</tr>
<tr>
<td>leadership</td>
<td>easy to drive engagement, establish funding and resourcing</td>
<td></td>
<td>investor day presentation and citizenship report</td>
</tr>
<tr>
<td>Middle-level</td>
<td>Leaders in IT, operations and commerce keenly jumped on the opportunity to</td>
<td>Engagement at the management level and the supplier level were key drivers</td>
<td>In addition to internal project team, supported by consultants, supplier</td>
</tr>
<tr>
<td>management leadership</td>
<td>pilot and learn</td>
<td></td>
<td>engagement was key</td>
</tr>
<tr>
<td><strong>Barriers/obstacles</strong></td>
<td>The pilot was inexpensive and different from RFID, did not require major</td>
<td>Investment was raised between CPO and CIO, as well as the consultant. The</td>
<td>Pilot scoped with focus to enable small budget and rapid ramp to pilot</td>
</tr>
<tr>
<td>Cost/financial</td>
<td>investment in coding or hardware. It did require resourcing across the</td>
<td>targeted scoping and scaling enabled a very affordable pilot budget</td>
<td></td>
</tr>
<tr>
<td>issues</td>
<td>stakeholders involved and consultant support. But because of the scope and</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>the desire of the consultant to learn with the client, these costs were</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>relatively low</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lack of understanding</td>
<td>The pilot was highly driven by a desire to develop understanding and provide</td>
<td>The pilot was driving by a desire to learn and experiment and consider future</td>
<td>Pilot centered around developing proof of concept of the technology</td>
</tr>
<tr>
<td></td>
<td>a basis for future larger scale roll out. Most of the RFID unknowns</td>
<td>scaling potential</td>
<td></td>
</tr>
<tr>
<td></td>
<td>mentioned in literature apply to blockchain</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technical issues –</td>
<td>In the pilot, there were few technological concerns; the technology is</td>
<td>Technology was not seen as a key bottleneck in the development of the pilot.</td>
<td>Proof of concept was established but to move from pilot to larger scale</td>
</tr>
<tr>
<td>internal and</td>
<td>relatively straight forward and coding</td>
<td>Scaling beyond the pilot</td>
<td>implementation requires</td>
</tr>
<tr>
<td>external</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table VII.  
Case Study findings  
(continued)
<table>
<thead>
<tr>
<th>Items from literature</th>
<th>Case study 1</th>
<th>Case study 2</th>
<th>Case study 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>only took a few weeks, Beyond the pilot, the lack of standards, possible interoperability between blockchains along the supply chain, as well as the need for computing power and correct data entry by staff can become issues. System reliability issues (a concern in RFID) is less of a concern than data accuracy and integrity issues</td>
<td>might lead to standardization issues and computing power concerns. The fact that manual data entry is required might limit the ability to scale and limit supplier acceptance, in particular if they get multiple requests for blockchain participation from multiple customers.</td>
<td>many more supply chain partners to join the blockchain and this may require more time and effort than getting the pilot scope up and running. Put simply, with proof of concept you do not have a supply chain implementation yet.</td>
<td></td>
</tr>
<tr>
<td>Privacy issues Less of a concern given the focus on transportation movements</td>
<td>Less of a concern due to the focus on the upstream supply chain, but there are concerns about protecting supplier data and confidentiality, and these run counter to the desire to drive transparency with blockchain.</td>
<td>Less of a concern because the pilot is focused upstream and does not include consumer data.</td>
<td></td>
</tr>
<tr>
<td>Lack of business case Less of a concern. Leadership interest and relatively inexpensive piloting disposed of the need to develop a full business case, at least for the pilot</td>
<td>Less of a concern, at least for the pilot; senior executive, supply chain, and management interest, coupled with limited investment requirements in the pilot, made it unnecessary to develop a full business case</td>
<td>Less of a concern; focus on piloting use case to evaluate if there is proof of concept.</td>
<td></td>
</tr>
<tr>
<td>Implementation Pilot that is customer facing in a small scale and scope (one route only) and is centered on international shipping.</td>
<td>Pilot that is supplier facing in a small scale and scope (a few ingredient suppliers only) and centered on the inbound supply line of ingredients.</td>
<td>Pilot is supplier facing and relatively small in scale and scope (a few suppliers only) but does cover multiple tiers in the supply chain.</td>
<td></td>
</tr>
<tr>
<td>Benefits Customer service Too early to tell given the stage of the pilot, but automation and information benefits are in scope, and, as with RFID, transformational benefits may be limited. While there is some costs potential from improved asset utilization in transport, the effectiveness and speed of the flow of goods are bigger improvements. Reduced staff costs may not be fully achieved, unlike in</td>
<td>Ultimately, this leads to a consumer benefit; creating visibility into energy and water consumption involved in the production of an individual product. Not really a target and outside of the scope; this is more about creating new capability than driving down costs and inventory.</td>
<td>Most critical benefit – improved product quality in the store without quality concerns and quality driven product outages. Not the main focus of the pilot but a side benefit of the faster response to safety issues is that there is less product waste.</td>
<td></td>
</tr>
</tbody>
</table>

Table VII. Exploring blockchain implementation.
6. Discussion of cross-method findings

Our findings indicate that the factors from the Reyes et al. (2016) framework are relevant for considering blockchain in the supply chain. For example, a number of internal and external drivers were found to be relevant considerations for blockchain in the supply chain. While RFID implementation was driven more by customer demands than blockchain is today, customer impact is still a key consideration. Leadership engagement in blockchain at both executive and operational levels is also relevant. This engagement, however, does not have to be universal; case companies engaged a few sponsors and participants for the initial implementation of blockchain in the supply chain. Engagement of 2–4 interested supply chain partners appears to be sufficient to start a pilot. Barriers to implementation may include a lack of understanding of blockchain, and implementation can vary by supply chain and use case. The benefits targeted with blockchain in the supply chain range from transparency and visibility to speed in the supply chain. And our findings do reinforce overlapping functionality between RFID and blockchain technologies in the transparency, visibility and traceability domain. Obviously, it remains key to ensure that use cases address specific supply chain benefits upfront in order to avoid a “solution looking for a problem” but we are encouraged to have found ample consideration being given to these by companies participating in our research.

As was the case with RFID, blockchain should not be approached as a new technology that is going to solve all supply chain challenges overnight. In particular, scaling to supply chain-wide implementation of blockchain will require time, investment and ongoing engagement of management. Blockchain is also not a technology that is going to make existing technology obsolete. In fact, it may leverage inputs from RFID and other existing supply chain technologies, which is in line with recent research from Saberi et al. (2018) pointing to the value of combined consideration of RFID and blockchain in the supply chain. Blockchain may, indeed, be a complement to the existing technology roadmap and technology infrastructure.
Beyond the relevance of the factors from the Reyes et al. (2016) framework, our findings indicate that there are some key differences between the implementation of RFID and blockchain technology in the supply chain. These differences can be used to adapt the Reyes et al. (2016) framework for blockchain implementation, as shown in Figure 4. Beginning with drivers, blockchain pilots appear to be driven more by executive interest and internal drivers, whereas customers often mandated RFID implementation. While the use cases in our case studies center around creating new customer value, they are not driven by customer mandates or requirements. The focus group findings indicated that customer pressures are low on the list of drivers behind blockchain. Consideration of blockchain in the supply chain includes customer and market benefits but tends to be initiated by internal factors.

Regarding leadership commitment, the interest in blockchain is helping drive use case and pilot development. The case study findings indicate that focusing on 2–4 interested supply chain partners will enable a fast start of a pilot. This may be somewhat different from RFID, as starting a pilot involves more hardware investment and physical infrastructure development. In that respect, barriers play a different role when it comes to blockchain. A business case is relevant, as indicated by both the survey and the focus group’s interest in understanding the benefits and returns of blockchain. However, our case studies indicate that with the right executive engagement and a focus on 2–4 supply chain partners, the investment may be limited and a business case may not be needed.

Lack of understanding was an important consideration for focus group participants, and the case study findings suggest that starting a pilot for the sake of learning and evaluating technical issues and establishing proof of concept is a meaningful solution. Privacy issues were of lesser concern for the case companies, but this may partially be due to the controlled pilot environment with few participants. Both focus group findings and case study findings indicate that the consideration of blockchain in the supply chain centers far less on the technology than it does on supply chain improvement opportunities and potential customer value impact. This is encouraging given Verhoeven et al.’s (2018) warning against technology-centricity and a “solution looking for a problem.” Our findings indicate that supply chain objectives are considered and that the companies currently piloting are centering their pioneering around supply chain objectives rather than just technology interest.

The case study findings regarding leadership commitment refine the findings from the survey. The survey findings indicated that engagement of executive and operational management is relevant for blockchain implementation in the supply chain. The exploration of survey data using correlation analysis further indicated that the is a strong relation between this engagement and the availability of a business case, roadmap and a strategy for blockchain in the supply chain. Case study findings indicate, however, that while this may be true and valid

<table>
<thead>
<tr>
<th>Similar to RFID implementation</th>
<th>Unique to blockchain implementation</th>
<th>Interpretation and discussion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drivers</td>
<td>• Customer considerations are important</td>
<td>• but less of a customer requirement, more of a market potential perspective</td>
</tr>
<tr>
<td>Leadership commitment</td>
<td>• Top and middle management support enables implementation of blockchain like it does of RFID</td>
<td>• but internal drivers are more prominent</td>
</tr>
<tr>
<td>Barriers</td>
<td>• Relevant to consider barriers upfront</td>
<td>• but executive engagement can greatly accelerate pilots</td>
</tr>
<tr>
<td>Implementation</td>
<td>• Implementation levels can vary from supply chain to supply chain</td>
<td>• and 2–4 engaged partner may suffice initially</td>
</tr>
<tr>
<td>Benefits</td>
<td>• Visibility and traceability stand out as similar benefits/functions, confirming the overlapping functionality and potential to complement RFID with blockchain</td>
<td>• For a pilot a formal business case is less needed and there is less upfront investment needed for blockchain</td>
</tr>
</tbody>
</table>

Figure 4. Similarities and differences between RFID and blockchain implementation, discussion of findings.
for larger scale implementation, a business case and strategy is not needed for the initial pilot stages, nor is complete executive and operational management engagement. The commitment of only a few leaders and supply chain partners may suffice for the pilot. Additionally, case companies engaged in the blockchain pilots to learn and inform further consideration of blockchain in the supply chain, not yet having fully developed a roadmap or a strategy. Implementation of blockchain across the supply chain is limited, so learnings from those at the frontier are limited when it comes to full-scale implementation. The case study findings indicate that scaling the implementation beyond the pilot and beyond the initial 2–4 supply chain players may lead to scalability concerns and higher implementation costs.

Regarding benefits, while focus group participants see many potential benefits of blockchain in the supply chain, the case companies are more centered on visibility and communication throughout the supply chain. This is perhaps a bit of a narrower set of benefits than those considered for RFID.

Figure 5 offers a framework for considerations during the different stages of the implementation process. This figure summarizes how these considerations may evolve and change as pioneers move from pilot to roll out. Internal drivers, while found to be most important initially, may not suffice for roll out. And while executive engagement make use case development easier and 2–4 engaged partners may make it possible to start a pilot, this will not suffice for a larger scale roll out. Lack of understanding is a key barrier considered and a business case and security are less of a concern initially. For a larger scale roll out further economic evaluation will likely be necessary, in particular if blockchain adoption is scoped beyond a narrow section of the supply chain, which is the typical scope of pilot adoption. Finally, visibility and traceability are key benefits considered in use cases and experienced in pilots. The implementation of blockchain can complement that of RFID, in stead of replace it, but further proof of concept of these benefits is being sought by case companies. This figure expands upon the Reyes et al. (2016) framework by offering blockchain-specific considerations and insight into how these evolve and how priorities may change over time. The figure may also support managerial decision making and point at further research opportunities.

6.1 Contributions and limitations
Beyond the contributions of our research to the advancement of the practice of operations management as outlined in the form of managerial implications in the next section, our

Figure 5. Importance and development of implementation considerations during blockchain implementation stages

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research also makes multiple contributions to the advancement of operations theory and research. First of all, our research contributes a wider and deeper exploration of blockchain in the supply chain, advancing research beyond the many conceptual or literature studies and the studies that consider (publicly available) high level use case descriptions only. Our research more widely explores perspectives of interested managers through focus group and survey and explores lessons that the few pioneers in this field are learning by studying case companies. Additionally, our case studies advance further into the implementation process than most existing blockchain research and consider lessons from the start of the actual implementation and proof of concept stage.

Our findings reinforce the relevance of Ferdows (2018) call to learn from pioneers. Not only does it add to limited amount of empirical data available. It also reveals that pioneers pilot to reduce the lack of understanding so widely reported by interested managers. And our findings indicate that they not only generate lots of learnings but also that their decision-making considerations evolve and change during the implementation process. Clearly indicating that there is a lot to learn and research beyond the use case stage.

Our research actively leverages research on the implementation of RFID in the supply chain to accelerate the learning process and to reduce the risk of “reinventing the wheel.” RFID research was selected because of the similarity in hype and functionality, its joined explicit focus on cross company implementation in the supply chain and the calls for complementary implementations. Our findings do indicate that there is indeed overlapping functionality between RFID and blockchain in the supply chain. Both technologies can contribute to greater visibility, transparency and traceability, but RFID may also be used for additional reasons such as inventory shrinkage. Our case study findings indicated that blockchain can indeed complement RFID technology by disseminating data captured by RFID more quickly throughout the supply chain. And while case study findings indicated that blockchain can drive upstream and downstream benefits in the supply chain, at the current stage of implementation blockchain is not yet implemented supply chain wide.

More specifically, our research approach focused on leveraging lessons learned from research into RFID research enabled the identification of high-level implementation factors such as internal and external drivers and leadership commitment. It also proved beneficial for identifying several specific considerations that are relevant for blockchain implementation, just as they are for RFID implementation. With many other newer technologies entering the supply chain, our research approach may be valid for wider use.

A specific contribution to the understanding of blockchain in the supply chain is captured in Figure 4 – the specific considerations and their interpretation for blockchain implementation. This figure not only leverages RFID insights and lessons from pioneers, it contributes to a more detailed understanding of implementation considerations and creates a framework for decision making. Further to that, Figure 5 makes additional contributions by capturing how considerations evolve and change from one implementation stage to the next. This finding reinforces the relevance of moving beyond the study of use cases as widely done in existing research. It also advances beyond the Reyes et al. (2016) framework as this framework did not distinguish between implementation stages.

As our research contributes nuance to the consideration of blockchain in the supply chain and grounds findings in empirical study, as opposed to theoretical consideration of technologic possibility, it can contribute to a more grounded, less hyped, discussion of blockchain in the supply chain, in industry and research. And while a lot is learned from the contributing managers and pioneers, it is also fair to say that we did not yet find supply chain-wide and full-scale implementations of blockchain. Clearly this represents fruitful area for further learning from pioneers.

While of value, our contributions are not without limitations. Many areas for further research remain in this dynamic and rapidly evolving terrain. First of all, our focus group and
survey where highly descriptive and used a convenience sample. As knowledge about
blockchain and interest in blockchain spreads, it will become possible to survey a random
sample of companies. This may allow for a more rigorous statistical analysis and potential
generalization of findings. Furthermore, our survey findings indicate correlations between items
surveyed; perhaps a more comprehensive survey would allow for multi-item scale development
of an engagement measure and also for other factors from the framework. This can support
progression from exploration and description into initial statistical generalization of findings.

While we were able to study pioneers at the frontier of the implementation of blockchain
in the supply chain, it is not fully adopted by any of the case companies in our research. As a
result, benefits, barriers and implementation paths need to be explored more fully. There is
opportunity to learn more as our case companies advance their implementation process into
larger scale implementation. We recommend not only continued study of the pioneers and
interested companies included in our research, but also more companies as they begin to
consider and adopt blockchain in their supply chain. It will thus become possible to expand
the number of cases studied and further explore blockchain implementation in different
operating and supply chain environments, segments and geographies.

Our research indicated that the consideration of blockchain in the supply chain can benefit
from lessons learned in RFID research. Our research also indicated that there are specific
reasons for considering lessons learned about RFID implementation including: similarity in
use cases, a similar focus on cross company supply chain settings as opposed to in-company
implementation such as is more common with ERP, a similar amount of interest in blockchain
as there was in RFID 15 years ago and a call for considering blockchain as a complement to
RFID implementations. However, there are several other existing technologies in the supply
chain that could also inform blockchain implementation. For example, AI and big data may
benefit from blockchain, or they may enable blockchain. Further to that, our findings indicated
that blockchain in the supply chain may indeed complement and use existing technologies
such as bar coding and RFID (instead of replace them). There are early use cases that combine
blockchain with other new technologies. Walmart for example has reportedly filed for a patent
on a robot delivery system that uses blockchain to record deliveries. Given that the benefits of
RFID are still being studied and are not fully understood today (Shin and Eksioglu, 2015),
another fruitful avenue for further research would be the impact of blockchain on existing
technologies. Can blockchain make RFID applications better by communicating data on the
blockchain? How does this change the investment in RFID and the return achievable?

7. Implications for managers
Our exploratory research offers several implications for managers considering blockchain in
the supply chain. The first implication is that fueled by the hype around blockchain there is a
wide interest in blockchain in the supply chain and it is recommended that managers that are
not yet considering blockchain for their supply chain do so, using the findings from this paper.
Those companies and managers that are already considering blockchain and that are piloting
are advised to ensure they have a use case that identifies relevant supply chain objectives and
consider drivers, engagement and barriers identified. Based upon our exploration and study of
pioneers in the field, Figure 4 offers relevant factors to consider and specific blockchain
considerations within that. Our findings can help managers move beyond discussions about
the theoretical potential of blockchain to a better understanding of what to consider.

Figure 5 provides a decision support framework for managers considering blockchain from
use case development, to pilot, to larger scale roll out. It clarifies how factors such as barriers and
benefits vary in importance from one stage to another, and it clarifies how specific considerations
evolve during the implementation process. This framework can support managerial decision
making beyond the Reyes et al. (2016) framework because it includes blockchain-specific
considerations and captures nuances in decision making by implementation stage.
Our case studies findings indicate that it can be relatively easy and inexpensive to start piloting blockchain in the supply chain when there are 2–4 interested parties and senior executive engagement and (modest) funding. In that respect, blockchain may be different from RFID, which requires larger upfront investments. For interested managers, the implication of this finding is that to get started engagement of a few sponsoring executives, operational managers and supply chain partners may suffice. It is key, however, is to ensure that a use case and pilot is focused and narrowly scoped to enable a faster start.

The case study findings indicate that blockchain may be approached as a complement to existing technologies rather than a replacement. In fact, it may use inputs from existing technologies. RFID and bar coding data, for example, are often used as data input in the blockchain implementation. As a result, managers should approach blockchain with nuanced consideration and not view it as the new panacea that will make all existing technology obsolete or irrelevant.

8. Conclusion
While there is great interest in blockchain in the supply chain, there is little empirical research and experience in industry to consider. As a result, it is relevant to consider lessons learned from RFID and to explore innovation at the frontier of practice as recommended by Ferdows (2018). While our research adds empirical findings beyond the scope of existing research on blockchain in the supply chain, while our research can help inform realistic expectations and develops a framework for considering blockchain in the supply chain, the exploration is far from over.

References


Further reading
## Appendix

### Drivers

**Internal drivers**
- Improve customer service: Reyes et al. (2016)
- Improve productivity: Reyes et al. (2016)
- Reduce operating costs in the supply chain: Vijayaraman and Osyk (2006), Li et al. (2010), Reyes et al. (2016)
- Enhance accuracy and availability of information: Chuang and Shaw (2007), Reyes et al. (2016)
- Better inventory visibility: Vijayaraman and Osyk (2006), Reyes et al. (2016)
- Better visibility into supply chain processes: Reyes et al. (2016)
- Reduce overstock inventory: Reyes et al. (2016)
- Improve reconciliation of perpetual inventory: Reyes et al. (2016)
- Reduction of out of stock: Karkkainen (2003), Vijayaraman and Osyk (2006), Li et al. (2010), Reyes et al. (2016)
- Improve asset management and tracking: Vijayaraman and Osyk (2006), Li et al. (2010), Reyes et al. (2016)
- Improve internal and external communication: Reyes et al. (2016)
- Better inventory tracking and tracing: Li et al. (2010)
- Increased automation: Chuang and Shaw (2007)
- Inventory reduction: Vijayaraman and Osyk (2006), Li et al. (2010)
- Lead time reduction: Li et al. (2010)
- Improved efficiency in operations: Hou and Huang (2006), Li et al. (2010)
- Improved labor efficiency: Vijayaraman and Osyk (2006), Li et al. (2010)
- Improve quality control: Li et al. (2010)
- Better ability to trace defects: Li et al. (2010)
- Improved accuracy in shipping and receiving: Li et al. (2010)
- Claims reduction: Vijayaraman and Osyk (2006), Li et al. (2010)
- Minimize inventory losses: Li et al. (2010)
- Reduced costs of labor for material handling: Chuang and Shaw (2007), Li et al. (2010)
- Strategic initiative: Li et al. (2010)
- Competitive advantage: Li et al. (2010)

**External drivers**
- Pressure from customer(s) to improve efficiencies, reduce lead time and track and trace: Hou and Huang (2006), Vijayaraman and Osyk (2006), Li et al. (2010), Bhattacharya (2012), Reyes et al. (2016)
- Keep up with competitors: Reyes et al. (2016)
- Improved store sales: Vijayaraman and Osyk (2006), Li et al. (2010)
- Improved store shelf inventory: Vijayaraman and Osyk (2006), Li et al. (2010)
- Improved customer service: Li et al. (2010)
- Improved response time to customer inquiries: Li et al. (2010)
- Increased collaboration and planning: Li et al. (2010)
- Improved supply chain information sharing: Li et al. (2010)

### Leadership Commitment

- Top management leadership
- Top management develops and communicates the RFID implementation plan: Reyes et al. (2016)
- Top management sets priorities for RFID implementation: Thiesse et al. (2011), Reyes et al. (2016)
- Top management participates in developing and implementing the policies and methods of RFID implementation: Reyes et al. (2016)

---

**Table AI.** Overview of items from literature on RFID implementation in the supply chain
Top management fosters communication among different departments concerning the RFID implementation

Top management assures the organization’s staff is trained to implement RFID

Reyes et al. (2016)

Middle-level management leadership

Department heads integrate the department’s RFID implementation plan with the organization’s RFID implementation plan

Department heads coordinate interdepartmental and intradepartmental RFID implementation decisions and activities

Department heads recommend resources needed to facilitate the RFID implementation plan

Reyes et al. (2016)

**Barriers/obstacles**

<table>
<thead>
<tr>
<th></th>
<th></th>
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<tbody>
<tr>
<td>Initial cost of implementation</td>
<td>Li et al. (2010), Fan et al. (2015), Reyes et al. (2016)</td>
</tr>
<tr>
<td>Return on investment too low/uncertain</td>
<td>Hou and Huang (2006), Attaran (2007), Miraglia et al. (2009), Li et al. (2010), Bhattacharya (2012), Lim et al. (2013), Reyes et al. (2016)</td>
</tr>
<tr>
<td>Costs of maintaining the system are high</td>
<td>Li et al. (2010)</td>
</tr>
<tr>
<td>Lack of funds</td>
<td>Vijayaraman and Ozyk (2006), Li et al. (2010)</td>
</tr>
</tbody>
</table>

**Lack of understanding**

<table>
<thead>
<tr>
<th>LOU about RFID technology and its implementation in the supply chain</th>
<th>Hou and Huang (2006), Bendoly et al. (2007), Ngai et al. (2007), Vijayaraman and Ozyk (2006), Reyes et al. (2016)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOU about potential benefits</td>
<td>Li et al. (2010), Reyes et al. (2016)</td>
</tr>
<tr>
<td>LOU about developing/integrating new process</td>
<td>Reyes et al. (2016)</td>
</tr>
<tr>
<td>LOU about determining potential costs and ROI</td>
<td>Miraglia et al. (2009), Li et al. (2010), Reyes et al. (2016)</td>
</tr>
<tr>
<td>LOU about technical limitations of RFID</td>
<td>Bendoly et al. (2007)</td>
</tr>
<tr>
<td>Training problems</td>
<td>Reyes et al. (2016)</td>
</tr>
<tr>
<td>LOU about security/regulation issues</td>
<td>Reyes et al. (2016)</td>
</tr>
<tr>
<td>Large number of stakeholders involved in the decision making</td>
<td>Reyes et al. (2016)</td>
</tr>
<tr>
<td>Payback period unclear</td>
<td>Li et al. (2010)</td>
</tr>
<tr>
<td>Lack of top management understanding of RFID</td>
<td>Li et al. (2010), Bhattacharya (2012)</td>
</tr>
</tbody>
</table>

**Technical Issues – internal and external**

| Technical issues with hardware and software | Attaran (2007), Bhattacharya (2012), Reyes et al. (2016) |
| Analysis and utilization of information generated from the RFID system | Reyes et al. (2016) |
| Usage difficulties for employees | Reyes et al. (2016) |
| Database integration difficulties | Bhattacharya (2012), Reyes et al. (2016) |
| Technology is too new | Li et al. (2010) |
| System reliability issues | Chuang and Shaw (2007), Delen et al. (2007), Ngai et al. (2007), Li et al. (2010), Lim et al. (2013) |
| Integration issues with existing technology | Attaran (2007), Niederman et al. (2007), Li et al. (2010), Lim et al. (2013) |

(continued)
Privacy issues
  Privacy concerns Ngai et al. (2007), Li et al. (2010), Bhattacharya (2012), Lim et al. (2013), Reyes et al. (2016)
  Security concerns about data integrity Reyes et al. (2016)
  Lack of business case Ngai et al. (2007), Reyes et al. (2016)
  Educating customers and employees about RFID and how the data will be used Reyes et al. (2016)

Security concerns about data integrity Ngai et al. (2007), Reyes et al. (2016)

Lack of business case Prater et al. (2005), Chuang and Shaw (2007), Li et al. (2010)

Expected benefits are not enough Vijayaraman and Osyk (2006), Li et al. (2010)

Implementation
  Not considering, considering, piloting, implementing Vijayaraman and Osyk (2006), Reyes et al. (2016)
  Implementation path; supplier facing diffusion or customer facing diffusion Lee et al. (2008)
  Scale of implementation (high – low) and scope of implementation (narrow – broad) Roh et al. (2009)
  Area of supply chain implementation (raw material flow, work in progress, finished goods Zelbst et al. (2012)
  Without understanding data, more data does not add value Delen et al. (2007)
  Innovation process: generation, acceptance, implementation Smart et al. (2010)

Benefits
  Automation benefits, information benefits, transformational benefits Visich et al. (2009)
  Benefits may not be balanced in the supply chain; retailer may benefit more Bottani and Rizzi (2008)
  Do not over focus on costs vs supply chain effectiveness Zelbst et al. (2012)

Customer service
  Improved service quality, service levels and on time delivery Sarac et al. (2010), Thiesse et al. (2011), Bhattacharya (2012), Zelbst et al. (2012)
  Delivery performance/Improving customer satisfaction with delivery fulfilment processes Lim et al. (2013), Zelbst et al. (2012), Reyes et al. (2016)
  Improving customer order tracking and visibility into customer needs Attaran (2007), Reyes et al. (2016)
  Improving customer satisfaction by mainstreaming administrative processes and reducing dwell time Kim et al. (2008), Reyes et al. (2016)
  Improved order forecasts Attaran (2007)
  Reduced stock outs/fill rate/on-shelf availability Prater et al. (2005), Bottani and Rizzi (2008), Thiesse et al. (2011), Bhattacharya (2012), Zelbst et al. (2012), Lim et al. (2013)
  Faster exception management and responsiveness Zelbst et al. (2012), Lim et al. (2013)
  Better expiry date management Lim et al. (2013)
  Improved returns/recall management Attaran (2007), Bhattacharya (2012)
  Gaining favor with retailers to better position products on shelves Attaran (2007), Bottani and Rizzi (2008), Sarac et al. (2010), Bhattacharya (2012)

Costs and productivity
  Reduced supply chain costs Attaran (2007), Sarac et al. (2010), Bhattacharya (2012), Zelbst et al. (2012), Lim et al. (2013)

Table AI. (continued)
<table>
<thead>
<tr>
<th>Category</th>
<th>Examples</th>
</tr>
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<tbody>
<tr>
<td>Improve support employees’ productivity/less direct labor</td>
<td>Kim et al. (2008), Veronneau and Roy (2009), Ferrer et al. (2010), Bhattacharya (2012), Lim et al. (2013), Shin and Eksioglu (2015), Reyes et al. (2016)</td>
</tr>
<tr>
<td>Lower inventory and safety stock</td>
<td></td>
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<tr>
<td>Improve material handling</td>
<td>Lim et al. (2013), Reyes et al. (2016)</td>
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<tr>
<td>Reduce fulfillment errors</td>
<td>Lim et al. (2013), Reyes et al. (2016)</td>
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<tr>
<td>Increasing productivity/throughput of service facilities/improved space utilization</td>
<td>Poon et al. (2009), Ferrer et al. (2010), Thiesse et al. (2011), Lim et al. (2013)</td>
</tr>
<tr>
<td>Accelerate the cash to cash cycle time</td>
<td>Zelbst et al. (2012)</td>
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<tr>
<td>Inventory days of supply reduction</td>
<td>Zelbst et al. (2012)</td>
</tr>
<tr>
<td>Asset Management</td>
<td></td>
</tr>
<tr>
<td>Improve the tracking, utilization and management of assets and equipment</td>
<td>Attaran (2007), Tzeng et al. (2008), Lim et al. (2013), Reyes et al. (2016)</td>
</tr>
<tr>
<td>Improve the preventive maintenance of equipment</td>
<td>Reyes et al. (2016)</td>
</tr>
<tr>
<td>Improve the utilization of reusable assets (totes for parts)</td>
<td>Reyes et al. (2016)</td>
</tr>
<tr>
<td>Communication</td>
<td></td>
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<tr>
<td>Improved/Ease of communication and data sharing between firm, customer and supply chain partners</td>
<td>Tzeng et al. (2008), Sarac et al. (2010), Lim et al. (2013), Reyes et al. (2016)</td>
</tr>
<tr>
<td>Improve internal communication among employees</td>
<td>Reyes et al. (2016)</td>
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<tr>
<td>Better determining of arrival and dispatch times</td>
<td>Lim et al. (2013)</td>
</tr>
<tr>
<td>Inventory shrinkage</td>
<td></td>
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<tr>
<td>Reduced inventory shrinkage due to greater visibility and improved prevention</td>
<td>Rekik et al. (2008), De Kok et al. (2008), Bhattacharya (2012), Dai and Tseng (2012), Lim et al. (2013), Fan et al. (2014), Fan et al. (2015)</td>
</tr>
<tr>
<td>Minimize inventory losses</td>
<td>Roh et al. (2009), Sarac et al. (2010), Ferrer et al. (2010), Li et al. (2010)</td>
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<tr>
<td>Reduced counterfeiting</td>
<td></td>
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<tr>
<td>Visiblity and tracking</td>
<td></td>
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<tr>
<td>Improve the tracking of supply and product throughout the supply chain</td>
<td>Attaran (2007), Lee and Ozer (2007), Sarac et al. (2010), Lim et al. (2013), Reyes et al. (2016)</td>
</tr>
<tr>
<td>Increased inventory visibility</td>
<td>Prater et al. (2005)</td>
</tr>
<tr>
<td>Accurate and timely asset tracking</td>
<td>Attaran (2007)</td>
</tr>
<tr>
<td>Greater data accuracy</td>
<td>Poon et al. (2009), Sarac et al. (2010), Bhattacharya (2012), Zelbst et al. (2012), Lim et al. (2013)</td>
</tr>
<tr>
<td>Enhanced visibility in the supply chain</td>
<td>Veronneau and Roy (2009), Sarac et al. (2010), Prater et al. (2005), Poon et al. (2009), Sarac et al. (2010), Bhattacharya (2012)</td>
</tr>
<tr>
<td>More real time information/time reduction in storing and retrieving information</td>
<td>Bottani and Rizzi (2008), Sarac et al. (2010)</td>
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<tr>
<td>Reduction in bullwhip effect</td>
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<tr>
<td>Speed and inventory flow</td>
<td></td>
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<tr>
<td>Cycle time reduction</td>
<td></td>
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<tr>
<td>Speed up operational processes such as tracking, shipping, checkout and counting</td>
<td>Roh et al. (2009), Ferrer et al. (2010)</td>
</tr>
<tr>
<td>Improved inventory flow</td>
<td>Sarac et al. (2010)</td>
</tr>
<tr>
<td>Speed of delivery relative to competitors</td>
<td>Zelbst et al. (2012)</td>
</tr>
<tr>
<td>Improved velocity by responding to demand signal faster</td>
<td>Attaran (2007)</td>
</tr>
</tbody>
</table>

**Table A1.**

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Industry 4.0 adoption as a moderator of the impact of lean production practices on operational performance improvement

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Abstract

Purpose – The purpose of this paper is to examine the moderating role of Industry 4.0 technologies on the relationship between lean production (LP) and operational performance improvement within Brazil, a developing economy context.

Design/methodology/approach – One representative from each of the 147 studied manufacturing companies filled in a survey on three internally related lean practice bundles and two Industry 4.0 technology bundles, with safety, delivery, quality, productivity and inventory as performance indicators. As this study was grounded on the contingency theory, multivariate data analyses were performed, controlling for four contingencies.

Findings – Industry 4.0 moderates the effect of LP practices on operational performance improvement, but in different directions. Process-related technologies negatively moderate the effect of low setup practices on performance, whereas product/service-related technologies positively moderate the effect of flow practices on performance.

Originality/value – With the advent of Industry 4.0, companies have been channelling their efforts to achieve superior performance by advancing levels of automation and interconnectivity. Eventually, widespread and proven manufacturing approaches, like LP, will integrate such technologies which may, in turn, impair or favour operational performance. Contrary to previous studies, the contingencies appeared to have a less extensive effect. The authors point to various options for further study across different socio-economic contexts. This study evidenced that purely technological adoption will not lead to distinguished results. LP practices help in the installation of organisational habits and mindsets that favour systemic process improvements, supporting the design and control of manufacturers’ operations management towards the fourth industrial revolution era.

Keywords Emerging economies, Lean production, Industry 4.0, Operational performance improvement

Paper type Research paper

1. Introduction

The fourth industrial revolution is increasingly in the spotlight of researchers, economic policymakers and manufacturers (Liao et al., 2017; Quezada et al., 2017). This new production era was labelled during the German 2011 Hannover Fair as “Industry 4.0” (Liao et al., 2017); it represents an industry characterised by interconnected machines, intelligent systems and products, and inter-related solutions (Tortorella and Fettermann, 2018). Industry 4.0 steers the establishment of smart and dynamic production systems and the mass production of highly customised products (Shrouf et al., 2014). This involves implementing integrated digital elements which monitor and control the physical devices, sensors, information and communication technologies (ICT) and Internet of Things (IoT).
applications (Lasi et al., 2014). Despite its growing notoriety, many companies are still struggling with how Industry 4.0’s high-tech practices should be implemented into their operations (Sanders et al., 2016, 2017; Erol et al., 2016). The feasibility and effectiveness of Industry 4.0 integration into existing manufacturing management systems is still understudied (Kolberg et al., 2017).

Specific aspects may undermine Industry 4.0 adoption, especially in manufacturing companies within developing economies, including overall lower technological intensity, restricted investment capital and human resources (Anderl, 2014). Developing economies encounter different challenges when investing in Industry 4.0. For instance, the Brazilian National Confederation of Industry (2016) identified the existing hurdles for Industry 4.0 implementation; the Mexican Ministry of Economy (2016) presented a roadmap for Industry 4.0 adoption in Mexico; and the Indian Government introduced an initiative aimed at positioning the country as one of the main hubs of manufacturing (Forbes India, 2016). Despite these initiatives, little is known about the effects of Industry 4.0 technologies adoption.

Lean production (LP), however, is common practice among several industries and countries, it entails a constant focus on reducing wasteful activities while also improving productivity and quality as seen from the customers’ perspective (Womack and Jones, 2003; Junior and Godinho Filho, 2010; Kroes et al., 2018; Narayanamurthy et al., 2018; Soliman et al., 2018). Implementing LP successfully requires a human-centred, low-tech organisational change approach which involves the adoption of various LP practices (Bortolotti et al., 2015; Soliman et al., 2018), a consistent, shared strategic vision with an aligned HR policy, and highly involved employees who have enough resources for continuous process improvement (Van Dun and Wilderom, 2012). Many lean initiatives start on the shop floor (Shah and Ward, 2007), and are then gradually introduced into other units including the corporate level (Hines et al., 2004; Mann, 2005).

Due to Industry 4.0 and LP’s convergent and divergent characteristics, it remains unclear whether their concurrent implementation in manufacturing companies will lead to improved performance. On the one hand, lean entails a constant focus on reducing wasteful activities while also improving productivity and quality as seen from the customers’ perspective (Womack and Jones, 2003; Junior and Godinho Filho, 2010; Kroes et al., 2018; Narayanamurthy et al., 2018). This psychologically safe shop-floor culture enables the clear identification of process status quo and information sharing (Van Dun and Wilderom, 2012, 2016), which may be further reinforced by the interconnectivity, data acquisition and analysis inherent to Industry 4.0 technologies (Sibatrova and Vishnevskiy, 2016). Furthermore, both LP and Industry 4.0 favour simple decentralised frameworks (Zühlke, 2010). On the other hand, LP entails socio-cultural changes that are stimulated daily through fast and simple work-floor experimentations (Baudin, 2007; Dora et al., 2016), which may conflict with the high levels of capital expenditure and technological expertise demanded by Industry 4.0 (Lasi et al., 2014). These conflicts may occur when both LP and Industry 4.0 practices are implemented in a developing economy context but empirical evidence for this assumption is still generally lacking (Gjeldum et al., 2016; Landscheidt and Kans, 2016; Kolberg et al., 2017) and what is available is contradictory (e.g. Erol et al., 2016; Schumacher et al., 2016; Sanders et al., 2016). The intention of this study, therefore, is to answer the following research question:

**RQ1.** How does Industry 4.0 adoption moderate the relationship between LP practices and operational performance improvement in a developing economy context?

We surveyed 147 Brazilian manufacturers that had implemented LP practices as well as Industry 4.0 technologies. This research, therefore, contributes to the theoretical fields of advanced manufacturing technology and operational performance improvement. The adoption and management of novel technologies have “gradually become an important task for manufacturing companies across the globe” (Cheng et al., 2018, p. 239). Our study provides a
better understanding of the interactions between the installed LP practices and Industry 4.0 technologies, and their effects on operational performance improvement. Moreover, we initialise the validation of a measure of Industry 4.0 technology adoption. The study may also enable managers to comprehend and anticipate better the advantages and difficulties of incorporating Industry 4.0 technologies into their LP systems. Since managers’ financial resources are often scarce, especially in developing economies, it is crucial that their new technology investments are well-informed by studies like ours. Finally, it is also noteworthy that this research expands upon Tortorella, Miorando, Caiado, Nascimento and Portioli Staudacher (2018), Tortorella, Giglio and Van Dun (2018) and Tortorella and Fettermann’s (2018) research.

This study was grounded on assumptions derived from the contingency theory (Sousa and Voss, 2006; Van de Ven et al., 2013; Romero-Silva et al., 2018). Contextual factors can influence the concurrent implementation of LP and Industry 4.0 (Tortorella and Fettermann, 2018; Rossini et al., 2019). The effect of operations management practices on performance was claimed to differ according to the contextual variables of each company (Sousa and Voss, 2008). Hence, the validity of “one-size fits all” or “best practice” concepts is probably reduced in operations management (Boer et al., 2017). Our study thus includes four contingencies (i.e. technological intensity, tier level, company size, and duration of LP implementation) and considers a specific Brazilian socioeconomic sample because national culture can significantly affect the results of LP (Kull et al., 2014; Erthal and Marques, 2018). We contribute to a better comprehension of the contingencies required to implement LP and Industry 4.0 concomitantly, by describing how their interaction impacts operational performance improvement in the manufacturing industry.

2. Literature review and hypotheses

2.1 LP practices

According to the conceptual definition proposed by Shah and Ward (2007, p. 799), LP covers six core internally related operational elements: pull, flow, low setup, controlled processes, productive maintenance and involved employees. Womack and Jones (2003) also listed: pull, flow and striving for perfection, e.g. low setup (or changeover) times. The aim of those key LP elements (García-Alcaraz et al., 2015) is to achieve smooth material and information flow throughout the value stream (Abdulmalek and Rajgopal, 2007). Yet, LP implementation by manufacturers in emerging economies has been argued to be less extensive than in companies located in developed economies (Saurin and Ferreira, 2009). Saurin et al. (2010) demonstrated an unbalanced knowledge and implementation level of LP practices in this industrial context. LP practices associated with just-in-time (JIT) production systems are more widely implemented and understood by manufacturers in emerging economies compared to more advanced statistical process control or total productive/preventive maintenance. Therefore, we assumed that narrowing our study to practices embraced by the Pull, Flow and Set up constructs, which tend to be closely related to JIT, would lead to more reliable and insightful results.

2.2 Industry 4.0 technologies

A wide variety of technologies fall within the fourth industrial revolution. Many researchers have tried to consolidate them into sets and implementation frameworks (e.g. Fettermann et al., 2018; Fatorachian and Kazemi, 2018; Xu et al., 2018). However, regardless of the differences in those frameworks and the categorisation of Industry 4.0 technologies, the latter’s overall aims are to enable improvements in companies’ value streams by addressing both process- and product/service-related issues (Liao et al., 2017; Buer et al., 2018). Examples of process-related issues that may be solved with technology are time-intensive, manual quality controls. Technologies may also help to reduce product/service-related issues such as inefficiencies that lead to a higher time to market. Since there is still a lack of
consensus on which technologies compose Industry 4.0, we consulted the Brazilian National Confederation of Industry (2016) outcomes of the cross-sector Industry 4.0 survey of 2,225 manufacturers. This survey uncovered the ten most likely digital technologies to be adopted within the Brazilian industrial sector.

Industry 4.0 technologies may not only have a positive impact on the way manufacturing shop floors are managed and organised but also influence organisations’ business models, products and services. While the adoption of certain technologies (e.g. digital automation and sensors for remote monitoring and control) may predominantly influence the manufacturing processes (Kolberg et al., 2017), other Industry 4.0 technologies (e.g. big data, cloud services and rapid prototyping) could help the accomplishment of significant improvements in product development and service innovation (Zühlke, 2010; Wan et al., 2015).

2.3 Contingency effects on LP and Industry 4.0
The contingency theory indicates that different environments/contexts often have different needs, thus requiring distinguished approaches to operations management (Sousa and Voss, 2008; Van de Ven et al., 2013; Romero-Silva et al., 2018). The contingency theory is a popular angle (Walker et al., 2015; Danese et al., 2018) and various studies have corroborated to our understanding of the effects of contingencies on LP implementation. Shah and Ward (2003), for instance, indicated a positive influence of plant size on the likelihood of LP implementation, whereas the influence of unionisation and plant age was less pervasive than expected. Kull et al. (2014) focused on comprehending how different dimensions of national culture moderate LP effectiveness. Later, Netland (2016) investigated how four contingency variables (corporation, factory size, stage of LP implementation and national culture) influence what practitioners see as success factors for LP implementation. Complementarily, Tortorella et al. (2017) studied the impact of plant size, supply chain level, level of onshore suppliers and age of the LP initiative on LP implementation in supply chains. Overall, most studies reinforce the necessity of primarily comprehending the context in which the organisation is embedded so that LP implementation can be properly tailored. Romero-Silva et al. (2018) further advised the examination of both organisational environment and organisational structure type, contingencies that together form the organisational system in which the LP practices are implemented.

Since Industry 4.0 is a more recent research topic, evidence on the effect of contingencies is much scarcer. The few existing studies have vaguely assessed the effect of certain contingencies, such as company size (Brettel et al., 2014) and technological intensity (Tortorella, Miorando, Caiaio, Nascimento and Portioli Staudacher, 2018), on the adoption level of Industry 4.0. In fact, most studies have only conceptually envisioned some contingencies that might affect Industry 4.0 adoption level, such as socioeconomic aspects (Vacek, 2016) and industry sector (Hofmann and Rüsch, 2017), but without any empirical validation. This research gap highlights the importance of our study because we assess the results from four organisational environment and organisational structure type contingencies (i.e. technological intensity, tier level, company size and duration of LP implementation). Hereby, we complement previous research and provide empirical evidence of the associations.

2.4 Pull practices and Industry 4.0
According to Rother and Shook (1999), a value stream comprises the sum of all the value provided through the required activities and steps in a company or supply chain from the raw state to its customers, linking both material and information flows (Duggan, 2012). Material flow represents the physical aspects encompassed in the manufacturing of an item; i.e., the processes, steps and activities that either enhance or transform the product according to customers’ expectations (Lummus et al., 2006). Information flow corresponds to the procedures, analyses, decisions and orders necessary to support the process in a sequenced way according to
customers’ expectations (Seth and Gupta, 2005; Lu et al., 2011), such as product and service development. A lot of the waste identified in manufacturing processes originates from problems that occur in product/service development (Hines et al., 1998; Sim and Rogers, 2008). Hence, to address improvement initiatives properly from a system-wide perspective, all elements of a value stream must be considered in the analysis (Hines et al., 2004; Karim and Arif-Uz-Zaman, 2013). However, their interaction effects on the achievement of higher operational performance are usually neglected (Hines and Rich, 1997; Seth et al., 2017; Hines et al., 2018).

The aim of pull practices is to facilitate manufacturing so that companies produce the required units on time and in the required quantities (Ohno, 1988). This includes kanban cards, the signals to trigger production. The successful implementation of pull is highly dependent on accurate and timely product and service information related to internal and/or external customers’ demands, thus avoiding overproduction due to misinterpretations or erroneous production triggers (Netland et al., 2015). The incorporation of Industry 4.0 technologies can enhance pull systems in terms of both product/service-related information and manufacturing processes.

First, regarding product/service development, the integration of such technologies as “IoT”, “cloud services” and “big data”, into kanban systems, has been denoted as e-kanban, i.e. digitalisation of the conventional kanban cards (Takeda, 2006; Junior and Godinho Filho, 2010). E-kanban allows the immediate detection of missing or empty bins, triggering automatic replenishment. Physical kanban systems are usually undermined due to card losses during their loops between workstations or facilities, leading to mistakes in production control or scheduling and, hence, reduced operational performance (Abdulmalek and Rajgopal, 2007; Marodin et al., 2015). Conversely, adjustments to inventory policies due to changes in batch sizes, market demands, work plans or cycle times tend to be much easier when technologies like e-kanban are incorporated into the pull system.

From a manufacturing process perspective, implementing technologies such as “production remote monitoring and control” and “sensors for the identification and control of product and operating conditions” can enable rapid identification of potential issues that may disturb the original production schedule and negatively impact the pace of production (Sanders et al., 2017; Buer et al., 2018). The application of ICT within manufacturing processes thus contributes to a quicker problem-solving timeframe as actions move from reactive to preventive (Lasi et al., 2014; Zawadzki and Żywicki, 2016). In turn, process stability increases and potential issues that jeopardise delivering according to internal/external customers’ needs (“pull”) can be anticipated.

However, the sole adoption of ICT (without effective pull systems) may facilitate the usual pushed systems and their underlying processes but might not benefit operational performance. To test how Industry 4.0 technologies, that support manufacturing processes and product/service development, interact with pull practices to enhance operational performance, we formulated the following hypotheses:

H1a. The adoption of Industry 4.0 technologies, that support manufacturing processes, positively moderates the effect of pull practices on operational performance improvement.

H1b. The adoption of Industry 4.0 technologies, that support product/service development, positively moderates the effect of pull practices on operational performance improvement.

2.5 Flow practices and Industry 4.0

Lean’s principle of creating flow focuses on establishing mechanisms that enable and ease the achievement of a continuous production stream (Rother and Harris, 2001).
Flow practices encompass improvements such as the definition of product families according to similar routines, layout arrangements planned according to these product families and balancing workstation cycle times (Doolen and Hacker, 2005). While providing inventory levels and lead-time reductions, flow ensures that production and quality issues are visible to all employees. Thus, its implementation is beneficial to a company’s operational performance (Duggan, 2012). However, if high levels of process stability are not achieved, continuous flow can cause unwanted side-effects, such as loss of deliveries and increased costs (Dora et al., 2016).

Industry 4.0 technologies like sensors, Manufacturing Execution System and Supervisory Control and Data Acquisition, can increase process and product connectivity and interaction, thereby enabling more efficient manufacturing processes (Hermann et al., 2016; Ganzarain and Errasti, 2016; Xu et al., 2018). Enhanced interconnection and communication between cells and workstations can facilitate a flexible, fast and high-quality material flow (Erol et al., 2016; Thoben et al., 2017), and, in turn, the feasibility of continuous flow implementation. However, the isolated adoption of technologies, like IoT, cloud services and additive manufacturing, can lead to marginal gains in product/service development, thus frustrating managers in terms of their high investments and expectations (Cheng et al., 2018). Adopting a novel ICT before implementing a reasonable level of “flow” practices leads to high capital expenditure on wasteful and ill-designed processes (Buer et al., 2018).

Flow practices continuously address low-tech improvement opportunities (Womack and Jones, 2003) but Industry 4.0 technologies may catalyse the outcomes of well-established manufacturing processes and product/service development activities (Kamble et al., 2018). Thoben et al.’s (2017) case of a German company that had organised its shop floor according to LP principles, illustrates how the introduction of a cyber-physical logistics system can enhance flexibility through autonomous decisions and reduce inventories by solving errors in real-time. Although there is an indication of a positive relationship between these approaches, limited empirical evidence confirms such an association. So, we hypothesise that:

**H2a.** The adoption of Industry 4.0 technologies, that support manufacturing processes, positively moderates the effect of flow practices on operational performance improvement.

**H2b.** The adoption of Industry 4.0 technologies, that support product/service development, positively moderates the effect of flow practices on operational performance improvement.

### 2.6 Low setup practices and Industry 4.0

As customers’ needs diversify, the product assortment also increases, with a consequent reduction in batch sizes. Hence, high changeover times (and, thus, process downtime) become an obstacle to high performance (Doolen and Hacker, 2005; Stone, 2012). Toyota overcame this by adopting the “single-minute exchange of die” (SMED) concept which enables smaller batches and shorter lead times by drastically reducing changeover times (Shingo, 1988). The full adoption of “low setup practices” improves the flexibility and agility in production delivery, since shorter setup times may lead to reductions in batch sizes (Furlan et al., 2011). Inventory levels are also likely to be reduced, which directly affects the organisation’s cash flow (Maskell et al., 2011).

Industry 4.0 technologies can enhance the impact of low setup practices on operational performance. Companies that adopt “rapid prototyping and 3D printing” and “product development and manufacturing integrated engineering systems” may observe lower changeover times due to a reduction in complexity by strict modularisation.
System modularity facilitates capacity adjustments in situations such as seasonal fluctuations, contributing to more flexible manufacturing processes. Manufacturing processes can become individual processes through modularity; yet, these can be closely interconnected, offering interchangeability (Lasi et al., 2014; Qin et al., 2016; Kamble et al., 2018). The concurrent implementation of such technologies with low setup practices could thus enhance the flexibility and productivity of manufacturing processes.

Plug’n’Produce and distributed systems are equipped with self-optimising and machine-learning behaviours, allowing companies to adapt machines to particular products and to produce small batch sizes (Brettel et al., 2014; Sanders et al., 2016). Low setup practices mainly focus on internal setup activities (Shingo, 1988; Nicholas, 2015), whereby Plug’n’Produce technologies reduce the amount of time required for changing tools and/or computer numerical control programmes, which typically requires the machines to be stopped. Similarly, “process control sensors” and “product and operating conditions identification” enable identifying process problems faster so that potential changeover issues can be anticipated. Hence, these technologies do not only mitigate the need for machine adjustments after setup (Fatorachian and Kazemi, 2018), but also increase the likelihood of correct first-time products (Albers et al., 2016).

Kolberg and Zühlke (2015) anticipated that standardised physical and ICT interfaces could expand SMED concepts from one work unit to whole manufacturing areas, leading to more assertive product/service developments. Likewise, Moeuf et al. (2018) identified that one of the main reasons for Industry 4.0 adoption by small-sized companies is the increased flexibility through cloud computing and radio-frequency identification whereby the right moments for machine changeovers can be predicted. The flexibility of both manufacturing processes and product/service development, due to increased levels of automation and changeability probably, reinforces the benefits of implementing low setup practices. Therefore, we propose:

\[ H3a. \] The adoption of Industry 4.0 technologies, that support manufacturing processes, positively moderates the effect of low setup practices on operational performance improvement.

\[ H3b. \] The adoption of Industry 4.0 technologies, that support product/service development, positively moderates the effect of low setup practices on operational performance improvement.

As elaborated below, the hypotheses were tested empirically in a cross-sector survey.

3. Methods
3.1 Sample selection and characteristics

We targeted respondents from Brazilian manufacturing companies with experience in both lean and Industry 4.0 technologies. The pervasiveness of both approaches across the industrial spectrum is still scattered, especially in emerging economies (Tortorella et al., 2015; Marodin et al., 2016; Tortorella and Fettermann, 2018). Therefore, to avoid excluding respondents who might meet the established selection criteria, thereby reducing sample size and impairing the application of a robust statistical analysis, we did not restrict our data collection to a specific industrial sector.

We sent the survey to 147 leaders of a diverse range of Brazilian manufacturing companies (see Table I). They were former students of different LP executive education courses offered in February, April, July and September 2017 and had agreed to receive updates about LP-related research. Following the ethical standards, we indicated in the invitation that participation was voluntary and anonymous. The participants mainly worked for large-sized companies.
(55.1 per cent); most of the companies belonged to the metal-mechanical sector (49.6 per cent). Examples of the “other” 23.8 per cent sectors were: civil construction, leather-footwear and graphical industry. A total of 65.9 per cent were involved in the first and second tiers. Regarding the companies’ technological intensity, 53.7 per cent were categorised as high or medium high (Brazilian National Confederation of Industry, 2016). Most companies (55.1 per cent) had begun their formal LP implementation more than two years previously, although the majority (53.7 per cent) of respondents’ personal experience with LP was less than two years. Regarding the respondents’ job positions, 42.2 per cent were either engineers or analysts, 36.0 per cent supervisors or coordinators and 21.8 per cent managers or directors.

3.2 Measures, construct validity and reliability
The survey comprised four main parts (see the Appendix): performance indicators, information on the respondents and their respective companies (see Table I), LP implementation and adoption level of Industry 4.0 technologies.

3.2.1 Operational performance improvement. We assessed the improvement level of the companies’ performance during the last three years. Since financial results are often carefully protected by companies and, sometimes, exclusively shared among a company’s senior managers, we used a composition of operational performance indicators as a proxy for financial performance. Improvements in operational performance are more likely to be perceived by a wider range of respondents, such as middle managers. Since LP implementation is known to impact a wide variety of performance aspects, we measured five process- and people-related indicators suggested by Bhasin (2012) and validated by survey-based LP studies (e.g. Tortorella and Fettermann, 2018; Tortorella, Miorando, Caiado, Nascimento and Portioli Staudacher, 2018; Rossini et al., 2019): productivity, delivery service level, inventory level, quality and safety (i.e. accidents). Each indicator was measured on a five-point scale (1 = worsened significantly; to 5 = improved significantly). We performed an exploratory factor analysis (EFA) through principal components analysis (PCA) with varimax rotation. Table II shows that all the performance indicators loaded on one factor, with an eigenvalue of 3.259 explaining 65.1 per cent of the variation. Cronbach’s $\alpha$ of this factor was 0.86.
3.2.2 Lean practices. The implementation level of lean practices related to the pull, flow and low setup constructs was assessed via Shah and Ward’s (2007) 11 items which had been translated into Portuguese. Each practice statement was evaluated through a Likert scale from 1 (fully disagree) to 5 (fully agree). As these practices had been previously validated, we performed a confirmatory factor analysis (CFA) of the three constructs (see Table III) using the lavaan R programming language package (Oberski, 2014) to confirm their convergent validity and unidimensionality. Initially, three CFA models (one for each construct) were estimated, with factor loadings above 0.45 (Tabachnik and Fidell, 2007). We then re-assessed each CFA model to check their goodness of fit based upon a \( \chi^2 \) test (\( \chi^2/df \)), comparative fit index (CFI) and standardised root mean square residual (SRMR). CFI values greater than 0.90 combined with SRMR values lower than 0.08 were used as thresholds, following Hu and Bentler’s (1999) recommendations for smaller sample sizes (< 250 observations). All items loaded satisfactorily on their constructs (\( > 0.45, p < 0.01 \)) and all had good Cronbach’s \( \alpha \) levels.

<table>
<thead>
<tr>
<th>Performance indicators</th>
<th>Mean</th>
<th>SD</th>
<th>Factor 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Productivity</td>
<td>3.795</td>
<td>1.193</td>
<td>0.590</td>
</tr>
<tr>
<td>Delivery service level</td>
<td>3.619</td>
<td>0.974</td>
<td>0.792</td>
</tr>
<tr>
<td>Inventory level</td>
<td>3.503</td>
<td>1.029</td>
<td>0.858</td>
</tr>
<tr>
<td>Quality (scrap and rework)</td>
<td>3.544</td>
<td>1.086</td>
<td>0.802</td>
</tr>
<tr>
<td>Safety (accidents)</td>
<td>3.156</td>
<td>1.083</td>
<td>0.707</td>
</tr>
</tbody>
</table>

Notes: \( n = 147. \) Extraction method: principal component analysis. Rotation method: varimax with Kaiser normalisation

<table>
<thead>
<tr>
<th>Construct</th>
<th>Questionnaire item</th>
<th>Coef.</th>
<th>AVE</th>
<th>( \chi^2/df )</th>
<th>CFI</th>
<th>SRMR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pull</td>
<td>Production is pulled by the shipment of finished goods</td>
<td>0.945</td>
<td>0.657</td>
<td>21.886/2</td>
<td>0.942</td>
<td>0.049</td>
</tr>
<tr>
<td></td>
<td>Production at stations is pulled by the current demand of the next station</td>
<td>1.073</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>We use a pull production system</td>
<td>1.158</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>We use Kanban, squares, or containers of signals for production control</td>
<td>0.845</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flow</td>
<td>Products are classified into groups with similar processing requirements</td>
<td>0.883</td>
<td>0.588</td>
<td>16.721/2</td>
<td>0.945</td>
<td>0.049</td>
</tr>
<tr>
<td></td>
<td>Equipment is grouped to produce a continuous flow of families of products</td>
<td>0.953</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Families of products determine our factory layout</td>
<td>0.857</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low setup</td>
<td>Our employees practice setups to reduce the time required</td>
<td>0.933</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>We are working to lower setup times in our plant</td>
<td>0.747</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>We have low set up times of equipment in our plant</td>
<td>0.795</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table III. LP operational constructs, measures and CFA factor loadings
Many possible extenuating situations can influence the $\chi^2$ test ($\chi^2/df$). It is extremely sensitive to sample size and the number of observed variables per construct so it should not be used as a sole acceptance or rejection criterion (Schermelleh-Engel et al., 2003). Moreover, there is no absolute consensus in the literature for acceptable normed $\chi^2$ values, whose indications vary between three and five (Marsh and Hocevar, 1985). According to Hair et al. (2014), the acceptability of a model’s goodness-of-fit should not be assessed from a single criterion. We, therefore, checked and reported both absolute ($\chi^2$) and incremental (CFI) goodness-of-fit measures. Many of the construct validity measures met the recommended thresholds, including the CFI and SRMR indices. Additionally, although the $\chi^2/df$ values were higher than the recommended thresholds, their respective $p$-values were lower than 0.01. They do not undermine our results and can therefore be accepted.

Finally, we checked the discriminant validity via average variance extracted (AVE). Each construct’s value should be greater than the squared correlation coefficients (Fornell and Larcker, 1981; Baggozzi and Yi, 1988). Our squared correlation coefficients were lower than the AVE of each construct. The only exception was the correlation between “Flow” and “Low setup” with a squared coefficient of 0.616, which was slightly above the AVE of 0.588 and 0.539, respectively. Table III shows that each latent variable’s AVE exceeded the cut-off value.

### 3.2.3 Industry 4.0 technologies

Industry 4.0 is a recent, shallowly understood approach by companies. Although some authors (e.g. Wan et al., 2015; Rüßmann et al., 2015; Fatorachian and Kazemi, 2018; Kamble et al., 2018; Moetü et al., 2018) argue that Industry 4.0 involves a set of digital technologies (embedded systems, wireless sensor network, 3D printing, cloud computing and big data), most of which were developed prior to 2011. Since many manufacturers might have adopted the technologies before they were deemed part of the fourth industrial revolution era, we investigated the adoption level of ten digital technologies (Brazilian National Confederation of Industry, 2016). Like Tortorella and Fettermann (2018), we explicitly did not mention that they are part of Industry 4.0, thereby mitigating any blurred perceptions. We used a five-point Likert scale where 1 meant “not used” and 5 referred to “fully adopted”. A PCA with varimax rotation was used to extract orthogonal components, resulting in two components (see Table IV). Oblique rotation gave similar results. Thus, as

<table>
<thead>
<tr>
<th>Industry 4.0 technologies</th>
<th>Mean</th>
<th>SD</th>
<th>Factor_1</th>
<th>Factor_2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i_1$ _non_sens_autom</td>
<td>2.63</td>
<td>1.22</td>
<td>0.483</td>
<td>0.133</td>
</tr>
<tr>
<td>$i_2$ _sens_autom</td>
<td>2.74</td>
<td>1.28</td>
<td>0.810</td>
<td>0.305</td>
</tr>
<tr>
<td>$i_3$ _remote</td>
<td>2.43</td>
<td>1.34</td>
<td>0.781</td>
<td>0.295</td>
</tr>
<tr>
<td>$i_4$ _prod_operationID</td>
<td>2.30</td>
<td>1.30</td>
<td>0.748</td>
<td>0.340</td>
</tr>
<tr>
<td>$i_5$ _integratedPD&amp;Manuf</td>
<td>2.46</td>
<td>1.27</td>
<td>0.562</td>
<td>0.424</td>
</tr>
<tr>
<td>$i_6$ _3Dprinting</td>
<td>2.01</td>
<td>1.18</td>
<td>0.416</td>
<td>0.464</td>
</tr>
<tr>
<td>$i_7$ _simulation</td>
<td>1.94</td>
<td>1.20</td>
<td>0.268</td>
<td>0.505</td>
</tr>
<tr>
<td>$i_8$ _big_data</td>
<td>2.27</td>
<td>1.28</td>
<td>0.268</td>
<td>0.732</td>
</tr>
<tr>
<td>$i_9$ _cloud</td>
<td>2.16</td>
<td>1.24</td>
<td>0.178</td>
<td>0.829</td>
</tr>
<tr>
<td>$i_{10}$ _services</td>
<td>2.10</td>
<td>1.22</td>
<td>0.583</td>
<td>0.599</td>
</tr>
</tbody>
</table>

<p>| | | | | |</p>
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<th></th>
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</thead>
<tbody>
<tr>
<td>Eigenvalues</td>
<td>2.256</td>
<td>1.085</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Initial % of variance explained</td>
<td>0.509</td>
<td>0.118</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rotation sum of squared loadings (total)</td>
<td>2.871</td>
<td>2.529</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of variance explained</td>
<td>0.287</td>
<td>0.253</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bartlett’s test of sphericity ($\chi^2$)</td>
<td>196.51</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kaiser-Meyer-Olkin factor adequacy (Overall MSA)</td>
<td>0.74</td>
<td></td>
<td></td>
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</tbody>
</table>

**Notes:** $n = 147$. Extraction method: principal component analysis. Rotation method: varimax with Kaiser normalisation
suggested by Tortorella, Miorando, Caiado, Nascimento and Portioli Staudacher (2018), the mainly manufacturing processes-oriented technologies were grouped into the “Process-related” construct, while the ones mainly focusing on supporting more efficient product/service development were combined into the “Product/Service-related” construct. Process-related technologies are mainly focussed on enhancing and facilitating the actual manufacturing processes, such as digital automation, sensors and Manufacturing Execution System. Additionally, these technologies are closely related to material flow improvement as they help to identify and address eventual issues on processes and machines. Such support allows a higher level of process stability through the reduction of variations and disruptions, which entails smoother and more reliable value streams (Rother and Harris, 2001; Duggan, 2012). The second, product/service-related technologies, such as virtual models and IoT, aim to improve and support processes related to product development and service innovation. The technologies included in this construct are likely to enhance information flows or to support management to develop products and services faster and more assertively, such as 3D printing (Tortorella, Giglio and Van Dun, 2018). These links were briefly envisioned by Lee et al. (2014) and Anderl (2014), but not empirically validated. We verified unidimensionality by using PCA at each component level (see Table IV). The \( \alpha \) values above 0.80 (see Table V) denoted high reliability.

3.2.4 Control variables. Regarding the effects of contingencies, company size is seen to influence the level of LP implementation (e.g. Shah and Ward, 2003; Tortorella et al., 2015). Tortorella and Fettermann (2018) indicated that company size can also affect the association between Industry 4.0 and LP, although not to the same extent. Second, the Brazilian National Confederation of Industry (2016) and Tortorella, Miorando, Caiado, Nascimento and Portioli Staudacher (2018) assessed the effect of technological intensity on the adoption level of Industry 4.0, suggesting that this variable may be have a positive influence on Industry 4.0 adoption. Furthermore, Marodin et al. (2016) and Tortorella et al. (2017) suggested that tier level has a significant effect on LP implementation, especially in the Brazilian industrial sector whose specific supply chain characteristics are different to most developed economies. Finally, the duration of LP implementation was argued as a critical contextual variable, since it may be used to represent a company’s LP maturity level (Netland, 2016; Netland and Ferdows, 2016). Rossini et al. (2019) also considered this in the analysis of Industry 4.0 adoption by European manufacturers. Hence, we included the following four contingencies as control variables in our study: technological intensity, tier level, company size and duration of LP implementation.

Technological intensity was classified into two categories based on their industrial sector suggested by the Organisation for Economic Cooperation and Development (OECD, 2011): high and medium-high, and low and medium-low. Moreover, we divided the companies into tiers 1 and 2, and tiers 3 and 4, as displayed in Table I. Company size was dichotomised as large (\( \geq 500 \) employees) and small and medium (\( \leq 500 \) employees) (SEBRAE, 2010). Finally, following Netland and Ferdows’ (2016) categorisations of the duration of LP implementation, the companies were divided into less than two years and more than two years of implementation.

3.3 Bias countermeasures. Non-response bias was analysed for each of the four surveyed executive education classes (\( n_1 = 35, n_2 = 41, n_3 = 37 \) and \( n_4 = 34 \)) using Levene’s test for equality of variances and a \( t \)-test for the equality of means (Armstrong and Overton, 1977). Both tests indicated that the four groups’ means and variations were not significantly different (\( p < 0.05 \)). So, there was no evidence of differences among these groups compared to the population.
<table>
<thead>
<tr>
<th>Variables</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Pull</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>2. Flow</td>
<td>0.667**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Low setup</td>
<td>0.635**</td>
<td>0.785**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Process-related technologies</td>
<td>0.259**</td>
<td>0.369**</td>
<td>0.401**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Product/service-related technologies</td>
<td>0.319**</td>
<td>0.291**</td>
<td>0.349**</td>
<td>0.143*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Operational performance improvement</td>
<td>0.356**</td>
<td>0.423**</td>
<td>0.505**</td>
<td>0.381**</td>
<td>0.216**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Technological intensity</td>
<td>-0.188**</td>
<td>-0.148</td>
<td>-0.192*</td>
<td>-0.077</td>
<td>-0.164*</td>
<td>-0.182*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Tier level</td>
<td>-0.096</td>
<td>-0.016</td>
<td>-0.090</td>
<td>0.050</td>
<td>0.030</td>
<td>0.155*</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9. Company size</td>
<td>-0.026</td>
<td>-0.049</td>
<td>0.050</td>
<td>0.278**</td>
<td>-0.039</td>
<td>0.100</td>
<td>0.049</td>
<td>-0.026</td>
<td></td>
</tr>
<tr>
<td>10. Duration of LP implementation</td>
<td>0.338**</td>
<td>0.418**</td>
<td>0.422**</td>
<td>0.315**</td>
<td>0.155*</td>
<td>0.259*</td>
<td>-0.177*</td>
<td>-0.008</td>
<td>0.343**</td>
</tr>
<tr>
<td>Cronbach's α</td>
<td>0.873</td>
<td>0.853</td>
<td>0.772</td>
<td>0.855</td>
<td>0.827</td>
<td>0.860</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Composite reliability</td>
<td>0.881</td>
<td>0.855</td>
<td>0.784</td>
<td>0.842</td>
<td>0.807</td>
<td>0.871</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: *p < 0.1; **p < 0.01 level (two-tailed)
Since single respondents answered both the dependent and independent variable questions, we took various countermeasures to avoid common method and source bias, following Podsakoff and Organ (1986) and Podsakoff et al. (2003). First, regarding the survey structure, the dependent variable items were far away from the independent variable items. Moreover, we kept the original scale labels: using different scale anchors is argued to curb covariation (Podsakoff et al., 2003). Naturally, we clarified that there were no right or wrong answers and the respondents’ responses would be treated anonymously. Also, the respondents had to be key lean implementers in their organisations and were thus appropriate informants. Finally, the Harman’s single-factor test, with an EFA including all the independent and dependent variables (Malhotra et al., 2006), displayed a first factor that explained only 23.5 per cent of the variance. Since no single factor accounted for most of the variance, common method variance was deemed minimal.

3.4 Data analysis
We performed a set of Ordinary Least Square (OLS) hierarchical linear regression models to test our hypotheses. Three models were examined. Model 1 only included the effect of the control variables (technological intensity, tier level, company size and duration of LP implementation). We also tested all the models with dummy industry sector variables because process considerations and external contingencies inferred by the industrial sector may explain the maturity level of both LP and Industry 4.0. The four industry-type dummies (see Table I) were not significant and the results remained the same on excluding these variables from the regression models. Thus, to increase the degrees of freedom and significance of our tests, we followed Tortorella, Fettermann, Frank and Marodin's (2018) procedure and disregarded industry sector in the regression. Model 2 included the direct effect of the three LP constructs and the two Industry 4.0 technologies constructs. Finally, Model 3 entailed adding the moderating effects of Industry 4.0 technologies.

As suggested by Hair et al. (2014), we checked for assumptions of normality, linearity, and homoscedasticity between independent and dependent variables. Residuals were verified to confirm normality of the error term distribution. We tested linearity by plotting partial regression for each model. None of the models rejected the hypothesis of adherence to the normal distribution of residuals (Kolmogorov-Smirnov test $p > 0.05$). Homoscedasticity was assessed by plotting standardised residuals against predicted value and a visual examination of those plots. Overall, our tests supported the necessary assumptions for an OLS regression analysis.

4. Results and discussion
Table V shows the correlations of all the variables, Cronbach’s $\alpha$s and composite reliabilities. All the independent variables presented a significant positive correlation with operational performance improvement. Technological intensity was significantly negatively correlated with pull and low setup practices as well as product/service-related technologies. Company size and duration of LP implementation were significantly positively correlated; while duration of LP implementation was significantly negatively correlated with technological intensity.

The regression results, with operational performance improvement as a dependent variable, are shown in Table VI. The unstandardised coefficients are reported here since each construct’s scales had already been standardised (Goldsby et al., 2013). Furthermore, multicollinearity was not a concern since the variance inflation factors in the regression models were all lower than 3.0.

The results suggest that the addition of both the independent variables (Model 2) and the interaction terms (Model 3) led to an incremental improvement of the model (i.e. the Change in Adj. $R^2$ was significant in both models). Model 3, which explains 33.1 per cent of the
variance ($F$-value = 5.812; $p < 0.01$), shows that the addition of the interaction terms significantly enhanced the prediction capacity of operational performance improvement, as indicated by the change in adjusted $R^2$. None of the contingencies seem to have had an impact on perceived operational performance improvement, with the exception of tier level which is positively associated ($\beta = 0.682; p < 0.01$).

Surprisingly, from the LP constructs investigated, only “low setup” presented a significant positive association ($\beta = 0.299; p < 0.05$) with operational performance improvement which contradicts previous research (e.g. Shah and Ward, 2003; Shah and Ward, 2007; Taj and Morosan, 2011). However, in the Brazilian manufacturing context, the effect of pull and flow practices does not seem to be as pervasive as in other contexts. Saurin et al (2010), Tortorella et al (2015), Marodin et al (2016) and Tortorella et al (2017) stressed that LP implementation in Brazilian manufacturing companies is less extensive than in developed economies and most companies continue to struggle with implementing practices that will provide minimum process stability. Therefore, it is reasonable to assume that practices which demand a deeper comprehension of LP as a true value-creation system, such as pull and flow practices, might not be associated with performance improvement.

Furthermore, a direct effect of Industry 4.0 technologies was observed for the process-related technologies. These are primarily related to improving and facilitating manufacturing processes (material flow) and appear to have a positive relationship with operational performance improvement ($\beta = 0.194; p < 0.05$). On the other hand, the product/service-related technologies, which mainly focus on supporting and enhancing product development and service innovation (information flow), do not show a significant direct effect on performance improvement. This may be due the fact that manufacturing companies located in emerging countries usually have fewer financial means than those in developed economies. Hence, the few implemented investments are usually focussed on manufacturing processes (Chen et al, 2011). Additionally, multinational companies located in emerging economies, as in our study, typically develop their manufactured products abroad, in sites with established engineering know-how and technological support (Bonaglia et al, 2007). Therefore, it is quite reasonable that the direct

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technological intensity (control)</td>
<td>$-0.338^{**}$</td>
<td>$-0.172$</td>
<td>$-0.121$</td>
</tr>
<tr>
<td>Tier level (control)</td>
<td>$0.476^*$</td>
<td>$0.567^{***}$</td>
<td>$0.682^{***}$</td>
</tr>
<tr>
<td>Company size (control)</td>
<td>$-0.071$</td>
<td>$0.075$</td>
<td>$0.186$</td>
</tr>
<tr>
<td>Duration of LP implementation (control)</td>
<td>$0.373^{***}$</td>
<td>$-0.043$</td>
<td>$-0.067$</td>
</tr>
<tr>
<td>Pull</td>
<td>$0.063$</td>
<td>$0.073$</td>
<td>$0.073$</td>
</tr>
<tr>
<td>Flow</td>
<td>$0.013$</td>
<td>$0.088$</td>
<td>$0.088$</td>
</tr>
<tr>
<td>Low setup</td>
<td>$0.382^{***}$</td>
<td>$0.299^{***}$</td>
<td>$0.299^{***}$</td>
</tr>
<tr>
<td>Process</td>
<td>$0.197^{***}$</td>
<td>$0.194^{***}$</td>
<td>$0.194^{***}$</td>
</tr>
<tr>
<td>Product/Service</td>
<td>$0.021$</td>
<td>$0.005$</td>
<td>$0.005$</td>
</tr>
<tr>
<td>Pull × Process</td>
<td>$0.110$</td>
<td>$0.110$</td>
<td>$0.110$</td>
</tr>
<tr>
<td>Flow × Process</td>
<td>$-0.296^{***}$</td>
<td>$-0.296^{***}$</td>
<td>$-0.296^{***}$</td>
</tr>
<tr>
<td>Low setup × Process</td>
<td>$0.022$</td>
<td>$0.022$</td>
<td>$0.022$</td>
</tr>
<tr>
<td>Pull × Product/Service</td>
<td>$0.366^{***}$</td>
<td>$0.366^{***}$</td>
<td>$0.366^{***}$</td>
</tr>
<tr>
<td>Flow × Product/Service</td>
<td>$-0.214$</td>
<td>$-0.214$</td>
<td>$-0.214$</td>
</tr>
<tr>
<td>$F$-value</td>
<td>4.111^{***}</td>
<td>7.676^{***}</td>
<td>5.812^{***}</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.103</td>
<td>0.334</td>
<td>0.400</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.078</td>
<td>0.290</td>
<td>0.331</td>
</tr>
<tr>
<td>Change in Adj. $R^2$</td>
<td>$-0.212^{***}$</td>
<td>$0.041^{*}$</td>
<td>$0.041^{*}$</td>
</tr>
</tbody>
</table>

Notes: $n=147$. Unstandardised regression coefficients are reported. Change in Adj. $R^2$ reports results compared with the previous model. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$
impact of product/service-related technologies on operational performance is still incipient and less significant than the direct effect of process-related ones.

However, when the interaction terms are taken into consideration, process-related technologies seem to moderate the effect of low setup negatively ($\beta = -0.296; p < 0.05$). This is contrary to common belief that Industry 4.0 technologies, which are primarily focussed on manufacturing processes, should positively reinforce the relationship between (lean) management practices and operational performance indicators (Subramaniam et al., 2009; Dworschak and Zaiser, 2014). Since Industry 4.0 tends to emphasise the reduction of complexity by strict modularisation, one would expect that the concurrent implementation of such technologies with low setup practices will increase the positive effects on operational performance. Nevertheless, our results do not bear such a moderating assumption. One explanation is that, although both low setup practices and process-related technologies seem to positively affect performance when analysed separately, Brazilian companies may not understand yet how to benefit from their concurrent adoption. As indicated by David et al. (2016) and Landscheidt and Kans (2016), the isolated initiative of investing in cutting-edge technology, without dealing with systemic process improvement and design, does not imply better operational performance. In other words, the incorporation of an acknowledged technology into ill-structured manufacturing processes will not give the expected results. Another reason for this finding could be the misconception of the adoption of process-related technologies in terms of simply increasing the level of machine automation. If they are not designed properly, higher levels of machine automation in production lines could entail a more rigid layout, undermining the flexibility of changing over and so increase the costs related to the introduction of new products (Takeda, 2006; Baudin, 2007). In this sense, if a misguided adoption of process-related technologies occurs, companies may perceive these technologies as being contradictory to the underlying concepts of low setup practices, entailing a negative effect on operational performance.

In turn, technologies related to products or services appear to positively moderate the relationship between flow and operational performance improvement ($\beta = 0.366; p < 0.05$). In fact, if product development and service innovations are properly supported by these Industry 4.0 technologies, it is reasonable to expect a positive impact on the effect of flow practices, through the reduction of time-to-market and, hence, a more reliable flow of value. Furthermore, assertive prototyping together with an integrated design and commissioning approach may anticipate manufacturing issues due to the availability, processing and analysis of big data (Hermann et al., 2016). These technologies might support problem-solving activities and thereby enable continuous flow strategies.

Overall, our study provides arguments for examining the interaction between both approaches, and suggests that LP implementation may, in part, benefit significantly from the adoption of Industry 4.0 technologies. Nevertheless, the pervasiveness of this relationship might change according to the context in which the manufacturing company is located (developed vs developing economy). Indeed, our results empirically support $H2b$ and reject $H3a$. Regarding the remaining hypotheses, our findings do not demonstrate a significant moderation effect of Industry 4.0 technologies.

5. Conclusions

5.1 Theoretical implications

With the advent of the fourth industrial revolution, the integration of smart technologies with LP implementation is acquiring special importance. Lean practices tend to be more impactful since Industry 4.0 allows a better understanding of customers’ demands and accelerates information sharing processes. This empowers employees’ engagement which is key in LP (Van Dun and Wilderom, 2016) as well as throughout the value chain. Industry 4.0 can boost the outcomes of traditional LP implementation, resulting in distinguished benefits.
performance levels. Our study provides empirical evidence for such an association and enhancement, thereby adding to the understanding of the adoption of advanced manufacturing technology (Cheng et al., 2018; Kamble et al., 2018).

In fact, a major theoretical contribution is the evidence that purely technological adoption does not lead to the expected results. LP practices help to install organisational habits and mindsets that favour systemic process improvements. Although Industry 4.0 may impact performance at a certain level (Zawadzki and Zywicki, 2016; Quezada et al., 2017), its effect might change when LP practices are implemented simultaneously. In other words, the socio-technical organisational changes that coincide with LP reinforce practices and behaviours which, when combined properly with today’s technological advancements, enable companies to compete successfully under the, at first sight, paradoxical scenario where high-tech applications and human-based simplicity exist concurrently. There is certainly an opportunity, while implementing LP, for companies to intelligently weigh the trade-offs when introducing novel technologies instead of simple standard operating procedures. Therefore, technology adoption does not necessarily lead to negative interactions with LP practices but, following Toyota’s principle, it must be applied in such a way as to create value for people and processes (Morgan and Liker, 2006; Liker and Morgan, 2011).

Our study also reinforces the validation of two bundles of Industry 4.0 technologies: process-related technologies that support the flow of materials and product/service-related technologies that support the flow of information. The Brazilian National Confederation of Industry (2016), on which our measure was based, originally grouped these technologies into three categories according to their focus, namely: process, product development and new business model/service innovation. Our validation shows that the original second and third clusters converge into one bundle. The process-related technologies include sensors, remote monitoring and integrated engineering systems; the product/service-related technologies involve rapid prototyping, virtual modelling and cloud services. The empirical validation of bundles of technologies that address material and information flows is somewhat consistent with the frameworks proposed by Anderl (2014) and Lee et al. (2014). They discussed the benefits of certain groups of technologies on manufacturing, product development and business innovation, but without testing their concurrent effects. In this sense, our research provides empirical evidence for Industry 4.0 technologies that behave similarly and, hence, could be adopted together. Follow-up studies should include even more advanced Industry 4.0 technologies.

The insights from this study were also examined from the perspective of the contingency theory, since they clarify some usual misunderstandings related to the contingent nature of LP and Industry 4.0. First, our findings do not support the assumption that Industry 4.0 adoption can have an indistinct impact on operational performance. In fact, our research suggests that novel technologies which focus on product development and innovation may not be as valued by manufacturers as expected, especially within the Brazilian industrial sector. This contingency also affects the referred LP practices, because our outcomes differ from studies performed in other socioeconomic contexts (e.g. Netland, 2016). Since this study was employed in Brazil, it adds to the predominantly US-based studies on context-practice-performance relationships that were published in the last 25 years in the International Journal of Operations & Production Management and the Journal of Operations Management (Boer et al., 2017). Second, we identified that some contingencies, like technological intensity, company size and duration of LP implementation, may have a less extensive effect on the interaction between LP and Industry 4.0 than indicated by previous studies. In fact, our research shows that of the four contingencies, only tier level plays a significant role in the resulting model. Although unexpected, this converges with Marodin et al.’s (2016) findings, suggesting that similar tier-level effects can also be observed when integrating Industry 4.0 with LP implementation. It may well be that organisations higher up in the supply chain are nowadays required to
focus more on operational performance improvement than those downstream, which could be achieved via novel technology adoption.

However, Industry 4.0 is still a relatively new concept, especially in economically emerging countries (Mexican Ministry of Economy, 2016; Tortorella and Fettermann, 2018), thus misunderstandings about its concepts and benefits might lead to counterintuitive moderating effects. A similar pattern occurred with regards to LP (e.g. Saurin and Ferreira, 2009; Hines et al., 2018); contrary effects ensued when the concepts were not understood well by the managers who implemented them. Our research emphasises that the integration of product/service-related Industry 4.0 technologies into flow practices can lead to significant operational performance improvements, but only if approached properly. Therefore, a better grasp of the meaning of Industry 4.0 technologies may support proactive initiatives that can potentially converge with previous efforts of implementing LP practices.

5.2 Managerial contributions
As manufacturers search for efficient and economic production systems, novel technologies can contribute to boosting their competitiveness. Industry 4.0 can facilitate the development of higher performance through new business models and services. However, its adoption entails additional challenges for companies, especially those in emerging economies. Therefore, our findings provide managers and practitioners with an indication of the right balance between the adoption of Industry 4.0 technologies and LP practices for improving operational performance within their companies. In fact, our study gives arguments to support managers’ decision-making processes: if they install many flow-related LP practices, they should prioritise the adoption of product/service-oriented technologies such as cloud services, IoT, or big data analysis, in order to achieve high operational performance levels. With advanced information and communication systems in place, along with a LP operating system, a company has the potential to expand with new performance standards. Industries now have the opportunity of combining the benefits of real-time integration with minimal waste generation in the whole value stream. In sum, our findings can help managers to anticipate operational difficulties when integrating process-related new technologies with flow practices. This information helps to set fair expectations, which support a manager’s investment decisions to achieve certain strategic objectives regarding Industry 4.0.

5.3 Limitations and future research
Our sample has certain limitations. First, our sample only confirmed some of the moderating effects of Industry 4.0 technologies on LP practices implementation. Hence, there is a need to develop and empirically test models with larger samples. Increasing the sample by replicating the study in different countries would support the inference of more generalisable results, regardless of the socioeconomic context. We used operational performance indicators as a proxy for financial performance, since financial results are often carefully protected by companies and difficult to obtain and the performance of certain financial indicators is only shared among senior managers. However, the observed improvements in the operational performance indicators probably had a direct impact on the company’s financial performance, mitigating any concerns related to that. Additionally, we examined operational performance as a single dimension comprised of five different indicators. Further studies could analyse the individual association of each of these indicators with LP and Industry 4.0 to understand how exactly a company’s performance is affected by both approaches.

Second, as discussed in Section 3.3, we took various countermeasures to curb the biases that may have resulted from our (cross-sectional) research design. Guide and Ketokivi (2015) recommended utilising multiple respondents per firm in order to mitigate common method bias. Although this approach was not feasible in our study, we invite others to determine firm-level outcomes based on multiple respondents.
Third, the different experiences of the companies using LP was also a sample limitation, possibly influencing respondents’ perceptions of LP practices implementation as their mindsets might have been at different lean maturity stages. Nevertheless, most participating companies had more than two years of lean implementation experience. A comparative study of companies in the same lean phase (Netland and Ferdows, 2016) could avoid any potential errors from the collected data. Also, further studies could include archival data (i.e. publicly available company-level financial reports) to validate the self-reported performance data. They could address the association between LP and Industry 4.0 from a practice level, providing additional details that complement our study. We may have lost specific aspects of the relationship by using EFA to combine individual technologies into multi-dimensional constructs that represent Industry 4.0.

Future longitudinal studies ought to collect more objective output measures or involve front-line supervisors in the rating of the implementation levels of LP and Industry 4.0. This also includes additional LP variables (e.g. the level of employee involvement, suppliers’ and customers’ relationship, total quality management and human resources management practices) or the use of multiple levels of analysis to observe the composed influence of these variables over time. Moreover, in-depth case studies that address common barriers or difficulties with LP implementation and Industry 4.0 adoption may allow a better understanding of the inherent challenges on implementing these approaches concurrently. The lack of empirical research in this emerging field (Kamble et al., 2018) provides ample opportunities for further investigation across different socio-economic contexts.

Note
1. To rule out the existence of any cross-loadings between the LP practices and I4.0 technologies measures in our survey, we ran an additional EFA with all 21 items. No cross-loadings were found (factor loadings $\geq 0.45$).

References


Appendix. Applied survey

1 – Please indicate below how the following operational performance indicators evolved in the last three years in your company:

* Scale from 1 (Worsened significantly) to 5 (Improved significantly)

<table>
<thead>
<tr>
<th>Performance evolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-Productivity</td>
</tr>
<tr>
<td>2-Delivery service level</td>
</tr>
<tr>
<td>3-Inventory level</td>
</tr>
<tr>
<td>4-Quality (scrap and rework)</td>
</tr>
<tr>
<td>5-Safety (accidents)</td>
</tr>
</tbody>
</table>

2 – Please indicate below the characteristics of your company:

(a) Industry sector: ____________________________

(b) Company size:  ( ) Up to 499 employees
                 ( ) More than 500 employees

(c) Tier level: ( ) 1st  ( ) 2nd  ( ) 3rd or more

(d) Time of Lean Production implementation in the company: ( ) ≤ 2 years
                 ( ) > 2 years

(e) Your experience with Lean Production implementation: ( ) ≤ 2 years
                 ( ) > 2 years

(f) Your job title within your company:  ( ) Engineer or Analyst
                                          ( ) Supervisor or Coordinator
                                          ( ) Manager or Director

2 – Please indicate for each statement below the agreement level according to your company’s reality:

* Scale from 1 (Fully disagree) to 5 (Fully agree)
3 – Please indicate below the adoption level of the following digital technologies within your company’s processes:

* Scale from 1 (Not used) to 5 (Fully adopted)

<table>
<thead>
<tr>
<th>Industry 4.0 adoption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agreement level</td>
</tr>
</tbody>
</table>

| 1 - Production is pulled by the shipment of finished goods |
| 2 - Production at stations is pulled by the current demand of the next station |
| 3 - We use a pull production system |
| 4 - We use kanban, squares, or containers of signals for production control |
| 5 - Products are classified into groups with similar processing requirements |
| 6 - Products are classified into groups with similar routing requirements |
| 7 - Equipment is grouped to produce a continuous flow of families of products |
| 8 - Families of products determine our factory layout |
| 9 - Our employees practise setups to reduce the time required |
| 10 - We are working to lower setup times in our plant |
| 11 - We have low set up times of equipment in our plant |

<table>
<thead>
<tr>
<th>Adoption level</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - Digital automation without sensors</td>
</tr>
<tr>
<td>2 - Digital automation with process control sensors</td>
</tr>
<tr>
<td>3 - Remote monitoring and control of production through systems such as Manufacturing Execution System and Supervisory Control and Data Acquisition</td>
</tr>
<tr>
<td>4 - Digital automation with sensors for product and operating conditions identification, flexible lines</td>
</tr>
<tr>
<td>5 - Integrated engineering systems for product development and product manufacturing</td>
</tr>
<tr>
<td>6 - Additive manufacturing, rapid prototyping or 3D printing</td>
</tr>
</tbody>
</table>
Corresponding author
Guilherme Luz Tortorella can be contacted at: gtortorella@bol.com.br
Understanding supply chain analytics capabilities and agility for data-rich environments

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Shahriar Akter
University of Wollongong, Wollongong, Australia

Abstract

Purpose – Big data-driven supply chain analytics capability (SCAC) is now emerging as the next frontier of supply chain transformation. Yet, very few studies have been directed to identify its dimensions, subdimensions and model their holistic impact on supply chain agility (SCAG) and firm performance (FPER). Therefore, to fill this gap, the purpose of this paper is to develop and validate a dynamic SCAC model and assess both its direct and indirect impact on FPER using analytics-driven SCAG as a mediator.

Design/methodology/approach – The study draws on the emerging literature on big data, the resource-based view and the dynamic capability theory to develop a multi-dimensional, hierarchical SCAC model. Then, the model is tested using data collected from supply chain analytics professionals, managers and mid-level managers in the USA. The study uses the partial least squares-based structural equation modeling to prove the research model.

Findings – The findings of the study identify supply chain management (i.e. planning, investment, coordination and control), supply chain technology (i.e. connectivity, compatibility and modularity) and supply chain talent (i.e. technology management knowledge, technical knowledge, relational knowledge and business knowledge) as the significant antecedents of a dynamic SCAC model. The study also identifies analytics-driven SCAG as the significant mediator between overall SCAC and FPER. Based on these key findings, the paper discusses their implications for theory, methods and practice. Finally, limitations and future research directions are presented.

Originality/value – The study fills an important gap in supply chain management research by estimating the significance of various dimensions and subdimensions of a dynamic SCAC model and their overall effects on SCAG and FPER.

Keywords Big data, Supply chain agility

Paper type Research paper

Introduction

Big data analytics (BDA) is defined as “a holistic process that involves 5V (volume, velocity, variety, value, and veracity) in terms of collection, analysis, use, and interpretation of data for various functional divisions, with a view to gaining actionable insights, creating business value, and establishing competitive advantages” (Fosso Wamba et al., 2015, p. 235). BDA is considered as “an end-all solution to supply chain problems” (Lopez, 2017, p. 1) or “a revolution that will transform supply chain design and management” (Waller and Fawcett, 2013, p. 77), or even the “silver bullet for supply-chain forecasting” (Snapp, 2017, p. 10). The high potential of big data-driven supply chain analytics capability (SCAC) (Tiwari et al., 2018) for business value has positioned it as an important game-changer in the supply chain and one of the “hottest topics” among supply chain managers (Tay, 2016). The objective of using BDA across all supply chain processes is to improve SCAC. As such, SCAC is assumed to improve supply chain agility (SCAG) by synchronizing demand and supply (Niu and Zou, 2017) and by enhancing the overall business value and performance (Gunesekaran et al., 2017; Hofmann, 2017; Brinch, 2018). Recent industry literature shows that the market of supply chain analytics is expected to grow from about $4.8bn 2019 (Newswire, 2015) to reach about $9.87bn by 2025 (Newswire, 2017a, b), thus growing potentially by 13.68 percent during the period 2017–2021 (Newswire, 2017a, b).
Although supply chain analytics is gaining momentum in the emerging big data economy, the steep growth curve of performance using analytics is flattening out for many companies (Kiron et al., 2014). A group of scholars have been persistently arguing that the investment in data-driven supply chain analytics and performance is a myth. The present study attempts to respond to this by providing an empirical evidence on how SCAC influences SCAG and FPER (Manyika et al., 2011; Ransbotham et al., 2016; Dubey et al., 2018a). It also seeks to examine the dimensions of SCAC in a big data environment and to model their overall effects on SCAG and FPER. Drawing on the resource-based view (RBV) and the dynamic capability theory (DCT), this study proposes management, technology and talent capabilities as the building blocks of SCAC to enhance SCAG and FPER. For example, Bowers et al. (2017) present the conceptual case of a US-based manufacturer and marketer of basic apparels that is using SCAC to enhance supply chain responsiveness. Lail and Richardson (2015) argue that SCAC could improve end-to-end supply chain productivity, while Orenstein et al. (2016) report that “if the supply chain data streams from multiple logistics providers would be integrated, this could eliminate current market fragmentation, enabling powerful new collaboration and services” (p. 36). McCrea (2017) demonstrates that SCAC could enhance SCAG by providing better diagnostic information, sensing external factors, forecasting robust demands, controlling variability in demand and cycle times, and preparing for the social media, news, event and weather data waves. Despite various anecdotal and fragmented success stories, the components of big data-driven SCAC are still not well explored as well as their overall effects on SCAG and FPER (e.g. Ashrafi et al., 2019; Dubey et al., 2018a; Giannakis and Louis, 2016). Also, the existing SCAC–SCAG-FPER relationship lacks strong theoretical grounding and empirical evidence. Thus, the following research questions are expected to be addressed here:

RQ1. What are the core components of SCAC in the big data environment?

RQ2. What is the impact of the overall SCAC on SCAG?

RQ3. Does SCAG mediate the relationship between SCAC and FPER?

To address these research questions, this study draws on the emerging literature on BDA, RBV and DCT to develop and test our proposed research model. The core of the paper starts with a presentation of the theoretical background, followed by the research method and an analysis of data and findings. The paper ends with the discussion of results and a review of a number of implications.

Literature review and theories

Theories: the resource-based view (RBV) and dynamic capability theory (DCT)

The RBV was developed and proposed by Barney (1991) as a strategic tool to understand how to create and sustain competitive advantage. RBV argues that the differences between competing firms in a given market arise from each firm’s unique capacity to identify and build a bundle of valuable, rare, inimitable and non-substitutable resources (e.g. assets, capabilities, organizational processes, firm attributes, information and knowledge) to create business value (Barney, 2001; Hoopes et al., 2003) and achieve sustainable competitive advantage (Barney, 1991). While RBV has been considered as an important strategic tool in supply chain management, it has also generated a lot of criticisms. For example, Priem and Butler (2001a, b) argue that the RBV is not “currently a theoretical structure” (p. 22), though they recognized that the RBV has assumed “stability in product markets and eschewed determining resources’ values” (p. 22). In another paper (2001), the same authors went as far as suggesting that there is a “tautology in the RBV” (p. 57). It should be noted that various authors successfully used the RBV (Ellinger et al., 2011; Chae et al., 2014; Gligor, 2014; Khanchanapong et al, 2014; Gligor et al., 2015; Hitt et al., 2016; Han et al., 2017) and DCT
(Gligor et al., 2015; Han et al., 2017). Some of them, including Chae et al. (2014), went further by demonstrating the potential of analytics to play the role of a distinctive resource for improving the performance of manufacturing plants. Others (e.g. Han et al., 2017) reported how this technology can efficiently enhance performance in any industry. Dubey, Gunasekaran, Childe, Fosso Wamba, Roubaud and Foropon (2019) saw in data analytics capability a unique building block for information processing capacity and supply chain resilience.

While RBV is proved to be useful in identifying valuable resources for SCAC, much light is yet to be shed on how to adapt resources such as talent/technology/management capability in a fast-changing big data environment. The theory about dynamic capability has emerged to address some of the issues raised about the RBV. Teece et al. (1997) extended the RBV to develop the DCT. The DCT helps organizations to assess the source of business value creation and to capture competitive advantage in volatile markets and changing environments (Winter, 2003; Rothaermel and Hess, 2007; Teece, 2012; Eckstein et al., 2015). The DCT argues that the realization of a sustained competitive advantage by a firm depends on its ability to integrate, build, and reconfigure its internal and external resources and competencies to better adapt in environmental turbulence (Teece and Pisano, 1994; Teece et al., 1997). Scholars suggest that organizations that can make good use of DC could achieve long-term competitive advantage (Augier and Teece, 2009; Cavusgil et al., 2007). In an industry where change is too frequent, dynamic analytics capabilities such as SCAG, supply chain adaptability (Blome et al., 2013; Eckstein et al., 2015; Rameshwar et al., 2018) and supply chain visibility (Rameshwar et al., 2018) can help firms and supply chain members to integrate, build and reconfigure strategic resources and capabilities to accelerate FPER. We draw from these prior studies and argue that SCAC and SCAG are complementary dynamic capabilities that could lead to sustainable competitive advantage. For example, SCAC can establish agility and enhance performance by means of data-driven insights regarding operations (Teece, 2014).

### Supply chain analytics capabilities as dynamic capabilities: dimensions and effects

Dynamic capabilities are defined as higher-order capabilities that organize resources to enhance the performance of an organization in changing contexts (Teece, 2014). The building blocks of the DC theory are appropriate for supply chain analytics as it leverages management, technology and talent capabilities to improve organizational agility (Akter et al., 2016). Drawing on the DC theory, we define SCAC as a holistic analytics process that provides robust insights for real-time decision making using various technological, managerial and personnel capabilities. Such an analytics platform utilizes sensor data, RFID data, location data through mobile devices, click-stream data (e.g. web and online advertisements, tweets, blogs, Facebook wall postings), transaction data, video data, voice data and consumer sentiments from social media to reinforce insights and decision making (Fosso Wamba, Gunasekaran, Akter, Ren, Dubey and Childe, 2017). For example, Rofmann et al. (2018) demonstrate the role of analytics technology to enhance demand forecasts, reduce safety stocks and improve the management of supplier performance. Similarly, Zhao et al. (2017) highlight analytics talent capability as a conducive means of developing an optimization model for the robust supply chain management. In a similar spirit, scholars indicate how it is urgent to embrace analytics management capability so as to improve supply chain efficiency (Gheorghe et al., 2015), develop compensation strategies in large-scale data breaches (Kude et al., 2017) and mediate the risk of default of trade credit in the supply chain (Tsao, 2017).

SCAG is defined as “a firm’s ability to perform operational activities together with channel partners in order to adapt or respond to marketplace changes in a rapid manner” (Liu et al., 2013, p. 1453). Lee (2004) discovered that SCAC creates SCAG to balance between...
demand and supply. Aslam et al. (2018), on their part, better explained the role of SCAC in developing an agile and ambidextrous supply chain. To Ketchen and Hult (2007), SCAC and SCAG are complementary dynamic capabilities that result in superior FPER. According to Peteraf and Barney (2003), FPER is reflected in the creation of more economic value than the marginal competitor in the supply chain industry. Overall, supply chain management firms are keen to develop analytics capabilities that can adapt to, orchestrate and innovate in changing markets (Teece, 2014). Although the components of SCAC have been identified under various dimensions, the extent literature identifies three overarching themes: SCAC management capability, SCAC technology capability and SCAC talent capability.

Research model and hypotheses development

The proposed model (see Figure 1) is based on the frequently cited dimensions in the analytics literature (see Table I) and on pertinent theoretical foundations (i.e. RBV and DCT) that impact SCAC. The review of big data literature and the theoretical exploration of the study showed that SCAC was repeatedly identified as a multidimensional, hierarchical construct with various subdimensions determining the primary dimensions. As such, we propose SCAC model as a third-order construct that also has three second-order dimensions (supply chain management capability (SCMAC), supply chain technology capability (SCTEC) and supply chain talent capability (SCTLC)). By doing so, we contribute to extending this stream of research in the supply chain context. Indeed, this unique configuration of SCAC could allow firm and supply chain members to create business value and achieve sustainable competitive advantage (Figure 1). Therefore, we propose that SCAC will have a significant positive impact on FPER through SCAG.

SCAG is now considered a key enabler of supply chain success in an extremely turbulent and fluctuating economic context (I. van Hoek et al., 2001; Sharifi et al., 2006, 2009; Najafi Tavani et al., 2013; Cerruti et al., 2016) that seeks to create business value and sustain a particular competitive advantage (Ngai et al., 2011). For example, Dwayne Whitten et al. (2012) argued that the success of supply chain members requires an agile supply chain environment (p. 30). As an operational (Liu et al., 2013; Yang, 2014) and relational capability...
Yang (2014), agility allows firms not only to quickly respond to customer requests and market changes (I. van Hoek et al., 2001), but also to face market uncertainty (Sharifi et al., 2006; Chiang et al., 2012), foster supply chain collaboration (Dwayne Whitten et al., 2012) and achieve time-to-market (Cerruti et al., 2016). It also enhances product customization, delivery performance and products development time (Swafford et al., 2008), while speeding access to new business opportunities (Sharifi et al., 2006). Given the magnitude of all these capabilities, some scholars have even suggested that SCAG could “act as a rare, valuable, and imperfectly imitable operational capability, which is critical to improving firm performance” (Liu et al., 2013, p. 1453).

A key driver of firm and SCAG is IT (Zhang and Sharifi, 2000). For example, IT capability is a strong predictor of SCAG (Yang, 2014) and can significantly improve the supply chain’s ability to respond to market changes (DeGroote and Marx, 2013), notably by reinforcing adequacy, accuracy, accessibility and the timeliness of information flow between supply chain members. In addition, IT capability has a direct positive impact on SCAG, which in turn has a positive effect on performance (Yang, 2014). Chan et al. (2017) showed that SCAG plays an important role in mediating the effects of both strategic and
manufacturing flexibilities on firm performance (p. 486). Liu et al. (2013) demonstrated that IT capability has a positive impact on FPER through SCAG and its absorptive capacity. On their part, Swafford et al. (2008) showed that IT integration positively influences SCAG, which, in turn, has a positive effect on competitive business performance.

In this study, we suggest that analytics-driven SCAG is a dynamic capability (Gligor and Holcomb, 2012) that will mediate the relationship between SCAC and FPER. Early studies (Sanders and Premus, 2005; Lin, 2007; Kim et al., 2011; Chen et al., 2014) and the emerging literature on BDA capability (Akter et al., 2016; Fosso Wamba, Gunasekaran, Akter, Ren, Dubey and Childe, 2017) have established a significant positive relationship between investment in SCAC and organizational outcomes. Dubey, Gunasekaran, Childe, Blome and Papadopoulos (2019) and Dubey, Gunasekaran, Childe, Posso Wamba, Roubaud and Foropon (2019) showed that BDA capability is an important facilitator of improved information-processing capacity and supply chain resilience, the objective of which is to reduce a ripple effect in supply chains or to rapidly recover from supply chain disruptions. SCAC could provide timely and accurate information about the spending patterns developed by firms to support strategic sourcing decisions (Tiwari et al., 2018). Moreover, SCAC allows end-to-end real-time information sharing as well as the monitoring of supply chain activities that could lead to improved supply chain decisions (Tiwari et al., 2018), and thus to enhanced SCAG (Giannakis and Louis, 2016; Tiwari et al., 2018) and FPER (Dubey, Gunasekaran, Childe, Blome and Papadopoulos, 2019; Dubey, Gunasekaran, Childe, Posso Wamba, Roubaud and Foropon, 2019). Based on this discussion, we propose the following hypotheses:

**H1.** SCAC has a significant positive impact on FPER.

**H2.** SCAC has a significant positive impact on SCAG.

In a similar spirit, the extant literature on supply chain management has found a significant link between SCAG and performance (see Swafford et al., 2006, 2008; Dwayne Whitten et al., 2012; Gligor et al., 2015; Eckstein et al., 2015; Dubey et al., 2018a, b). For instance, Srinivasan and Swink (2018) highlighted the role of SCAG in cost reduction, while Ayinder et al. explored the exponential growth of supply chain performance through SCAG. Gligor and Holcomb (2012, p. 299) argue that SCAG could foster operating routines modification, facilitate organizational resource reconfiguration and improve organizational sensing ability. Eckstein et al. (2015) revealed that SCAG plays a critical role in balancing supply and demand, reducing the cost of inventory and transportation. By exploiting the agility of their supply chains, firms can enhance their own performance as throughput and set-up times will be improved, the replacement times of materials and services shortened, and the production processes quickly adjusted in order to customize products cost-efficiently while avoiding product markdowns caused by excess inventory (Lee, 2004). Indeed, SCAG enables organizational capabilities to achieve improved FPER and sustained competitive advantage. Similarly, it is an important driver of organizational logistics performance (Dubey et al., 2015). Based on this discussion, we hypothesize that:

**H3:** SCAG has a significant positive impact on FPER in the context of BDA environment.

SCAG can improve FPER through the mediating role of other dynamic capabilities (Eckstein et al., 2015; Dubey et al., 2018a, b). SCAG depends on SCAC to implement and leverage the subdimensions of various analytics capabilities. Fosso Wamba, Gunasekaran, Akter, Ren, Dubey and Childe (2017) highlighted the dynamic capability of SCAG to sense, seize and transform supply chain processes in order to synchronize demand and supply. According to the extant research on supply chain management, a high level of SCAC can strengthen firms’ core characteristics such as ambidexterity, adaptability and swiftness (Gunasekaran et al., 2017; Hofmann, 2017; Brinch, 2018). Therefore, firms can upgrade their
performance in terms of sales, profit and return on investment if their supply chain processes are robust. Thus, we hypothesize that SCAG, as a strategic dynamic capability, will mediate the relationship between SCAC and FPER:

\[ H4. \text{ SCAG mediates the relationship between SCAC and FPER.} \]

Research methodology
This study used a web-based survey to collect data from supply chain professionals, managers and mid-level managers in the USA. The survey was realized by a market research firm with more than 11 million panelists across 40 countries. Our study was mainly interested by supply chain professionals and managers in the USA with at least three years' experience in supply chain analytics. More precisely, an invitation explaining the objectives of the study was sent to the targeted panelists in 2017, including supply chain executives in charge of activities such as logistics, procurement, supply chain planning, purchasing, transportation, warehousing, production or shipping. A total of 679 persons from among those contacted agreed to participate in the study. At the end of the data collection process, we received 281 completed questionnaires or a response rate of 41 percent. Prior to the final data collection, a survey pre-testing was realized with seven scholars working on BDA-related projects.

All the constructs used in the study were derived from prior studies and adapted to fit our research context of BDA in the supply chain context. Using a seven-point Likert scale ranging from (1) “strongly disagree” to (7) “strongly agree”, the items were measured. Data analysis was realized using a partial least squares structural equation modeling (PLS-SEM) tool called SmartPLS 3.0 (Ringle et al., 2014). Table AI describes all the scales and items.

Analysis and findings
Based on the established guidelines on model development (Chin, 2010; Ringle et al., 2012), we identify that the mode of measurement as reflective-formative as the first and second-order dimensions are reflective (Mode A) but the third-order dimensions are formative (Mode B). The study applies PLS path modeling to establish more theoretical parsimony and less model complexity (Wetzels et al., 2009). Specifically, it applies PLS to avoid the limitations regarding sample size and distributional properties (Hair et al., 2011). The study used SmartPLS 3.0 (Ringle et al., 2014) nonparametric bootstrapping (Efron and Tibshirani, 1993; Chin, 1998a, b; Tenenhaus et al., 2005) with 5,000 replications. The study estimated the model for the inside approximation using a path weighting scheme (Hair et al., 2013). Following the procedures of higher-order modeling (Becker et al., 2010; Chin, 2010), the study repeatedly used indicators at first-order and second-order levels to estimate the score of the third-order construct. Therefore, the highest-order SCAC construct consists of all the items of the corresponding first-order latent constructs.

Measurement model
The study confirms the convergent and discriminant validity of the first-order measurement model using PLS path modeling (Table II). The 11 supply chain analytics subdimensions which represent the first-order model are encapsulated under three second-order dimensions: SCMAC, SCTEC and SCTLC. First, the measurement model results show that items loadings are significant at \( p < 0.001 \) and all they exceed 0.7 threshold value. Second, the study calculated average variance extracted (AVE) to measure the amount of variance and composite reliability (CR) to measure internal consistency (Fornell and Larcker, 1981; Chin, 1998a, b) that indicates the reliability of all the measurement scales.
### Reflective constructs

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### Formative construct

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Table II.
Assessment of first-order, reflective model
Both CRs and AVEs of all scales are either equal to or exceed 0.80 and 0.50 cut-off values, respectively (Fornell and Larcker, 1981; Hair et al., 2013), which confirms corresponding reliability and convergent validity of first-order constructs (Fornell and Larcker, 1981). The study also confirmed that the weights of formative items are significant at $p < 0.01$ and the variance inflation factor (VIF) is less than the cut-off value of 5. Thus, the findings of the measurement model confirm adequate reliability and validity for all the constructs.

Table III shows the correlation matrix reporting the $\sqrt{AVE}$ in the diagonals, which shows adequate discriminant validity as it exceeds inter-correlation with other LVs in the first-order model (Fornell and Larcker, 1981; Chin, 1998a, b, 2010). This also indicates that constructs are conceptually different from each other (Chin, 2010). Further discriminant validity was confirmed by assessing the cross-loadings, which reflects constructs with a strong correlation with their own items than others (Fornell and Bookstein, 1982; Chin, 1998a, b). Overall, the evidence of adequate reliability (AVE $> 0.50$, CR $> 0.80$), convergent validity (loadings $> 0.80$), and discriminant validity ($\sqrt{AVE}$ > correlations) demonstrates the robustness of the first-order measurement model. As a result, the measurement model was considered satisfactory and employed for testing the higher-order measurement model and the structural model in the next sections.

**Higher-order measurement model**

Due to the hierarchical nature of the research model, we calculated the measurement properties of the second-order management, technology and talent constructs and third-order supply chain analytics (SCAC) construct. The highest-order SCAC construct represents 44 indicators. The formative nature of the highest-order SCAC construct indicates that its relationship with second-order constructs is significant ($p < 0.05$). For example, management capability explains 36 percent of variance, technology capability explains 28 percent of the variance and talent capability explains 39 percent of variance in SCAC. Table IV shows that management capability was reflected by planning (92 percent), investment decision making (94 percent), coordination (95 percent) and control (95 percent). Similarly, technology capability was explained by connectivity (95 percent), compatibility (96 percent) and compatibility (96 percent). Finally, technology capability was explained by business knowledge (96 percent), technology management knowledge (96 percent), technical knowledge (94 percent) and relationship knowledge (94 percent), which are significant at $p < 0.01$ through the path coefficients between second-order and third-order constructs.

**Structural model**

Table V shows the validity of the structural model by estimating the path coefficients, $t$-statistics and the $R^2$ (Falk and Miller, 1992; Stone, 1974; Geisser, 1975). The findings provided a standardized path coefficient of 0.386 from SCAC to FPER ($H1$), 0.865 from SCAC to SCAG ($H2$) and 0.515 from SCAG to FPER ($H3$). The findings of the study confirm the significance of these path coefficients, thus supporting $H1$–$H3$.

The study followed the guidelines proposed by Preacher and Hayes (2008) to estimate the indirect (or, mediating) effect of SCAG between SCAC-SCAG-FPER link using bootstrapping on a 95% of confidence interval. The findings show that the size of the mediating effect is 0.445, which is the product of the path coefficients from SCAC to SCAG and from SCAG to FPER significant at $p < 0.01$. Overall, the study proved that SCAG is a significant partial mediator between SCAC and FPER, thus supporting $H4$ (Hair et al., 2017).

**Additional analyses**

Following Armstrong and Overton's (1977) guidelines, this study conducted a non-response bias analysis. First of all, the first and the last quarter of the pilot data ($n = 71$) were
<table>
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<tr>
<th>Construct</th>
<th>Mean</th>
<th>SD</th>
<th>5.645</th>
<th>1.305</th>
<th>0.919*</th>
<th>Supply chain planning (SCPL)</th>
<th>5.675</th>
<th>1.247</th>
<th>0.535</th>
<th>0.355</th>
<th>0.897*</th>
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<tr>
<td>Supply chain investment decision (SCID)</td>
<td>5.645</td>
<td>1.247</td>
<td>0.535</td>
<td>0.355</td>
<td>0.897*</td>
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<td>0.532</td>
<td>0.552</td>
<td>0.897*</td>
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<tr>
<td>Supply chain control (SCCT)</td>
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<td>0.552</td>
<td>0.897*</td>
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<tr>
<td>Supply chain connectivity (SCCN)</td>
<td>5.522</td>
<td>1.370</td>
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<tr>
<td>Supply chain compatibility (SCCM)</td>
<td>5.572</td>
<td>1.296</td>
<td>0.542</td>
<td>0.552</td>
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<tr>
<td>Supply chain technology management knowledge (SCTM)</td>
<td>5.697</td>
<td>1.265</td>
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<td>0.552</td>
<td>0.897*</td>
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<td>Supply chain technical knowledge (SCTK)</td>
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<td>1.275</td>
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<td>0.552</td>
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<td>Supply chain business knowledge (SCBK)</td>
<td>5.750</td>
<td>1.195</td>
<td>0.542</td>
<td>0.552</td>
<td>0.897*</td>
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<tr>
<td>Supply chain relational knowledge (SCRK)</td>
<td>5.767</td>
<td>1.222</td>
<td>0.542</td>
<td>0.552</td>
<td>0.897*</td>
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<td>Supply chain agility (SCAG)</td>
<td>5.714</td>
<td>1.296</td>
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<tr>
<td>Performance of the firm (FPER)</td>
<td>5.752</td>
<td>1.175</td>
<td>0.535</td>
<td>0.552</td>
<td>0.897*</td>
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Table III. Correlations of LVs, AVEs and descriptive statistics*
compared for each first-order SCAC response. The findings did not show any significant variation across the constructs, and no non-response bias was found in the pilot study. Then, the main study \((n = 281)\) followed the same procedure by using the first and last 10 percent of respondents across the first-order SCAC constructs. The findings were consistent with the first-round, and no concern of non-response bias was noticed. Finally, a comparison test was made with the data from Study 2 (i.e. main study) and Study 1 (i.e. pilot study), and the \(\chi^2\) tests did not present any significant difference \((p > 0.05,\) that is, Study1 \(=\) Study 2) in terms of demographic characteristics (e.g. gender, age, education and experience) (Stanko et al., 2012; Akter et al., 2016). In addition, the potential risk of CMV from a single-respondent survey design was addressed using research design and statistical techniques. This implies that the study established a psychological separation between antecedents and outcome variables to ensure adequate causality in the relationship; and the Herman’s single-factor test was conducted, and no construct was found to be contributing for more than 30 percent to the variance (Podsakoff and Organ, 1986). To address the limitation of this test, we also applied the marker variable technique (Lindell and Whitney, 2001) by including a weakly related item as a marker variable in the SEM model. Overall, we did not find any significant relationship between the marker variable and any construct, which means that no CMV was found in the study.

Discussion
The study addressed three research questions as follows:

\textit{RQ1.} What are the dimensions of supply chain analytics capabilities (SCACs)?

\textit{RQ2.} Is there any impact on SCACs on FPER?

\textit{RQ3.} Is there any mediating effect of SCAG between SCAC and performance?
We answered these questions by conceptualizing hierarchical SCACs as dynamic capabilities, which are able to sense, seize and reconfigure operations by rendering them more agile. Upon the development and validation of SCACs as dynamic capabilities, we were in a position to model their overall effects on outcome construct and to assess the mediating effects of SCAG.

The findings show that SCTLC emerged as the strongest second-order construct ($\beta = 0.391$) to form dynamic SCAC. Ransbotham et al. (2015a, b) highlight the role of talent capability in gaining a competitive advantage with BDA. In addition, the role of SCMAC was selected as a critical construct ($\beta = 0.362$) implying that accelerating FPER with SCACs relies heavily on decision makers. Finally, SCTEC was found as a significant dimension ($\beta = 0.281$), emphasizing the need for establishing a robust technology platform using big data, AI and machine learning. For example, Davenport (2013, p. 67) highlights that “innovative technologies of many kinds had to be created, acquired, and mastered […] To complement them, new ‘agile’ analytical methods and machine-learning techniques are being used to produce insights at a much faster rate.” Although the findings showed the rank order importance of three SCAC dimensions, all the dimensions are equally important as the magnitude of difference among them are minimal.

The findings show that the importance of overall SCAC is associated with construct and sub-construct levels. For example, the role of SCMAC is determined by the level of planning, investment, coordination and control. Similarly, technology and talent capability could be improved by enhancing their sub-dimensions, respectively. These findings have a direct impact on industries such as, retail, manufacturing, healthcare, which constantly struggle to develop analytics capabilities. For example, by developing SCAC and agility, supply chain managers could enhance FPER and, thus, create new products and services (70 percent), increase sales and revenue (76 percent) and expand into new markets (72 percent) (Columbus, 2014). Overall, the findings of the study propose SCAC as a driver of accelerating FPER (explaining 77 percent of the variance) by establishing robust agility in operations (44 percent of the variance). Overall, the empirical findings of our study answer our research, and provide adequate evidence for the conceptual foundation of Kiron, Prentice et al. (2014, p. 10), “an analytics culture is built on the backs of more advanced data management processes, technologies and talent.”

Before discussing the implications of our study, it is important to highlight some of the limitations related to this study. First, the study uses a cross-sectional study as a quick, easy and cost-effective way to collect data among supply chain professionals, managers and mid-level managers in the USA (Sedgwick, 2014), thus using only one data collection point. Future studies should consider using a mixed-methods research approach that combines the strengths of qualitative and quantitative approaches to study the adoption, use and impact of BDA in the supply chain (Venkatesh et al., 2016). Another research avenue is the use of a longitudinal case study to validate our current research findings. Second, the data collection was done only in the USA, future studies should consider collecting data in various countries with different cultural and economic characteristics (e.g. developing and developed countries).

Implications for research
This study has several theoretical implications for key issues such as data-driven SCAC, SCAG and FPER. Although the findings of our study are aligned with the results of a number of operations and supply chain management studies (see Kristal et al., 2010; Blome et al., 2013; Aslam et al., 2018), SCAC driven by big data-driven analytics capability has become an important challenge in operations discourse and no consensus has been reached on how to resolve this dilemma. In their recent attempts to bridge the gap, Dubey et al. (2018a), Dubey, Gunasekaran, Childe, Blome and Papadopoulos (2019), Dubey, Gunasekaran,
Childe, Fosso Wamba, Roubaud and Foropon (2019), Srinivasan and Swink (2018) and Chen et al. (2015) failed to articulate the SCAC dimensions and their effects on SCAG and FPER. By integrating findings from RBV, DC and emerging big data theories, we have achieved some success, which has specific theoretical implications. The first of them is that this study has pioneered the conceptualization of SCAC, the modeling of its impact on FPER and the evaluation of the mediating effect of SCAG on the relationship between SCAC and FPER. Hence, the study extends the research stream BDA capability (Akter et al., 2016; Fosso Wamba, Gunasekaran, Akter, Ren, Dubey and Childe, 2017) using the DCT in the supply chain context. The second implication is that this study tested and confirmed the mediating effect of SCAG on the relationship between SCAC and FPER, and thus confirmed the importance of investing in complementary assets (e.g. SCAG) to leverage a firm analytics platform (Kohli and Grover, 2008; Anand et al., 2013). By doing so, the study proposes an integrated model that links SCAC, SCAG and FPER. While this study extends directly the modeling of SCAC, our findings that SCAG plays an instrumental role between analytics capability and FPER (Srinivasan and Swink, 2018; Gunasekaran et al., 2017) challenges the existing assumption that BDA capability is the only solution for superior supply chain performance (see Akter et al., 2016; Fosso Wamba, Gunasekaran, Akter, Ren, Dubey and Childe, 2017).

Implications for practice
Our findings identified a significant positive relationship between SCAC and FPER as well as a mediating effect of SCAG on this relationship. These findings could guide managers’ decisions to invest in SCAC. They should also consider investing in complementary assets such as SCAG in order to achieve a high-level sustained competitive advantage. Furthermore, firms should invest in an appropriate business model enabled by SCAC (Hartmann et al., 2016). It should be noted that this study identified the three main subconstructs of analytics capability in the supply chain context on which managers should focus when exploring the adoption and use of big data. The findings of the study can be used as a diagnostic tool to identify gaps in BDA capability. For example, the model obtained can help managers to identify any analytics sub-dimension that is lowly performant and poorly contributes to a particular dimension (i.e. talent, technology or management). The measurement of the relative contribution of any particular dimension to agility and performance can also rely on the findings of this study.

Conclusion, limitations and the way forward
In terms of contributions, this study has succeeded in identifying the key constructs and subconstructs that are required by SCAC for improved FPER, and, thus, help in a better understanding of the SCAC construct within the emerging big data literature. The second contribution resides in that this study tested the direct impact of SCAC on FPER as well as the mediating effect of SCAG on this relationship. Drawing on the emerging literature on big data, RBV and the DCT, and based on data collected from 281 supply chain managers in the USA, this study found a positive significant impact of SCAC on FPER and the mediating effects of SCAG on this relationship. This study contributes to the understanding of big data adoption, use and impact at the firm and the supply chain levels. Our proposed research model can be used as a baseline model for future studies on BDA-enabled supply chain optimization.

This study is bounded in many ways. First, we only consider SCAG as the single mediator of the relation between SCAC and FPER. However, just aligning the SCAC and FPER is not enough. Future studies should consider integrating more capabilities such as supply chain adaptability, and other alignments that could mediate the relation between SCAC and FPER (Rameshwar et al., 2018). Second, while this study provides some...
important dimensions of SCAC needed to foster FPER, more investigations are welcome for the holistic IT infrastructure that is needed to capture and share real-time information across the supply chain, and thus support big data, emerging processes and people’s activities (Kache and Seuring, 2017); and the ultimate goal remains an improved decision-making process and a sustained competitive advantage (Brinch, 2018). Another future research avenue should consist in exploring the impact of investing in big data in order to create a higher-order capabilities or dynamic capabilities that will be used to sense customers needs and market opportunities, mobilize the required resources to seize opportunities (or the seizing capability) and readjust them to face the identified customers’ needs and market opportunities (or the reconfiguring capability) (Teece, 2014). Third, this study uses a survey-based questionnaire to collect data, which holds the risk of self-report bias (Fosso Wamba, Bhattacharya, Trinchera and Ngai, 2017; Fosso Wamba, Gunasekaran, Akter, Ren, Dubey and Childe, 2017). Therefore, future studies should consider using case studies or longitudinal studies to validate our current findings and uncover the impact of the lag effect of big data investments (Kohli and Grover, 2008).

References


McCrea, B. (2017), “6 ways BIG DATA is enhancing the global supply chain”, *Logistics Management*, Vol. 56 No. 9, pp. 64S-72S.


<table>
<thead>
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<th>2nd-order constructs</th>
<th>Type</th>
<th>1st-order constructs</th>
<th>Type</th>
<th>Item labels</th>
<th>Items</th>
<th>Sources</th>
</tr>
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<tr>
<td>Supply chain analytics management</td>
<td></td>
<td>Supply chain planning</td>
<td>Reflective</td>
<td>SCPL1</td>
<td>We continuously examine the innovative opportunities for the strategic use of supply chain analytics</td>
<td>Boynton et al. (1994), Sabherwal (1999), Segars and Grover (1999), Karimi et al. (2001), Kim et al. (2012)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Reflective</td>
<td>SCPL2</td>
<td>We enforce adequate plans for the introduction and utilization of supply chain analytics</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Reflective</td>
<td>SCPL3</td>
<td>We perform supply chain analytics planning processes in systematic and formalized ways</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Reflective</td>
<td>SCPL4</td>
<td>We frequently adjust supply chain analytics plans to better adapt to changing conditions</td>
<td></td>
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<tr>
<td>Supply chain investment decision-making</td>
<td></td>
<td></td>
<td>Reflective</td>
<td>SCID1</td>
<td>When we make supply chain analytics investment decisions, we think about and estimate the effect they will have on the productivity of the employees' work</td>
<td>Sabherwal (1999), Ryan et al. (2002), Kim et al. (2012)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Reflective</td>
<td>SCID2</td>
<td>When we make supply chain analytics investment decisions, we consider and project how much these options will help end-users make quicker decisions</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
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<td>Reflective</td>
<td>SCID3</td>
<td>When we make supply chain analytics investment decisions, we think about and estimate the cost of training that end-users will need</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Reflective</td>
<td>SCID4</td>
<td>When we make supply chain analytics investment decisions, we consider and estimate the time managers will need to spend overseeing the change</td>
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<td>Supply chain coordination</td>
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<td></td>
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<td>SCCO1</td>
<td>In our organization, supply chain analysts and line people meet frequently to discuss important issues both formally and informally</td>
<td>Boynton et al. (1994), DeSanctis and Jackson (1994), Karimi et al. (2001), Li et al. (2003), Kim et al. (2012)</td>
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<td></td>
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<td>Reflective</td>
<td>SCCO2</td>
<td>In our organization, supply chain analysts and line people from various departments frequently attend cross-functional meetings</td>
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<td></td>
<td></td>
<td></td>
<td>Reflective</td>
<td>SCCO3</td>
<td>In our organization, supply chain analysts and line people coordinate their efforts harmoniously</td>
<td></td>
</tr>
</tbody>
</table>
|                                          |      |                      | Reflective | SCCO4 | In our organization, information is widely shared between analysts and line people so that those who make decisions or perform jobs have access to all available know-how | (continued)
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<tr>
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<th>1st-order constructs Type</th>
<th>Item labels</th>
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<td>Supply chain control</td>
<td>Reflective SCCT1</td>
<td>In our organization, the responsibility for analytics development is clear</td>
<td>Karimi et al. (2001), Kim et al. (2012)</td>
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<td></td>
<td>Reflective SCCT2</td>
<td>We are confident that analytics project proposals are properly appraised</td>
<td></td>
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<tr>
<td></td>
<td>Reflective SCCT3</td>
<td>We constantly monitor the performance of the analytics function</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>Reflective SCCT4</td>
<td>Our analytics department is clear about its performance criteria</td>
<td></td>
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<tr>
<td>Supply chain analytics technology capability (SCTEC)</td>
<td>Reflective SCCN1</td>
<td>Compared to rivals within our industry, our organization has the foremost available analytics systems</td>
<td>Duncan (1995), Terry Anthony Byrd (2000), Kim et al. (2012)</td>
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<td></td>
<td>Reflective SCCN2</td>
<td>All remote branches and mobile offices are connected to the central office for analytics</td>
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<td></td>
<td>Reflective SCCN3</td>
<td>Our organization utilizes open system network mechanisms to boost analytics connectivity</td>
<td></td>
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<td></td>
<td>Reflective SCCN4</td>
<td>There are no identifiable communications bottlenecks within our organization when sharing analytics insights</td>
<td></td>
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<tr>
<td>Supply chain compatibility</td>
<td>Reflective SCCM1</td>
<td>Software applications can be easily transported and used across multiple analytics platforms</td>
<td>Duncan (1995), Terry Anthony Byrd (2000), Kim et al. (2012)</td>
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<td></td>
<td>Reflective SCCM2</td>
<td>Our user interfaces provide transparent access to all platforms and applications</td>
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<tr>
<td></td>
<td>Reflective SCCM3</td>
<td>Analytics-driven information is shared seamlessly across our organization, regardless of the location</td>
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<tr>
<td></td>
<td>Reflective SCCM4</td>
<td>Our organization provides multiple analytics interfaces or entry points for external end-users</td>
<td></td>
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<tr>
<td>Supply chain modularity</td>
<td>Reflective SCMD1</td>
<td>Reusable software modules are widely used in new analytics model development</td>
<td>Duncan (1995), Broadbent et al. (1999), Terry Anthony Byrd (2000), Kim et al. (2012)</td>
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<td></td>
<td>Reflective SCMD2</td>
<td>End-users utilize object-oriented tools to create their own analytics applications</td>
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<td>Reflective SCMD3</td>
<td>Object-oriented technologies are utilized to minimize the development time for new analytics applications</td>
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<td></td>
<td>Reflective SCMD4</td>
<td>Applications can be adapted to meet a variety of needs during analytics tasks</td>
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(continued)
<table>
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<td>Supply chain</td>
<td>Molecular</td>
<td>Supply chain technical knowledge</td>
<td>Reflective</td>
<td>SCTK1</td>
<td>Our analytics personnel are very capable in terms of programming skills</td>
<td>Boar (1995), Lee et al. (1995), Broadbent et al. (1999), Terry Anthony Byrd (2000), Kim, Shin et al. (2012)</td>
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<tr>
<td>analytics talent capability (SCTLC)</td>
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<td>Reflective</td>
<td>SCTK2</td>
<td>Our analytics personnel are very capable in terms of managing project life cycles</td>
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<td>Reflective</td>
<td>SCTK3</td>
<td>Our analytics personnel are very capable in the areas of data and network management and maintenance</td>
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<td></td>
<td></td>
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<td>SCTK4</td>
<td>Our analytics personnel create very capable decision support systems driven by analytics</td>
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<tr>
<td></td>
<td>Reflective</td>
<td>SCTM1</td>
<td>Our analytics personnel show superior understanding of technological trends</td>
<td>Terry Anthony Byrd (2000), Tippins and Sohi (2003), Kim et al. (2012)</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Reflective</td>
<td>SCTM2</td>
<td>Our analytics personnel show superior ability to learn new technologies</td>
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<td></td>
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<tr>
<td></td>
<td>Reflective</td>
<td>SCTM3</td>
<td>Our analytics personnel are very knowledgeable about the critical factors for the success of our organization</td>
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<tr>
<td></td>
<td>Reflective</td>
<td>SCTM4</td>
<td>Our analytics personnel are very knowledgeable about the role of big data analytics as a means, not an end</td>
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<td></td>
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<tr>
<td></td>
<td>Reflective</td>
<td>SCBK1</td>
<td>Our analytics personnel understand our organization’s policies and plans at a very high level</td>
<td>Duncan (1995), Terry Anthony Byrd (2000), Tesch et al. (2003), Kim et al. (2012)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Reflective</td>
<td>SCBK2</td>
<td>Our analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions</td>
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<td></td>
<td>Reflective</td>
<td>SCBK3</td>
<td>Our analytics personnel are very knowledgeable about business functions</td>
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<td></td>
<td>Reflective</td>
<td>SCBK4</td>
<td>Our analytics personnel are very knowledgeable about the business environment</td>
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<td></td>
<td>Reflective</td>
<td>SCRK1</td>
<td>Our analytics personnel are very capable in terms of planning, organizing, and leading projects</td>
<td>Boar (1995), Duncan (1995), Lee et al. (1995), Terry Anthony Byrd (2000), Jiang et al. (2003), Kim et al. (2012)</td>
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<td></td>
<td>Reflective</td>
<td>SCRK2</td>
<td>Our analytics personnel are very capable in terms of planning and executing work in a collective environment</td>
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| | Reflective | SCRK3 | Our analytics personnel are very capable in terms of teaching others | (continued)
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<thead>
<tr>
<th>2nd-order constructs</th>
<th>Type</th>
<th>1st-order constructs</th>
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<th>Item labels</th>
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<th>Sources</th>
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<tbody>
<tr>
<td>Supply chain agility</td>
<td>NA</td>
<td>NA</td>
<td>Reflective</td>
<td>SCRK4 Our analytics personnel work closely with customers and maintain productive user/client relationships</td>
<td>Setia and Patel (2013)</td>
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<td></td>
<td></td>
<td></td>
<td>Reflective</td>
<td>AGIL1 Our organization works hard to promote the flow of information with its suppliers</td>
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<td></td>
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<td></td>
<td>Reflective</td>
<td>AGIL2 Our organization works hard to develop collaborative relationships with suppliers</td>
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<td></td>
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<td></td>
<td>Reflective</td>
<td>AGIL3 Our organization builds inventory buffers by maintaining a stockpile of inexpensive but key components</td>
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<td>Reflective</td>
<td>AGIL4 Our organization draws up contingency plans and develops crisis management teams</td>
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<td></td>
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<td>Reflective</td>
<td>AGIL5 Our organization has a dependable logistics system or partner</td>
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<tr>
<td>Firm performance</td>
<td>NA</td>
<td>NA</td>
<td>Reflective</td>
<td>Using supply chain analytics improved ____ during the last 3 years relative to competitors</td>
<td>Tippins and Sohi (2003)</td>
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<td>(FPER)</td>
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<td>FPER1 ____Customer retention</td>
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<td>FPER2 ____Sales growth</td>
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<td>FPER3 ____Profitability</td>
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<td>FPER4 ____Return on investment</td>
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The interplay between smart manufacturing technologies and work organization

The role of technological complexity

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School of Management, Politecnico di Milano, Milano, Italy
Annachiara Longoni
Ramon Llull University, Barcelona, Spain, and
Emilio Bartezzaghi
School of Management, Politecnico di Milano, Milano, Italy

Abstract

Purpose – The purpose of this paper is to provide evidence on how smart manufacturing (SM) affects work organization at both micro-level – i.e. work design, described in terms of operator job breadth and autonomy, cognitive demand and social interaction – and at macro-level – i.e. organizational structure, described in terms of centralization of decision making and number of hierarchical levels in the plant.

Design/methodology/approach – The paper reports on a multiple-case study of 19 companies implementing SM.

Findings – Results present four main configurations differing in terms of technological complexity, and micro and macro work organization.

Research limitations/implications – The paper contributes to the academic debate about the interplay between technology and work organization in the context of SM, specifically the authors find that the level of technology complexity relates to different characteristics of micro and macro work organization in the plant.

Practical implications – Findings offer valuable insights for practice, with implications for the design of operator jobs, skills and plant organizational structure, in light of the challenges generated by the implementation of SM technology. Guidelines on how policymakers can foster the implementation of SM technology to enhance social sustainability are proposed.

Originality/value – This study advances a novel focus in studying SM, i.e. work organization implications of this new manufacturing paradigm instead of its mere technological implications.

Keywords – Manufacturing technology, Organizational structure, Plant design

Paper type – Research paper

Introduction

Manufacturing paradigms are facing dramatic changes as a consequence of the 4.0 technological revolution. Our study focuses in particular on the concept of smart manufacturing (SM) that refers to networked information-based technologies for manufacturing enterprises (Hirsch-Kreinsen, 2016). So far, the majority of studies focused on technological implications of SM adoption, and its impact on operators’ competences. However, there is wide evidence that technological changes often fail due to organizational misalignment, such as lack of employees’ empowerment to exploit the new technologies (e.g. Kolodny et al., 1996). Thus, we propose that studying the link between technology and work organization at the micro-level (i.e. work design) and macro-level (i.e. organizational structure) is of utmost relevance, also for SM successful implementation.

The authors kindly acknowledge Laboratorio CISL Industria 4.0, and in particular Luigi Campagna and Luciano Pero as Scientific Committee (together with Emilio Bartezzaghi) for the possibility to use the empirical data coming from their research project.
At a more general level, the interplay between implementation of (new) manufacturing technologies and work organization has been debated since a long time (e.g. Cagliano and Spina, 2000; Trist et al., 2013; Bendoly et al., 2006). Literature on technological implementation in general and on Advanced Manufacturing Technologies (AMTs) – defined as the application of information and communication technologies with the main goal of automating and integrating the different stages of the manufacturing process (Russell and Taylor, 2002; Waldeck and Leffakis, 2007) – has been considered as a reference point for understanding SM implications on organizational aspects. Although SM could be considered a further advancement or extension of the concept of AMTs and other IT-based technologies, there are also unique characteristics of these new technologies that might ask for further exploration of the interplay between technology and work organization (Kusiak, 2018).

Given this, the aim of the paper is to explore how SM technologies interplay with work organization at the micro and macro-level to configure new socio-technical systems. We do so assuming a socio-technical perspective, which considers the company as a system characterized by both technological variables and social variables, such as the people, the organizational structure and the culture. According to this view, both types of variables should be taken into account when designing an effective organization (Trist et al., 2013).

**Theoretical background**

Work organization in SM setting belongs to the broad category of phenomena related to the interplay between technology and organization. To build a proper theoretical background about the relationship between SM technologies and work organization, different streams of literature have been investigated, due to the interdisciplinary nature of the topic. The main constructs that will be presented in the theoretical background section are the following: the distinguishing features of SM, discussed by organizational, operations management and information system literature; the interplay between technology and work organization based on insights from past and more recent studies about technology implementation and AMTs in the operations management and organizational literature; and recent debates on work organization implications of SM from organizational and engineering literature.

**Smart manufacturing**

Manufacturing processes are significantly changing as a consequence of the so-called 4.0 technological revolution, but there is a paucity of proved successful cases related to the implementation of SM technologies (European Commission, 2017). The number of theoretical studies and contributions are still greater in number than the studies providing empirical evidence and insights (e.g. Buer et al., 2018; Frank et al., 2019).

SM refers to the pervasive implementation and application of networked, information-based technologies throughout the manufacturing and supply chain enterprise (Davis et al., 2012; Hirsch-Kreinsen, 2016), which results in creating a flexible and intelligent manufacturing system which is able to adapt in real-time to changing conditions (Kusiak, 2018; Wang et al., 2016). SM can be adopted in different variations characterized by different levels of complexity depending on the range and integration of technological applications involved (e.g. Frank et al., 2019; Kusiak, 2018 – see a list in Table I).

Interconnectivity and intelligence features are the characteristics that enable the 4.0 technological revolution, and therefore make SM a new manufacturing paradigm which is different from the previous ones (Frank et al., 2019). Such features and SM technological complexity are challenging organizations to reshape the work environment, working activities and – eventually – the organization of the factories (Maghazei and Netland, 2017). However, empirical evidence on how these technologies and organization design are interplayed is limited.
Technology and work organization: findings from previous literature on IT-based technology implementation and advanced manufacturing technologies

The main theoretical lens adopted by the operations management literature when studying the technology-organization design interplay is the socio-technical theory (Trist et al., 2013). In this perspective, workplace is the result of the opportunities and constraints deriving from the available technology (i.e. the production process) and opportunities and constraints of social nature (i.e. the actors involved and their objectives and needs). Opportunities and constraints of social nature are usually analyzed from a work organization and design perspective (e.g. Parker et al., 2017). According to the dominant approach in organization studies, work organization can be investigated at two different levels: the micro-level and the macro-level. In particular, the micro-level refers to work design of the individual roles in terms of: job breadth (also called task variety), as the number of tasks that an individual job has to perform; job autonomy, as the autonomy that an individual has in deciding time and methods regarding core activities; cognitive demand, as presence of monitoring or problem-solving activities; and social interaction, as the exchange of information with other individuals (e.g. Wall et al., 1990). The macro-level instead, typically refers to the centralization of decision making power and hierarchical structure (Mintzberg, 1980).

A first approach that can be of useful reference for SM refers to the broad theme of implementation and adoption of IT-based technologies, such as enterprise resource planning (ERP). This approach takes into consideration users’ needs and perception with the concept of task-technology fit (TTF) (e.g. Bendoly, 2007; Bendoly and Cottelee, 2008; Kositanurit et al., 2006). In particular, TTF is originally defined as “the degree to which a

<table>
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<tr>
<th>Category</th>
<th>List of technologies</th>
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<tr>
<td>Automation and advanced</td>
<td>Robots</td>
</tr>
<tr>
<td>manufacturing</td>
<td>Collaborative robots</td>
</tr>
<tr>
<td></td>
<td>Automatic non-conformities identification in production</td>
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<tr>
<td>Additive manufacturing</td>
<td>Additive manufacturing (3D-printers connected to softwares)</td>
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<tr>
<td>Augmented and/or virtual reality</td>
<td>Augmented and/or Virtual Reality software and devices for</td>
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<td></td>
<td>Smart training</td>
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<td>Smart maintenance</td>
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<td>New product development</td>
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<td>Virtual commissioning (digital twin)</td>
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<td>Simulation of processes (digital manufacturing)</td>
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<td>Vertical integration and</td>
<td>Sensors, actuators and programmable logic controllers (PLC)</td>
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<td>horizontal integration</td>
<td>Manufacturing execution system (MES)</td>
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<td></td>
<td>Supervisory control and data acquisition (SCADA)</td>
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<td>Machine-to-machine communication (M2M)</td>
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<td>Remote operations</td>
<td>Remote production through software and devices</td>
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<td>Traceability</td>
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<td>Artificial intelligence</td>
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<td>Artificial intelligence for production</td>
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<td>Energy management</td>
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<td>Energy efficiency improving system</td>
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<td>Connectivity and analytics</td>
<td>Internet of Things</td>
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<td>-enabling technologies</td>
<td>Cloud computing</td>
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<td></td>
<td>Big data</td>
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<td>Analytics</td>
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Source: Adapted from Frank et al. (2019)

Table I. Smart manufacturing technologies list
technology assists an individual in performing his or her portfolio of tasks” (Goodhue and Thompson, 1995, p. 216). In other words, the assumption of TTF theory is that technology positively affect performances if there is a fit between the characteristic of the task and the characteristic of the technology utilized for that task, which is at the basis of users’ reaction and adaptation to the new technology. Many different studies have applied TTF theory to show interesting relationships between users’ perception about the TTF and users’ reaction to the technology (e.g. circumvention of the new technological systems in case of misfit) in the investigation of use of different technologies and different kinds of workplace (e.g. Bendoly, 2007; Bendoly and Cotteleer, 2008). However, TTF has been recently criticized for different reasons, such as the fact that it is not able to clearly separate the characteristics of the technology and the characteristics of the task; that outcomes such as users’ reaction are treated as outcomes of the TTF even if they should be considered as part of the construct; that the majority of the studies do not really study the concept of “fit” since they do not propose technology-task effective pairings in a given context; and for measurement-related issues (see Howard and Rose, 2019). To overcome limitations of past studies, a recent piece (e.g. Howard and Rose, 2019) suggests to measure TTF and in particular the characteristics of the task by using the dimensions of work design (Wall et al., 1990) to map the different characteristics of the tasks, such as task variety and task autonomy. Nevertheless, TTF is a useful reference model because it shows that tasks and technologies may interact to produce effects that are greater than the sum of their parts (Howard and Rose, 2019), bringing the attention on observing the contingencies of the context in which technologies are applied (Bendoly and Cotteleer, 2008).

The interplay between both micro- and macro-level work organization dimensions and technology is also considered by the operations management literature on the adoption of computer integrated manufacturing and the AMTs (Cagliano and Spina, 2000). At the micro-level, some studies show that AMTs increases the job breadth of the operator (e.g. Morris and Venkatesh, 2010); but other studies instead do not support this hypothesis (e.g. Bayo-Moriones et al., 2017). Results are mixed also in terms of job control and autonomy (e.g. Wall et al., 1990), but they seem to support the general argument that AMTs may increase job autonomy both at the individual and team level (e.g. Bayo-Moriones et al., 2017). In terms of cognitive demand, previous contributions show that AMTs may require more monitoring and problem-solving for the operator (e.g. Shulman and Olex, 1985). Finally, evidences about the relationship between AMTs and social interaction are not conclusive. Several studies show how AMTs might decrease the social interaction (e.g. Wall et al., 1990); however, other studies show how AMTs might foster social interaction and team working (Bayo-Moriones et al., 2017; Basaglia et al., 2010). Overall, evidence suggests a shift toward richer and broader jobs, with higher autonomy and social interaction, but also that there is high variation due to a number of contingent factors (Parker et al., 2017). Instead, very little empirical evidence can be found on the effects of AMTs on work organization at the macro-level, i.e. on the centralization of decision-making power and the number of hierarchical levels (Stock and McDermott, 2001).

In addition, both streams of operations management literature on IT-based technologies and AMTs consider that the levels of automation and integration of the technology adopted affect organization design dimensions resulting in different organizational models (Altmann et al., 1992; Zuboff, 1988) and performance (e.g. Cagliano and Spina, 2000). For example, available knowledge shows that companies that implement stand-alone AMTs, instead of AMTs integrated across the different phases of the manufacturing process, do not have significant improvements in performance (e.g. Cagliano and Spina, 2000; Das and Jayaram, 2007). This is particularly true for those systems in which interdependencies between
different tasks, processes and units are high, and where technologies such AMT and ERP should support workers with difficulties associated with breakdowns in information flow (Bendoly et al., 2006). As a consequence, it can be inferred that also in SM implementation, specific characteristics of work at the micro and macro-level might depend on the level of technological complexity, defined as number of SM technologies implemented and level of integration between the different technologies.

Work organization in smart manufacturing
Recent contributions on the organizational implications of SM build on the concept of cyber-physical systems, which are autonomously controlled physical entities (i.e. machines and also single components) that make decentralized decisions, communicating with each other in an internet of data and services (Lee et al., 2015). These studies pertain to two main domains: one focuses on the effects of cyber-physical systems on operators’ work design with a systemic view; and one more oriented to study the design of the interface and interaction between the cyber-physical systems and the operator on the single tasks or activities.

Concerning the interplay between cyber-physical systems and operators’ work design, theoretical arguments developed so far analyze this broader topic by identifying possible alternative future scenarios often summarized in two opposing views: Automation and job polarization vs complementarity (Ganz, 2014; Hirsch-Kreinsen, 2016; Kurtz, 2014). In the automation scenario, human activities are governed and ruled by autonomous machines. In this case, automation refers to the transfer to the cyber-physical system of tasks related to governance and control of manufacturing processes. Thus, the manufacturing process can be managed by the cyber-physical system thanks to the adoption of sensors and other digital infrastructures. The operator’s work is therefore subordinated to the directives of the cyber-physical systems, which become the neuralgic center of the value chain of the manufacturing process. Operator activities are just limited to monitoring the cyber-physical systems. Jobs are characterized by a low number of simple operational activities, with little or no room for maneuver, in a way that can be addressed to as “Digital Taylorism.” Within this scenario, there is still space for few jobs characterized by high autonomy and cognitive content, mainly related to the design, implementation and “training” of the cyber-physical systems. In other words, automation implies job polarization, defined as the distinction – brought by the introduction of a specific technology – between operators that perform standard and routine jobs on one hand, and operators or specialists that carry out activities related to control and problem solving on the other hand (Goos and Manning, 2007). In the complementarity scenario instead, automation concerns manual routinized task, while operators would have full control over the cyber-physical systems and would use it to collect information to better control and to improve sub-processes when the right circumstance occurs. We would see a reduction of low skilled manual jobs but there would be an increase of both highly skilled personnel and of operators with average technical qualifications, able to communicate and interact with advanced digital tools (Autor et al., 2003) and a high number of multitasking positions - characterized by a high degree of structural openness, a very limited division of labor and high flexibility (Böhle and Rose, 1992).

The human-centric literature within the engineering field takes a particular focus on the human-machine interplay. Contributions analyze how the automation shape and re-shape tasks performed by operators and decision making, with a design perspective (Bannat et al., 2011; Romero et al., 2016) and study how cyber-physical systems should be designed to support operators in physical and or cognitive tasks when interacting with automated machines, following technological progress and technological constraints and limitations. This stream of literature considers the operator at the center of manufacturing processes and shows how the evolution of traditional manufacturing technology brings a growing
centrality of the cognitive contents of operators’ tasks thanks to an augmentation potential of the technologies themselves (Bannat et al., 2011).

Recently this stream of literature focused on SM implementation. For example, Romero et al. (2016) proposed a classification of the “Operator 4.0,” extending the concept of cyber-physical system by stressing the central role of the operator and the role of technology to “augment” the capabilities and capacity of operators. They talk about the human cyber-physical system, defined as “engineered systems of systems [...] using context-sensitive, advanced communication and adaptive control technologies to support inter-agent systems of humans, machines and software to interface in the virtual and physical worlds towards a sustainable and human-centric production system” (p. 8). They propose specific examples of Operators 4.0 based on their interaction with a specific SM technology. However, they mainly aim at giving prescriptive indications on how to design the human-machine interfaces, without considering the actual impact that technologies have on the organizational characteristics.

The two above-cited literature streams on SM technologies do not provide conclusive indications on organizational implications at the micro-level since they are mainly theoretical speculations of possible scenarios rather than clear indications coming from empirical evidence. Moreover, studies from these domains lack considerations at the macro-level on the organizational structures and models that can better support SM. Therefore, the research framework of the present study builds in particular on the consolidated dimensions of analysis coming from AMTs and IT-based technology implementation studies, which can be considered the “backbone” of the more recent theoretical argumentations about organization of SM (Hirsch-Kreinsen, 2016).

Research questions and framework
To extend previous studies on the interplay between technology and work organization at the micro and macro-level and provide specific evidence related to SM, we adopt the socio-technical systems approach as a general frame for our inquiry. According to this view, it is not advisable to separately design (and manage) the technical and social subsystems; also, it is possible to identify different work organization configurations that are equally effective with the same technology, and that are selected on the basis of social and contingent characteristics (Trist et al., 2013). This approach, in fact, assumes that the co-design of a configuration consisting of both technological and work organization elements is more effective in terms of productivity and competitiveness, and also on employees-related performance (Van Eijnatten et al., 2008).

Following the evidence of the IT-based technology implementation and of the AMTs literature, we expect that different socio-technical system might emerge as a consequence of the introduction of SM, due to different degrees of technological complexity - meaning number of technologies and level of integration between different technologies and processes at a local, process or system level - may enable different choices of work design and different organizational structures at the macro-level (Bendoly et al., 2006). We consider this frame to fit the SM context since the ongoing discussion on the effects of SM technologies on operator roles and their work environment shows how work organization and technology are interdependent (e.g. Romero et al., 2016). Therefore, the following research questions are formulated and summarized in the conceptual framework proposed in Figure 1:

\textbf{RQ1.} What are the socio-technical configurations that emerge in manufacturing plants that adopt SM technologies?

\textbf{RQ2.} Does the work organization at micro and macro-levels differ depending on the technological complexity?
In line with the socio-technical approach, the socio-technical configuration is mapped as a combination of technical and social system characteristics. The technical system is described in terms of technological complexity of SM technologies present in the company, with the following specific dimensions (Singh, 1997): number of SM technologies implemented; and level of integration between the different technologies along manufacturing processes (the integration is realized through the use of one or more inter-connected technologies). The social system is described in terms of work organization dimensions at the micro-level and at the macro-level (Wall et al., 1990).

**Methodology**

In order to inquire the above research questions, we applied an inductive methodology (Gioia et al., 2013; Corbin and Strauss, 2008). While deductive studies aim to test hypotheses, our study aims to generate new theoretical implications through an inductive approach. Specifically, a multiple case-study research has been carried out. A case study is an empirical research investigating a phenomenon within its real context (Denzin and Lincoln, 1994). It is a methodology particularly appropriate to cope with situations where there are more variables of interest than data points and where new phenomena are inquired (Yin, 2014). Thus, case study was identified as the appropriate methodology due to the novelty related to SM topic, since this methodology allows to thoroughly inquiry and understand the complexity and the nature of the phenomenon under inquiry (Voss et al., 2002).

**Case selection**

Purposeful, non-random samples based on theoretical underpinnings are suggested for qualitative studies to increase content validity and generalizability (Eisenhardt, 1989). Thus, selection was performed to control for extraneous factors and increase generalizability. For example, we selected companies of different size (medium and large), different industries, and adopting different SM technologies to increase generalizability but we focused on a single country (i.e. Italy) since the study was framed into a broader Italian project. This choice is also reasonable from a methodological point of view. Country legislation and policies might affect the adoption of SM and the underlying approach to automation.
For example, being the Italian incentive scheme strongly favoring the purchase of new technologies belonging to the Industry 4.0 cluster, many companies just bought the technology without deeply reflecting on the changes they would need to implement it in their processes and organization. At the same time, no incentives were given for organizational redesign and training support, so these aspects were often overlooked. However, the most relevant criteria that did not allow for a random selection was the identification of companies at a mature stage of SM implementation to investigate their adoption process and results. For this reason, the research process was carried out within the “Laboratorio Industria 4.0,” a project managed in collaboration with one of the major Italian Unions, which was interested in identifying some guidelines for the successful implementation of new SM technologies both for the social and economic sustainability of manufacturing companies. The process adopted a collaborative research orientation, in order to achieve rigorous and significant results (Canterino et al., 2016). A research team composed by researchers and union delegates was constituted, with researchers informing the research protocol and process to ensure rigor, and with union delegates being involved in the data collection as insider action researcher (Bartunek, 2007; Maestrini et al., 2016). To ensure comparability of the findings, beyond the formal research protocol, union delegates were trained on interviewing for case study purpose and in their first interviews the union delegates have been always coupled with a researcher (Coghlan, 2007).

The case selection process was carried out in two main steps. First, a list of 35 Italian companies of the manufacturing industries that applied for incentives in the context of Italian “Piano Calenda” (i.e. the national program for incentivizing Italian companies to implement SM technologies through fiscal and tax benefits) was compiled with the help of the Union and on the basis of the previously listed criteria. Second, to ensure that the new technologies were applied in the production process at a stable regimen, and that the effect of the new technologies on the work organization was then observable, data were collected about the actual level of implementation of SM technologies through interviews with the top management, visit to the plants, and secondary data. The final selected sample included therefore 19 case companies, from different industries and of different size, and with different SM technologies implemented that could provide an interesting setting for the study.

Data collection
The unit of analysis is the plant interested by the implementation of SM technologies. Data were collected from October 2016 to December 2017 through semi-structured interviews with employees having different roles at different organizational levels such as operators, supervisors, union representatives, top managers and plant managers. The interviewed roles are different in different companies because for every single case the roles more involved in the implementation of the SM technologies were different. The interview protocol (see Online Appendix A, available at: https://bit.ly/2LxFlq) followed the research framework and was structured in five sections, collecting information about: the background of the interviewee and the company; information on the SM project; job content at the individual and group level; organizational structure and coordination mechanisms; and achieved results and performances.

Data collection was conducted on site (Yin, 2014) in Italian by at least two between researchers and union delegates, following the interview protocol and in line with the collaborative research orientation of the study (Bartunek, 2007). The audio of interviews has been integrally recorded and transcribed. After each site visit, each interviewer edited the field notes and checked them for accuracy. Questions arising from the interview notes were answered by interviewees through follow-up e-mails and telephone calls. Furthermore, after conducting the interviews and the analysis, description of findings regarding their case were shared with informants to increase interpretative validity. In addition, secondary data
about SM technologies implemented by the company were collected from internal documents, archive material and websites, to complement primary data from interviews. Table II summarizes the companies analyzed and the data sources for each company. See Online Appendix B (available at: https://bit.ly/2lLxF1q) for description of SM technologies adopted in each company and their level of integration.

Data coding and measurement

About 130 transcribed pages of primary sources were collected. Coding and measurement were performed with the aims of reducing the potential that confirmation bias could influence the results and of increasing descriptive validity and theoretical validity (Strauss and Corbin, 1990). Thus, each transcribed source was read, coded and analyzed by different researchers, through a series of meeting, re-reading and re-coding (Gioia et al., 2013). Through a process of comparison and understanding, the relevant codes were detected. Specifically, the variables have been assessed according to what illustrated in Table III.

Data analysis

The data analysis involved two stages: a within-case analysis and a cross-case analysis. In the first stage, to increase descriptive validity, multiple data sources and multiple researchers were involved in the analysis to triangulate the information. The researchers identified the main concepts and attributes related to each company in terms of SM technologies implementation and work organization characteristics before and after the implementation of SM technologies, by combining data from the interviews and secondary data sources. Then, they met to consider alternative evaluations concerning the concepts, attributes and assessment of the studied company until they all agreed. The output of this stage has been the creation of a first table, describing each case in terms of technological complexity and work organization characteristics both before and after the technological implementation. In the second stage, cross-case analysis was performed to identify socio-technical configurations in the context of SM. First, the plants were grouped based on the SM technological complexity identifying four main technological complexity scenarios. Based on this categorization, similarities and differences among groups of plants in terms of work organization after the introduction of SM were identified. See Online Appendices C and D (available at: https://bit.ly/2lLxF1q) for details on cross-case analysis and exemplary coding.

Findings

In order to answer to the research questions plants have been grouped based on technological complexity with the identification of the following combinations: the implementation of a small number of different SM technologies integrated only within the production process (Configuration 1 – process-automated factory); the implementation of a low-medium number of different SM technologies to integrate different processes of the production system (Configuration 2 – partially integrated factory); the implementation of a medium/high number of different SM technologies to integrate different processes within the production system and the production system with other departments, such as Engineering or R&D (Configuration 3 – fully integrated factory); and the implementation of a medium/high number of different SM technologies that integrate internal operations processes also with suppliers and/or customers (Configuration 4 – smart factory). Each group of plants has then been characterized in terms of social system features, namely, job breadth, job control and autonomy, cognitive demand, social interaction at the micro-level, and centralization of decision making and hierarchical levels at the macro-level. This classification allows to highlight four different socio-technical configurations, thus answering to RQ1 (see Figure 2).
<table>
<thead>
<tr>
<th>Company</th>
<th>Industry</th>
<th>Size</th>
<th>Respondents’ position and No of interviews</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alfa</td>
<td>Food and beverage</td>
<td>€2.774bn</td>
<td>Plant supervisor; operator; union representative (4 interviews)</td>
</tr>
<tr>
<td>Beta</td>
<td>Furniture</td>
<td>€1.73bn</td>
<td>CEO, operator (and union representative) (2 interviews)</td>
</tr>
<tr>
<td>Gamma</td>
<td>Textile</td>
<td>€1.5bn</td>
<td>Plant Manager; union representative; operator (3 interviews)</td>
</tr>
<tr>
<td>Delta</td>
<td>Electronics</td>
<td>€5.5bn</td>
<td>Plant responsible; operators (2) (3 interviews)</td>
</tr>
<tr>
<td>Epsilon</td>
<td>Food and beverage</td>
<td>€1.7bn</td>
<td>Plant manager; HR Director; operator (2); union representative (5 interviews)</td>
</tr>
<tr>
<td>Zeta</td>
<td>Energy</td>
<td>€70bn</td>
<td>Local network manager; union representative; operator (2) (4 interviews)</td>
</tr>
<tr>
<td>Eta</td>
<td>Automotive</td>
<td>€11.3bn</td>
<td>Plant Manager; plant specialist; operator (2); union representative (4 interviews)</td>
</tr>
<tr>
<td>Theta</td>
<td>Food and beverage</td>
<td>€10.3bn</td>
<td>Plant manager; team leader; operators (3) (5 interviews)</td>
</tr>
<tr>
<td>Iota</td>
<td>Furniture</td>
<td>€319m</td>
<td>CEO, operator (and union representative) (3 interviews)</td>
</tr>
<tr>
<td>Kappa</td>
<td>Chemical processes</td>
<td>419 million</td>
<td>Plant manager; union representative; operator (4 interviews)</td>
</tr>
</tbody>
</table>

Table II. Description of the sample and data sources

<table>
<thead>
<tr>
<th>Table II. Description of the sample and data sources</th>
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<tbody>
<tr>
<td>922 IJOPM 39,6/7/8</td>
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</tbody>
</table>
TABLE III. Assessment of variables

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technological variables</td>
<td>Number of technologies&lt;br&gt;Low – one main type of SM technology implemented&lt;br&gt;Low/Medium – 2-3 types of SM technology, but few different specific technologies for each type implemented&lt;br&gt;High – Above 4 types of SM technologies, and several different technologies for each type implemented</td>
</tr>
<tr>
<td>Level of integration</td>
<td>Integration mainly at production phases level&lt;br&gt;Integration mainly at production processes level&lt;br&gt;Integration between production processes and other departments&lt;br&gt;Full integration of operation processes</td>
</tr>
<tr>
<td>Organizational variables</td>
<td>Job breadth&lt;br&gt;Limited – low variety and number of tasks assigned to the same worker&lt;br&gt;Multi-tasking – high variety and number of tasks assigned to the same worker</td>
</tr>
<tr>
<td>Job control and autonomy</td>
<td>Low – Prescription of work procedure&lt;br&gt;Medium – Prescription of work procedure and autonomy in controlling&lt;br&gt;High – Autonomy in controlling and problem solving</td>
</tr>
<tr>
<td>Cognitive demand</td>
<td>Manual job&lt;br&gt;Both manual and cognitive (monitoring and controlling) job&lt;br&gt;Only cognitive (monitoring and controlling/problem solving) job</td>
</tr>
<tr>
<td>Social interaction</td>
<td>Individual job&lt;br&gt;Formal team working and interaction mainly with the team leader that coordinates individual work&lt;br&gt;Formal team working and intra-team coordination&lt;br&gt;Formal team-working and inter-team interaction</td>
</tr>
<tr>
<td>Centralization of decision making</td>
<td>Centralization at plant management level&lt;br&gt;Decentralization at team level&lt;br&gt;Decentralization at the worker level</td>
</tr>
<tr>
<td>Hierarchical structure</td>
<td>Vertical organization&lt;br&gt;Presence of bottom-up flows in vertical organization&lt;br&gt;Flat organization</td>
</tr>
</tbody>
</table>

The role of technological complexity

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Figure 2. Description of configurations in terms of technical and social system characteristics
Process-automated factories

Results show that process-automated factories – comprised with companies that show limited complexity in SM technology – exploit isolated applications of the SM technology related to automation and advanced manufacturing to increase formalized work design, routines and procedures at the micro-level. After the implementation of the SM technologies, job breadth of operators is low with a limited number of activities performed by the same operator, work is mainly manual and activities are formalized with limited autonomy. The new activities introduced by the SM technology are managed by new dedicated roles. Social interaction is increased, since in all the cases the SM technology allows to implement formalized team working with a formal team leader, but the work remains individual and each operator performs the tasks independently from the others belonging to the same formal team. The interaction is mainly between the single individual and the team leader, and not intra-team between peers. Decision making is centralized at the plant management level, with no delocalized power at more operational levels. The hierarchical structure is vertical as it was before the implementation of the SM technologies. In some cases, when the formal team-working with a team leader is introduced, the number of hierarchical levels of the plant even increases.

One exemplary case of this type of configuration is the Gamma case in the textile industry. Gamma implemented 36 new waving machines that can be programmed centrally and that produce a finished garment in wool or cotton, with a single thread and without seams. After the implementation of this new equipment in some phases of the production line, specialization of job is reinforced. In fact, for each new task introduced by the SM technology – which was mainly manual – a new dedicated role has been created. Some examples of these new roles are: the programmer of the machines, who follows a specific procedure; the maintenance man, who is responsible for maintenance procedures on all the machines including the programmable ones; the model maker.

The same operators that were using the old looms, are now using the modern machines, after some training that was needed to explain them how to manage the same tasks but with a new procedure. For the new tasks, such as the programming of the machine, we decided to create a new dedicated role, to maintain work specialization and the distinction between different types of workers (Plant manager, Gamma).

The work is carried out by teams, because individual tasks are interconnected both in terms of timing and method, but the teams do not have a formal responsibility for the results and no interaction between team members is needed, with the team leader coordinating the activities of individuals:

The kind of activities I carry out with the new machines are very similar to the ones that I was carrying out before, it’s just a new procedure. I need to wait for the machines to be programmed but then I do not need additional information from my colleagues on the line. I follow the procedure (Operator of the weaving department, Gamma).

In terms of decision making, SM technologies did not change the centralization at the plant management level in terms of scheduling of activities and monitoring of performance. The hierarchical structure remained vertical with no change in number of hierarchical levels.

Partially integrated factories

Partially integrated Factories are comprised with companies that implement a medium number of SM technological applications that integrates all or almost all the different processes of the production system. Results show that, after the implementation of SM technologies, job breadth of the operators generally increases, with more activities assigned to the same operators, requiring both manual and cognitive work. After the
introduction of SM technological applications, the same operator typically carries out activities related to production and to control of the machines. Work procedures remain formalized, with prescription of activities and limited autonomy. Social interaction is increased, because in all the cases belonging to this group the new set of tasks are more interdependent and the member of the same formal team exchange information not only with the team leader but also with the other team members. Also, the team is often responsible for giving feedbacks and suggestions for further technological improvement. Decision making is centralized at the plant level for all the decisions about scheduling of activities and monitoring of performance. The formal hierarchical structure does not change, with the number of hierarchical levels remaining the same and with the macro organizational structure being vertical both before and after the implementation of the SM technologies. However, in all the cases, after the implementation of SM technologies, some bottom-up flows of information are reinforced.

An example of this type of configuration is Nu case, which is a motorbike manufacturer that introduced robots and a software to partially automate and exchange information about the painting activities across the new product development, manufacturing and assembly process of some specific models of motorbikes. With this new SM technology, no new roles are created, but the operators become multi-tasking, since they carry out activities related to both product transformation, remote control of the robots and quality control. The operators’ work content is both manual and cognitive. In fact, some activities such as the application of the sealant on the body of motorbike and the quality control remain manual also after the implementation of the SM technologies. Some new cognitive activities related to the remote control of the robots and data management are also introduced with the SM technologies:

During the painting phase, I can remotely control the painting robots through a tablet. Then, I need to control that the paint is uniform and as a final step I have to manually apply the sealant and grind the camshaft (Operator of the painting department, Nu).

The work is performed in team, and the new software foster intra-team communication and group discussion on the daily work routine. The team is also responsible of suggesting further technological improvements:

We now can communicate more with the colleagues of different shifts through the notes that we leave in the dedicated section of the software on the tablet. Since we are all aligned on what happened, it’s easier to discuss in groups possible improvement of the procedure based on what didn’t work (Operator from painting department, Nu).

The macro-level organization has not changed with the introduction of SM technologies: decision making is centralized at the plant level and there has been no change in the hierarchical structure which has remained vertical also after the technological change. However, the automation and digitalization of the process, together with the feedback from the teams allows bottom-up exchange of information about the production process:

The new technology allows us to gather very useful suggestions from operators about possible improvements of the technology and of the procedures. Before the implementation of the technology, we had a formal system for suggestions with a suggestion box, where operators at the end of the shift could leave their feedbacks with a hard-copy form. But it was seldomly used. Now they communicate information to us with the tablet almost daily, sharing the suggestions they discussed in teams (Plant manager, Nu).

Fully integrated factories
The fully integrated factories configuration is comprised with companies that implement a high-medium number of SM technological applications along different processes of the
manufacturing system carried out with other departments of the company, such as the Engineering department, the Sales department or the R&D department. This group of companies is characterized by a shift toward less formalized and centralized work routines. After the implementation of SM technologies, job breadth increases since operators become multi-tasking, performing activities related to production, control and information gathering. Job autonomy also increases in activities related to monitoring and controlling. Activities become mainly cognitive and manual work is limited, with machines substituting the human work in performing repetitive and simple tasks. Social interaction is increased: work is performed in team as it was before the SM implementation in all the cases classified in this group; with the interaction being now not only intra-team, but also inter-team. Decision making is decentralized at the team level in terms of objectives and problem-solving. Interestingly, this group of plants shows how the introduction of SM technologies that integrate production processes with other departments allowed to reduce the number of hierarchical levels, shifting from a more vertical organization toward a flatter organization.

One exemplary case of this type of configuration is Theta case in the food and beverage industry. Theta is a manufacturer of branded chocolate and confectionery products that implemented different SM technologies, namely: smart packaging machines with touch screen and simple and intuitive control, and self-analysis in case of stops or technical problems; automated and programmable lifting and palletizing devices; labeling systems, identification and handling systems with bar code recognition and QR code for products and raw materials; and automated warehouse interconnected with SAP management system, enabling to manage stocks and production peaks in real time. The specific nature and characteristics of work of the operators depend on the specific process, but in general the operators are responsible for supervision, control and direct intervention in case of malfunction. After the implementation of SM technologies, the prescriptive procedures are abandoned, and the operator is expected to solve problems and decide what to do by herself:

Before the implementation of the new technology, I had to move pallets partially manually and partially with the forklift. It was a kind of repetitive and strenuous task. Now my daily routine has completely changed: I control smart machines, and I have to solve problems when machines are not able to perform autonomously 100% of the movements. For me, this is a real “philosophical” change of my role, since now I don’t see myself just as an executor of manual activities (Operator of the warehouse, Theta).

Work is performed in teams. Each team has weekly meetings to share objectives and solving problems. Moreover, intra-team meetings are called for improvement of processes across production boundaries:

We realized that SM can really empower employees to have a more active and proactive role not only in their daily routines, but also for continuous improvement and for learning and development of new practices. We are now organizing periodical workshops in which operators work together with people from other departments to identify areas of improvement and innovations related to processes across production boundaries, such as traceability of product and raw materials (Plant manager, Theta).

After the implementation of the SM technologies some mid-management hierarchical levels have been removed, passing from a traditional vertical structure to a flatter organization:

The smart technologies have been implemented with the objective to empower the operators and exploit their potential. For doing so, we have also reduced the number of hierarchical levels and the supervision roles in the plant, empowering more the teams of operators which can autonomously decide how to organize for achieving assigned objectives (Plant manager, Theta).
Smart factories

The last configuration is the Smart Factory. This group is comprised with companies that show a highly integrated SM approach, integrating production processes not only with other departments and processes inside the company, but also with suppliers and/or customers operations system. This type of configuration is characterized by a social system in which operators experience autonomy in work procedures, related to controlling and problem-solving. Operators are multi-tasking also in this case: activities are related to production, control of the machines, data gathering and data analysis. The job is mainly cognitive, since the operators are responsible for supervision of the machines and should take decisions on the basis of the available information. Formal team working is present, with intra team, inter-team and across-hierarchy interactions. Decision making on how to organize work is decentralized at team and operator level. Hierarchical structure is characterized by a limited number of hierarchical levels, generally with a flat organization. It is important to underline that the macro organizational structure characterized by flat organization and decentralization was already present in most cases before the SM implementation and was not modified by the SM technologies, as instead happened to the micro-level dimensions such as job breadth, job control, cognitive demand and social interaction. In three cases (namely Rho, Sigma and Zeta) an organizational re-design toward a flatter organization was considered as necessary requirement for the implementation of such technologies, in order to simplify and optimize operations and decision-making processes.

One exemplary case for the Smart Factory configuration is the Xi case in the mechanical industry that produces machines for ceramics, packaging, food and automation. Xi implemented during the recent years many different SM technologies related to connectivity and analytics, vertical and horizontal integration, artificial intelligence, additive manufacturing and energy management. The technological advancement in SM technologies is widespread in the various phases of the production process, with integration with the suppliers and customers. The processes involved by the introduction of these technologies are new product development, manufacturing and assembly and after-sales logistics. New technologies have made it possible to improve customer service – thanks to remote assistance and customer care, to reduce lead times and delivery times, faults and costs associated with waste and rework; further improvements in ergonomics and a reduction in the physical fatigue of operators are also planned. Job breadth, autonomy and cognitive demand of the operators on the production line and also of operators that support customers have further increased thanks to the latest SM technologies. One straightforward example is represented by the operators of the department dedicated to the fabrication of machinery for ceramics production, in which a new 4.0 machine has been developed. This new machine is able to print customized tiles through an additive manufacturing technology that allows the production of tiles with any kind of drawing or graphic required by the customer. Operators working in this department are now asked to carry on, besides traditional activities, new activities related to programming of the machine, but also activities related to the coordination with the R&D department and even related to the support to the final customers in the customization process:

Traditional tiles production is still carried out with standard machines, but all the operators have learned also to work with the new 3D printing machines. This new technology brought a number of new activities for me, for which I have to interact with both the R&D Departments and the final customers. […] With the support of the sales people, we [team of operators in the tiles production department] can organize meetings in the production department with the customer, in order to explain the main functionalities and the levels of customization that can be obtained, showing sample tiles realized from previous production. Before the implementation of this new machine, it rarely happened to speak with the final customer! I consider this as radical change for my role (Operator in the tile production department, Xi).
About the macro-level, flat organization and decentralization of power were put in place way before the implementation of SM, with the adoption a lean organization, which has been considered by the company as a fundamental aspect to manage technological complexity but also customer satisfaction:

If we put the sensors on the production line without analysing the process, I'm digitizing the waste. First you have to optimize the process, and design the content of the work, and then you have to introduce the technology (Plant Manager, Xi).

The machine must be designed on the operator, and not vice versa, otherwise overheads are created on the single workstation which will worsen productivity and in the end affecting performance towards the final customer (R&D Manager, Xi).

Discussion

Our findings shed light on the interplay between SM technologies and work organization. By providing empirical evidence on the relationship between SM technological complexity and work organization at micro and macro-levels in a plant, the study contributes to the operations management literature on different aspects, that will be now illustrated together with directions for future research and managerial implications.

**Peculiarities of SM technology in affecting work organization at the micro-level**

First, our analysis of the four types of socio-technical configurations shows how technological complexity is coupled with specific choices in terms of work design at the micro-level. In particular, findings show that for low levels of SM technological complexity – i.e. few technologies adopted in a specific manufacturing process- the associated social system is characterized by not-empowered operators that have limited job breadth and job autonomy, and do mainly manual work with limited exposure to monitoring, control and decision-making tasks. Instead, in presence of higher levels of SM technological complexity, operators are empowered through higher levels of job breadth and job autonomy, and the cognitive demand they experience increases.

If we draw back our results to the literature that analyses the impact SM have on operators’ work design at a theoretical level, the first case is aligned with the automation and job polarization scenario; instead the second case is aligned with the complementarity scenario, where the operator has full control over the cyber-physical systems, being multitasking and interacting with the technology to elevate its tasks (Böhle and Rose, 1992; Kurtz, 2014; Ganz, 2014; Hirsch-Kreinsen, 2016). This is interesting because, despite the literature presents these two scenarios as competing explanations of the impact of SM on the work organization, we propose that the level of technological complexity discriminates between these two situations. Specifically, when the application of SM technologies is used to enable the integration with different manufacturing processes and with processes involving also other departments, customers and suppliers, there is an increase in the number of operators’ activities. Similarly, higher levels of SM technological complexity also bring an increase in the operator experienced control on the activities performed and decision making, as compared to the situation before the SM implementation. All this brings higher operator cognitive demand and more responsibility. In addition, higher levels of SM technological complexity foster team working and higher interaction because they facilitate the information flow and they increase the interdependency between different activities (Bayo-Moriones et al., 2017; Basaglia et al., 2010; Waldeck and Leffakis, 2007). In other words, findings underline how different levels of integration between processes result in different levels of intelligence and adaptability of the SM system – where intelligence and adaptability are the result of both the technical and the social components of the
socio-technical system. In the presented cases, the higher the intelligence of the technological system, the more empowered and enriched roles are needed, since rich and complex data are generated to support operators in decision making instead of substituting human intelligence. Therefore, technological complexity can be considered as an important variable that pushes toward the adoption of swarm organizations. This view is also in line with the dominant perspective in the human-centric literature, that views SM technology as an enabler of operators manual and cognitive activities (e.g. Longo et al., 2017; Romero et al., 2016). Our findings allow to give both an empirical support to this conceptual position and a further indication on how the organization of work actually changes as a consequence of this potential use of SM technology.

The above-mentioned aspect can also be considered as a further distinguishing feature of SM technologies if compared to other IT-based technologies previously studied in manufacturing settings, as they not only provide information, but they also support the operator in decision making, empowering the more operational roles (Bendoly and Cotteleer, 2008).

**Work organization at the macro-level as a possible enabler for SM technologies**

At the macro-level, findings provide evidence on the interplay between technological complexity and the work organization despite not being investigated by previous SM literature. In particular, also in this case different levels of SM technological complexity are associated with different work organization characteristics at the macro-level. Specifically, higher levels of SM technological complexity are associated to the introduction of a flat organization in the plant.

We can argue that for the most complex SM technology applications, macro-organizational choices may be considered as enablers of successful technological implementation. In other words, Smart Factories show how highly complex SM technology applications can be successfully implemented only “on top” of a coherent re-organization at the macro-level, with organizational choices being antecedents for the successful implementation of complex integrated SM systems. This consideration supports recent argumentations on possible links between lean organization and SM (Buer et al., 2018), and in particular on the few studies that suggest that lean manufacturing – including the so called “soft practices” are antecedents of SM implementation (e.g. Wang et al., 2016).

**Directions for future research**

Based on what discussed above, our results suggest that the types of SM technologies implemented and their level of integration along manufacturing processes are key variables to include when studying the effects of SM on the role of the operator and the micro-level work organization. If this element is not considered, biased results could be found leading to misleading implications and categorization of different technologies. This result is for example relevant to interpret results from previous works (e.g. Frank et al., 2019) that consider as separate SM technologies from smart working technologies (i.e. technologies that support and empower operators’ work). Therefore, an interesting area for future research could be related to further clustering of different technologies on the basis of their different purposes and on the basis of associated tasks characteristics. Moreover, this study opens up the need for further research on the macro-organizational dimensions in operations management when studying SM implementation, which have been rather neglected so far (Stock and McDermott, 2001). Further research could also be developed in order to understand if contingent variables other than technological complexity might also influence the extent to which SM lead to the implementation of the swarm organization model.

Finally, this study highlights several further areas that, although not included in the original aim of the paper, could be of utter relevance for future research on organizational implications of SM. These areas relate to the possibility for SM of enabling informal and
bottom-up processes that modify micro and macro work organization (e.g. job crafting) of work, and the implications related to quality of work and stress due to new settings in job autonomy.

The limitations of this study also set the avenues for further future research. First, by studying only Italian cases in which the unions have an active role, we did not take into consideration two “higher level influences” (Parker et al., 2017) such as: the national culture dimensions (e.g. power distance and uncertainty avoidance) that may bias formalization and centralization of decision making related to work organization; and the role of the unions (organizations where unions are highly participating may bring to fostering bottom-up processes). Future studies should take into consideration these dimensions by including in the sample companies differentiated by national culture and with different levels of unionization. Second, since selected companies showed different levels of awareness about organizational structure, further research should be conducted in order to develop a clearer understanding if organizational maturity can be considered as an antecedent of the technological complexity or vice versa. This could bring to a more effective identification of the most appropriate technological choices and work organization implications also in SM scenarios and could inform the process to be used to design and implement SM strategies.

Managerial implications
Besides the theoretical contributions discussed above, this work contributes also to practice by offering to operations managers that implement SM technologies insights on the importance of taking into account the relation between technological choices and the work organization in the plant; our results offer also interesting implications for policymakers that have to plan regulations and incentives to stimulate and support the adoption of such technologies.

For operations managers, the most important implication is related to the importance of considering the plant organizational structure and operators work design together with the technological strategy of the company when introducing SM technologies, since the intelligence and flexibility of the system may have different effects on shaping and re-shaping the role of the operators and their empowerment in the plant. First, companies must understand and reflect on their as-is approach to work organization, namely, the set of choices at the micro and macro-level which characterize the plant before the implementation of SM technology. Second, companies should reflect on which is the organizational configuration that they want to implement in coherence with their SM strategy. These considerations should take into account the actual and desired level of SM technological complexity, which should also be carefully identified. In this sense, this study offers a guide to map work design dimensions at the micro-level (namely operator job breadth, job autonomy and control, cognitive demand, social interaction) and at the macro-level (namely centralization of decision making power, number of hierarchical levels in the plant) that appear to be coherent with different levels of technological complexity in the SM context. Specifically, companies have two main options: adopting SM technologies at an incremental level fostering traditional work organization at the plant level characterized by limited operator roles and vertical organizations; or adopting SM technologies through an advanced approach by creating new organizational environments characterized by empowered operators and flat organization at the plant level. This last option is in line with both recent technological and organizational trends oriented to new forms of work organization fostering both organizational performance and worker well-being (Longoni et al., 2014).

For policymakers, we show that different SM technological settings lead to different approaches of work organization. Policymakers should be very careful when incentivizing the adoption of SM technologies. Both academics and practitioners are debating whether SM will be an enabler of better jobs and operator well-being or be a crucial tool for firm
efficiency but negatively affecting jobs (i.e. reducing work opportunities and salaries) (World Economic Forum, 2016). Our study shows that depending on the SM technological choice the socio-technical configuration to adopt might change with more technologically complex solutions being associated to empowered operators and new forms of work organization; and less complex SM solutions being associated to traditional and mechanistic work environments with limited operator roles and traditional top-down governance structures. Thus, policymakers aiming to increase firm efficiency as well as operator well-being might consider incentivizing not only more advanced and complex SM technological solutions, but also the careful re-design of work organization.

Conclusions
SM is in the spotlight of both practice and research. SM technological change, that may be implemented with different levels of technological complexity, is expected to strongly impact work organization at different levels. However, so far operations management literature and scientific studies have mainly dealt with the technological aspects of SM and their implications on company processes and operator competences. The purpose of this study was to address the understudied area of work organization in the plant, and in particular which is the interplay between technological complexity and work organization at the micro and macro-levels in SM context.

Four configurations have been identified, characterized by different levels of technological complexity, i.e. with a different number of SM technologies implemented and different levels of integration among them. Findings show how low levels of technological complexity in the SM context are associated with an organizational scenario in which operators perform a limited number of tasks, with limited job autonomy, cognitive demand, while higher levels of technological complexity are associated to an increased number tasks, job autonomy and cognitive demand for operators. Similarly, a higher level of technological complexity is associated to decentralization of decision making and a reduction in the number of hierarchical levels.

Assuming a socio-technical perspective, findings empirically support preliminary insights provided by SM studies that foresee the suitability of SM in enabling more effective human-centric and socially sustainable manufacturing and organizational paradigms (Romero et al., 2016). In addition, we identify the level of technological complexity as the discriminant for such work organization in comparison to a traditional one. Moreover, the study offers valuable practical insights related to the importance of including work organization considerations when defining the technological strategy within companies.

To conclude, our findings show how the interplay between technology and work organization cannot be considered in a deterministic way – i.e., there is just one best way to organize work as a consequence of the opportunities and constraints introduced by the new technology – as it is argued in a number of academic contributions – mainly in the manufacturing field – and by many practitioners (e.g. Khanchanapong et al., 2014). A strategic choice is possible to design the work organization in a way that is coherent with the vision and aims of each specific company, in line with what is showed in the large body of literature that studied previous waves of technological change.

References


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The impact of 3D printing implementation on stock returns
A contingent dynamic capabilities perspective

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Abstract
Purpose – The purpose of this paper is to theoretically hypothesize and empirically test the impact of 3D printing (3DP) implementation on stock returns. It further explores how the stock returns due to 3DP implementation vary across different industry environments.

Design/methodology/approach – This paper integrates the dynamic capabilities view with contingency theory to provide a contingent dynamic capabilities (CDC) perspective on 3DP implementation. It argues that implementing 3DP enables firms to enhance their manufacturing capabilities and gain a competitive advantage, but the extent to which the competitive advantage can be realized is contingent on the fit between 3DP-enhanced manufacturing capabilities and firms’ operating environments. Those arguments are tested based on an event study of 232 announcements of 3DP implementation made by US publicly listed firms between 2010 and 2017.

Findings – The event study results show that firms implementing 3DP gain higher stock returns compared with their non-implementation industry peers over two years after the implementation. Such stock returns due to 3DP implementation are more pronounced for firms operating in more munificent, more dynamic and less competitive industry environments. Those findings are consistent with the CDC perspective.

Originality/value – This is the first research empirically examining the impact of 3DP implementation on stock returns. It provides important implications for managers to implement 3DP to enhance firms’ manufacturing capabilities and for researchers to study 3DP implementation from the CDC perspective.

Keywords Additive manufacturing, 3D printing, Dynamic capabilities, Contingency theory, Event study, Stock returns

Paper type Research paper

1. Introduction
Investment in appropriate manufacturing technology has been a critical managerial decision, not only because it usually involves substantial resource commitments, but also due to its potential in creating competitive advantage (Grant et al., 1991). In today’s rapidly evolving business world, companies are making continuous efforts to identify innovative technologies that suit their market environments and support strategic goals (Grant et al., 1991). 3D printing (3DP), also known as additive manufacturing, has caught noticeable attention from the business community in recent years (Ernst & Young, 2016; d’Aveni, 2015). Former US President Obama highlighted the strategic importance of 3DP by saying that “3DP has the potential to revolutionize the way we make almost everything” (Gross, 2013). An Ernst & Young (2016) global survey shows that 36 percent of the firms have already implemented or are considering the implementation of 3DP. Originally adopted as a prototyping technology...
about 30 years ago, 3DP has evolved to be a direct manufacturing technology for the production of components, parts and even end-use products in different industries (Atzeni and Salmi, 2012; Ernst & Young, 2016). For example, GE aviation used 3DP to build the Advanced Turboprop, the components of which were reduced from 855 to only 12. The simplified design reduced the weight of the engine by 5 percent, ultimately saving 20 percent of fuel and achieving 10 percent more power than its competitors (Van Dusen, 2017). The transformation grows with a more astonishing speed in the US hearing aid industry, which converted to 100 percent additive manufacturing in less than 500 days (d'Aveni, 2015).

Despite the great progress of 3DP within the past few years, little empirical evidence has been provided of its impact on firm performance. Most previous research of 3DP concentrates on its technological features and industrial applications (Lam et al., 2002; Ventola, 2014; Williams et al., 2010). Recently, the business implications of 3DP have received greater attention, though the majority of the studies only provide qualitative discussions of its benefits, limitations and socio-economic impact (Huang et al., 2012; Petrick and Simpson, 2013; Weller et al., 2015; Ford and Despeisse, 2016; Shukla et al., 2018; Eyers et al., 2018). For example, prospective economic benefits of 3DP implementation discussed in the literature include improved resource efficiency, production flexibility and enhanced mass-customization (Huang et al., 2012; Shukla et al., 2018). Moreover, sustainability benefits such as reduced waste during manufacturing, less energy consumption and extended product life are also identified by researchers (Ford and Despeisse, 2016). In recent years, quantitative empirical investigations of 3DP implementation start to emerge. While some researchers have examined the antecedents of 3DP adoption using surveys (Schniederjans, 2017) or investigated the business models enabled by 3DP using computer modeling and simulation (Jia et al., 2016), there is a lack of empirical research investigating the performance impact of 3DP implementation at the firm level.

Our study fills this important gap in the literature by providing an empirical investigation of the impact of 3DP implementation on stock returns, which are regarded as a proxy for overall firm value and more likely to capture the full performance impact due to 3DP implementation (Joshi and Hanssens, 2010; Sorescu et al., 2017). Specifically, we conducted an event study based on 232 announcements of 3DP implementation made by US publicly listed firms between 2010 and 2017. Our event study results suggest that firms implementing 3DP gain higher stock returns compared with their non-implementation industry peers over two years after the implementation. This finding is consistent with our dynamic capabilities view (Barreto, 2010; Schilke et al., 2018) which argues that 3DP implementation enables firms to enhance their manufacturing capabilities and gain a competitive advantage, resulting in positive stock returns.

However, it is less likely that firms operating in different environments will gain the same benefits from their 3DP implementation. For example, while implementing 3DP may enable firms operating in dynamic environments with changing customer preferences and fluctuating market demands to gain a competitive advantage due to its ability to enhance firms' manufacturing capabilities to satisfy the requirements emerging from such environments (Jansen et al., 2006), firms operating in less munificent environments without sufficient resources and support available may encounter difficulty in implementing 3DP to enhance their manufacturing capabilities, thus preventing them from reaping the benefits of 3DP innovation (Park and Mezias, 2005). Therefore, our research further considers how the stock returns due to 3DP implementation vary across firms operating in different environments. In particular, we deploy contingency theory (Reinking, 2012; Sousa and Voss, 2008) to hypothesize how external contingent factors in terms of industry munificence, dynamism and competition affect the extent to which firms benefit from 3DP implementation. Consistent with the contingency perspective, our cross-sectional regression analysis shows that the stock returns due to 3DP implementation are more
pronounced for firms operating in more munificent, more dynamic and less competitive
industry environments. These findings highlight the importance of the fit between
3DP-enhanced manufacturing capabilities and firms’ operating environments.

Our study makes several important contributions. First, this is one of the first research
efforts that empirically examine the impact of 3DP implementation on firm performance in
terms of stock returns. The positive stock returns documented in our research provide
empirical support for firms to implement 3DP. Moreover, our research further shows the
moderating role of operating environments in the 3DP implementation–stock returns
relationship, urging firms to take account of their operating environments in order to reap
more benefits from 3DP implementation. On the other hand, we integrate the dynamic
capabilities view with contingency theory to offer a more comprehensive and
complementary explanation of the 3DP implementation–stock returns relationship. Our
theoretical perspective helps explain not only how 3DP implementation enables firms to
gain a competitive advantage through enhancing manufacturing capabilities but also how
the competitive advantage can be realized depends on the fit between 3DP-enhanced
manufacturing capabilities and firms’ operating environments. This perspective can serve
as a useful theoretical foundation for future 3DP research. It also extends the research on
manufacturing capabilities beyond the structure-conduct-performance framework (Terjesen
et al., 2011) as we view environmental conditions as a moderator, rather than a driver, in the
manufacturing capabilities–firm performance relationship.

2. Hypothesis development

2.1 Literature review

The extant research about 3DP has primarily focused on its technological advancements
and industrial applications (Lam et al., 2002; Ventola, 2014; Williams et al., 2010). Although
the manufacturing process of 3DP may use different printer technologies or printing
materials, the basic steps remain the same: first, a computerized 3D model of the object to be
manufactured is developed in a computer-aided design (CAD) file. Second, the printer
follows the instructions of the CAD file to build a foundation of the object by moving the
printhead along the x-y plane. Third, the printhead then moves along the z-axis to add
materials layer by layer. The additive manufacturing process differs from conventional
manufacturing techniques which subtract materials from a larger piece (Ventola, 2014). 3DP
has been adopted by manufacturers as a complementary technology for rapid prototyping
since 1980s (Huang et al., 2012). About 30 years into its development, 3DP has revealed great
potential as a direct manufacturing technique in various contexts including repairing
existing products, manufacturing parts and machine parts and manufacturing end-use
components and products (Atzeni and Salmi, 2012; Thomas-Seale et al., 2018).

Studies seeking to understand the implications of 3DP implementation have started to
come in recent years (Dong et al., 2017; Ford and Despeisse, 2016; Holmström et al., 2016;
Huang et al., 2012; Petrick and Simpson, 2013; Weller et al., 2015; Shukla et al., 2018; Eyers
et al., 2018; Jia et al., 2016). On the one hand, these studies provided preliminary discussions
about the advantages of 3DP such as accelerating product development, offering customized
products, and increasing production flexibility. For instance, Huang et al. (2012) claimed that
3DP by nature eliminates the need for tooling, molding, warehousing, transportation and
packaging. The simplified supply chain leads to improved material efficiency, resource
efficiency, part flexibility and production flexibility, thus enabling on-demand manufacturing.
Shukla et al. (2018) discussed the impact of 3DP implementation on mass-customization and
proposed that 3DP facilitates four key practices in mass-customization including agility,
customer involvement, postponement (i.e. “print-to-order”) and modularization. Dong et al.
(2017) conducted one of the few analytical studies about the optimal manufacturing strategy
under traditional flexible technology and 3DP. They proved that, compared with traditional
flexible technology, 3DP excels in enhancing product diversity by allowing firms to choose a large product assortment with little profit loss.

On the other hand, previous studies also indicated that 3DP has not been accepted as a standard production technology due to limitations including technological constraints, investment costs and business challenges (Attaran, 2017; Shukla et al., 2018; Thomas-Seale et al., 2018; Weller et al., 2015). First, compared with conventional subtractive manufacturing, 3DP lacks economy of scale. Different from conventional injection molding, the production throughput speed of the additive manufacturing process is rather low, so 3DP is mostly adopted and advantageous in multi-variant and low-volume production (Petrick and Simpson, 2013). Second, the limitations of printing materials, colors and surface finishes could impede broader applications of 3DP (Petrick and Simpson, 2013; Weller et al., 2015). For example, at current stage, additive manufacturing still cannot compete with the subtractive manufacturing in terms of precision (Shukla et al., 2018). As a result, significant efforts are required for the polishing and finishing surfaces afterwards. Third, the purchasing costs for 3D printers are unneglectable, not to mention additional costs including supporting machinery, printing materials and highly skilled personnel (Huang et al., 2012; Shukla et al., 2018). Last but not least, “soft barriers” such as the lack of technological know-how (Thomas-Seale et al., 2018), CAD software complexity (Shukla et al., 2018) and unestablished global quality and test standards (Weller et al., 2015) may also hinder the implementation of 3DP.

Taken together, although previous research has adopted various research methods such as case studies and analytical modeling to explore the opportunities and challenges of 3DP implementation (Dong et al., 2017; Eyers et al., 2018; Shukla et al., 2018), the question remains whether, and to what extent, 3DP implementation affects firm performance. Our study complements the literature by theoretically hypothesizing and empirically testing the impact of 3DP implementation on firm performance in terms of stock returns.

2.2 A contingent dynamic capabilities perspective on 3DP implementation

We integrate the dynamic capabilities view with contingency theory to provide a contingent dynamic capabilities (CDC) perspective on the 3DP implementation–stock returns relationship, for several reasons. First, different from the static resource-based view of the firm that is focused on a firm’s existing resource base, the dynamic capabilities view stresses a firm’s capacity to “purposefully create, extend, or modify its resource base” (Helfat et al., 2007, p. 1). This conceptualization enables us to adopt the dynamic capabilities view to theorize how firms implement 3DP to renew their resource base and enhance manufacturing capabilities. Moreover, the dynamic capabilities literature has commonly linked firms’ dynamic capabilities to competitive advantage (Barreto, 2010; Schilke et al., 2018), consistent with our research objective which is to investigate the impact of 3DP implementation on firm performance in general and stock returns in particular. However, although the dynamic capabilities view is concerned with the “rapidly changing environments” (Teece et al., 1997, p. 516) or dynamic environments, it pays less attention to other dimensions of the environments such as environmental munificence. We thus adopt contingency theory to further explore how the impact of 3DP implementation is contingent on different dimensions of firms’ operating environments. Contingency theory suits our research well as it focuses on the fit between firms’ internal endogenous processes or practices (e.g. 3DP implementation) and external exogenous contexts (e.g. operating environments) (Chavez et al., 2013; Wong et al., 2011). Also, consistent with the dynamic capabilities view, firm performance is a typical dependent variable investigated in the contingency literature (Sousa and Voss, 2008). Therefore, a combination of the dynamic capabilities view and contingency theory provides a complementary and comprehensive perspective on not only the direct relationship between 3DP implementation and stock
returns but also the indirect moderating role of firms’ operating environments. In what follows, we first deploy the dynamic capabilities view to theorize how 3DP implementation enables firms to broaden their operational scopes without cost penalties, thus enhancing manufacturing capabilities and gaining a competitive advantage. We also explain how the competitive advantage can be quantified as stock returns. We then adopt contingency theory to explore the fit between 3DP-enhanced manufacturing capabilities and industry environments in terms of industry munificence, dynamism and competition, thus moderating the 3DP implementation–stock returns relationship. Our research model is shown in Figure 1.

Previous studies have identified operational scope as a multi-dimensional concept, comprised of product/service scope, geographic scope and process scope (Clark and Huckman, 2011; Hitt et al., 1997; Kovach et al., 2015). Product/service scope is the breadth of the product/service portfolio offered by a firm (Clark and Huckman, 2011). Geographic scope is the breadth of expansion into different geographic locations or markets (Hitt et al., 1997). Process scope is the level of flexibility to cope with the change in output (Anand and Ward, 2009). A consensus has been reached concerning the trade-off between operational scope and efficiency in existing research (Clark and Huckman, 2011). It has been well acknowledged that diversification is not free, and expanding operational scope almost inevitably increases operational complexity and inflates costs (Hitt et al., 1997; Ramdas, 2009).

3DP potentially challenges this conventional wisdom as it implies increased operational scope without cost penalties, thus renewing firms’ resource base and enhancing their manufacturing capabilities (Petrick and Simpson, 2013; Schniederjans, 2017; Weller et al., 2015). Specifically, first, 3DP expands product scope through cost-effective and time-efficient product innovation, customization and intricacy (Shukla et al., 2018; Weller et al., 2015). Traditionally, offering a diverse product portfolio incurs additional operational costs such as tooling and variety-related inventory holding costs (Kovach et al., 2015). However, as there are no tooling requirements nor minimum batch size pressure in the one-step additive manufacturing process, diversified product design can be achieved without additional tooling costs or inventory holding of a large variety of products (Weller et al., 2015). Moreover, 3DP enhances new product development by removing the restrictions of innovation. 3DP can be used to manufacture any sophisticated parts that can be imaged without the need to compromise on the functionality for the ease of manufacturing (Attaran, 2017). Beyond manufacturing settings, 3DP has also been adopted to provide services of producing 3D-printed items for customers, mostly in healthcare, retailing, logistics and transportation industries (Ernst & Young, 2016). For example, Henry Schein, a worldwide Dental Supplier, provided 3D-printed mouth guards for their customers using intra-oral scanners (Bloomberg, 2017). UPS, aside from package delivery service, has expanded its service scope to provide 3DP services in UPS stores since 2013 (Carey, 2016).

Second, 3DP expands the geographic locations where firms produce and sell products through decentralized manufacturing (Attaran, 2017). With a 3D printer, customers are
allowed to download digital models from websites, and then additively manufacture the parts in need by themselves at almost any locations. Manufacturing at the point of use is expected to reduce the requirement of extensive physical inventory and large-volume logistics and transportations. For instance, Ford launched an online 3DP store to provide 3DP services that allow customers to “print” the scale automotive models with the digital models downloaded from their website (McCue, 2015).

Third, 3DP achieves broad process scope with increased production flexibility. Process scope is associated with both mix flexibility and volume flexibility (Kovach et al., 2015). 3DP increases mix flexibility in the manufacturing process as any changes of design are allowed by simply modifying the 3D model stored in the CAD file. Moreover, 3DP enables direct manufacturing without the need for tools or molds, so the design changes can be easily transferred into production (Ernst & Young, 2016). In addition, 3DP substantially reduces manufacturing steps by removing the processes of casting, molding, machining and assembly, thus reducing manufacturing costs. The negligible changeover costs and simplified manufacturing steps contribute to the increased flexibility of adjusting production according to varying designs, sequences or volumes (Weller et al., 2015).

The above discussion suggests that 3DP implementation helps firms broaden their operational scopes (i.e. product/service scope, geographic scope and process scope) and mitigate operational complexities and costs, thus enhancing manufacturing capabilities. The dynamic capabilities literature has commonly agreed that improved firm capabilities enable the focal firm to gain an advantage over its competitors (Barreto, 2010; Schilke et al., 2018). Empirically, the operations management literature has well documented the positive relationship between enhancing manufacturing capabilities and various dimensions of firm performance such as sales growth, cost reduction and profitability improvement (White, 1996; Terjesen et al., 2011; Corbett and Claridge, 2002). We thus expect 3DP implementation to foster a competitive advantage for firms through enhancing their manufacturing capabilities. While prior dynamic capabilities research has used different performance measures such as profitability, growth and survival to indicate a firm’s competitive advantage (Schilke et al., 2018; Shamsie et al., 2009), we quantify it in terms of abnormal stock returns in this research. This is because abnormal stock returns, as measured based on the event study method discussed in Section 3, are the difference in stock returns between firms implementing 3DP and their industry peers without 3DP implementation, which is more in line with the concept of competitive advantage discussed in the literature. Moreover, such “abnormal” stock returns are consistent with the “above average returns” or “abnormal rents” emphasized in prior research on dynamic capabilities (Jiang et al., 2015; Oliver and Holzinger, 2008). Therefore, we hypothesize that:

H1. Firms’ 3DP implementation has a positive impact on their stock returns.

2.3 The contingent role of industry environments

Contingency theory submits that there is no one best way of organizing or one-size-fits-all strategy (Chavez et al., 2013; Zhang et al., 2012). Instead, the contingency literature has commonly agreed that firms do not operate in a vacuum and better firm performance is a consequence of the proper alignment of firms’ internal characteristics with external contextual factors (Sousa and Voss, 2008; Wong et al., 2011). Put into our research context, it is possible that the extent to which the competitive advantage due to 3DP implementation can be realized depends on the alignment of the 3DP-enhanced manufacturing capabilities with firms’ operating environments. For example, if firms’ operating environments do not provide sufficient resources and support for firms to implement 3DP, it may be difficult for the firms to reap the benefits of 3DP innovation. Similarly, if firms’ operating environments do not present the need for more advanced
manufacturing capabilities, the manufacturing capabilities enhanced by 3DP implementation may not help firms to gain a competitive advantage.

In fact, although the positive relationship between manufacturing capabilities and competitive advantage has been well documented in the literature, some prior studies have shown non-significant or even negative relationships under certain circumstances. For instance, a meta-analysis conducted by White (1996) suggested that the manufacturing capabilities–business performance relationships as documented in the literature range from positive to non-significant, while Corbett and Claridge (2002) showed that such relationships could be negative in some industries. Kim and Arnold (1993) also questioned whether manufacturing capabilities matter in all industries or they matter more in some specific industries. Informed by the findings of those prior studies and through the lens of contingency theory, we consider how industry environments moderate the impact of 3DP implementation on stock returns. In particular, we focus on three industry characteristics, namely munificence, dynamism and competition (Jansen et al., 2006; Park and Mezias, 2005) in this research because they represent different levels of environmental support and environmental requirement for 3DP implementation, as discussed below.

Industry munificence refers to the level of resources available to support the sustained growth of the firms in the industry (Dess and Beard, 1984; Park and Mezias, 2005). It is primarily determined by the rate of sales growth in the industry (Dess and Beard, 1984). In an industry with high level of munificence, firms are more likely to accumulate slack resources such as venture capital, government funds, labor markets and suppliers (Dess and Beard, 1984; Park and Mezias, 2005). Dess and Beard (1984) indicated that these slack resources not only function as buffer during times of scarcity, but also facilitate organizational innovation. Firms implementing 3DP in munificent industries are more likely to gain benefits because the effectiveness of 3DP depends on the availability of several critical resources such as qualified experts, software vendors and investment capitals (Huang et al., 2012; Shukla et al., 2018; Thomas-Seale et al., 2018). On the contrary, firms in the industry with low level of munificence could encounter several obstacles preventing them from accessing the resources for development. These obstacles may include tax burdens, fragile infrastructure, inaccessible technology support from educational institutions and lack of qualified labor (Chen et al., 2014). In general, 3DP implementation is more likely to be effective when firms are operating in more munificent industries (Chen et al., 2014; Terjesen et al., 2011). Thus, we hypothesize that:

\[ H2. \] The impact of 3DP implementation on stock returns is higher for firms operating in more munificent industries.

Industry dynamism refers to the instability of the environment (Dess and Beard, 1984; Jansen et al., 2006). Dess and Beard (1984) further emphasized that dynamism should be restricted to the changes which are unpredictable. Dynamic industries are characterized by changeable customer preferences, unpredictable technology development, fluctuated market demand and inconstant government regulations (Anand and Ward, 2009; Stoel and Muhanna, 2009). Anand and Ward (2009) indicated that in order to cope with a large number of unpredictable scenarios, firms are required to broaden process scope by maintaining diverse capabilities and building up excess capacity, which inevitably leads to higher costs. As a result, manufacturing capabilities play a significant role in gaining competitive advantage in dynamic industries. Firms investing in 3DP are allowed to move between different product designs and production volumes with less incurring time and cost penalties, and thus are likely to gain greater advantages. Similar to Stoel and Muhanna’s (2009) argument about externally oriented IT, we believe that the effectiveness of 3DP is more pronounced in dynamic environments in that it enables firms to better sense the market through customization and timely respond to the fluctuations in customer and
suppliers' demand. Overall, we expect the 3DP-enhanced manufacturing capabilities to enable firms to better meet the requirements induced in more dynamic industries and gain a competitive advantage. Therefore, we hypothesize that:

H3. The impact of 3DP implementation on stock returns is higher for firms operating in more dynamic industries.

Industry competition refers to intensity of competition in an industry, often reflected in the number of competitors and the concentration of market shares (Jansen et al., 2006; Melville et al., 2004). Low level of concentration represents a competitive market with market shares almost evenly distributed among a large number of competitors, while high level of concentration depicts a monopoly or oligopoly industry with a small number of competitors dominating the market (Azadegan et al., 2013). While industry munificence and industry dynamism indicate the levels of environmental support and environmental requirement, respectively, for 3DP implementation, industry competition implies a more complicated situation. First, similar to industry dynamism, industry competition can represent the level of environmental requirement for 3DP implementation. For example, in highly competitive industries, firms are motivated to break out the price war by differentiating themselves from their competitors who are providing homogeneous products or services (Chen et al., 2014). In particular, through product innovation, new market exploration and enhanced tailoring of products or services, firms are able to gain an advantage over their competitors (Jansen et al., 2006). The implementation of 3DP can help firms achieve such differentiations and satisfy the requirements arising from the competitive markets. Specifically, 3DP facilitates product innovation by eliminating the iteration costs and manufacturing limitations in the product design process (Weller et al., 2015). 3DP also allows customization without cost penalties, consequently increasing customers' perceived values and willingness to pay (Shukla et al., 2018). Therefore, it is possible that 3DP implementation will be more valuable for firms in industries with high level of competition. As a result, industry competition is expected to have a positive moderating effect on the 3DP implementation–stock returns relationship such that the impact of 3DP implementation on stock returns will be higher for firms operating in more competitive industries.

However, industry competition can also be related to the level of environmental support for 3DP implementation. This is because in highly competitive industries with a large number of competitors, resources are relatively scarce as firms compete not only for customers and market shares but also for inputs into the production processes such as qualified labors and investment capitals (Prajogo and Oke, 2016). Moreover, due to low entry barriers and intensive competition in such industries, the adoption of new innovation such as 3DP will be aggressively matched by competitors, reducing the adopters' first-mover advantage and the power to generate abnormal rents from the innovation adoption (Jansen et al., 2006; Melville et al., 2004). As a result, competitive industries exhibit a low level of environmental support for firms to implement 3DP. By contrast, in monopoly or oligopoly industries with a small number of competitors, resources are readily available to a few dominant players to support their 3DP implementation. Due to low competition, they have strong power to charge a price premium for the products and services offered by them. Weller et al. (2015) also suggested that "in a monopoly, the adoption of AM [additive manufacturing] allows a firm to increase profits by capturing consumer surplus when flexibly producing customized products" (p. 43). Therefore, from the environmental support perspective, industry competition will have a negative, rather than positive, moderating effect on the 3DP implementation–stock returns relationship such that the impact of 3DP implementation on stock returns will be higher for firms operating in less competitive industries.

The above discussion suggests two opposite moderating roles for industry competition. In fact, past empirical studies have also documented mixed results regarding the role of
competition (Prajogo and Oke, 2016; Wilden et al., 2013). For example, Wilden et al. (2013) found that the performance impact of dynamic capabilities improves in competitive environments, whereas Prajogo and Oke (2016) showed that competitive environments weaken the relationship between service innovation advantage and business performance. Informed by the findings of those past studies and based on the above discussion, we propose two competing hypotheses for the role of industry competition:

**H4a.** The impact of 3DP implementation on stock returns is higher for firms operating in more competitive industries.

**H4b.** The impact of 3DP implementation on stock returns is higher for firms operating in less competitive industries.

### 3. Methods

#### 3.1 Sample

We attempt to identify the population of US publicly listed firms that announced the implementation of 3DP. Consistent with prior studies (Ding et al., 2018; Sorescu et al., 2017), we conducted a comprehensive search in the Factiva news database with 3DP-related keywords to collect firm announcements of 3DP implementation across all industries between 2010 and 2017. The keywords used in this study are (NASDAQ or NYSE or AMEX) and (3D print* or three-dimensional print* or additive manufactur* or rapid manufactur* or rapid prototyp*). We reviewed all the announcements collected from Factiva to ascertain that they meet the following criteria. First, the announcement should be related to applying 3DP technology to the firm’s business practices such as product design and development, rapid prototyping, specialized manufacturing, service providing and other related activities. Announcements only informationally associated with 3DP without applications were excluded. For example, the announcement about Staples becoming the first US retailer to sell 3D printers was eliminated. Second, for the same type of 3DP implemented by a firm, only the earliest announcement was included (Ding et al., 2018). However, announcements made by the same firm reporting different types of 3DP implementation were included. For example, the announcement about Ford using 3DP to produce prototype parts and the announcement about Ford launching an online 3DP store to provide scale model printing services for customers were both included. Third, announcements made by private firms or firms not listed on NYSE, AMEX or NASDAQ were excluded. The process resulted in 242 announcements made by 132 firms. For further matching process, we excluded seven firms without data in Compustat and three firms with negative book to market ratios. The final sample consists of 232 announcements made by 122 firms. Some examples of the announcements are shown below:

- Under Armour’s 3D-printed shoes bring computer designer to heel;
- Ford begins large-scale 3DP trial;
- Amazon offers 3DP to customize earrings, bobble head toys; and
- UPS store makes 3DP accessible to start-ups and small business owners.

A key challenge of relying on announcements for this kind of research is the issue of “decoupling,” meaning that firms may not actually implement 3DP after they make the announcements. To verify the consistency of words and deeds, we further searched in Google to check whether firms implemented the announced 3DP based on information from various sources. For each of the 232 announcements, our search included the type of 3DP mentioned in the announcement and the name of the announcing firm. We were able to identify 207 announcements with information related to the implementation of the
3DP announced, representing about 89 percent of the 232 announcements used in our research. As most announcements have been verified, we believe the decoupling issue is not a major concern in our research.

Table I presents the distributions of the announcements across years and industries and the descriptive characteristics of the announcing firms. It shows that the majority (81 percent) of the announcements were made in the recent four years from 2014 to 2017, indicating soaring adoption rates. Most of the announcements (66 percent) are from manufacturing industries, while the remaining are from service industries or others[1]. The average market value of the announcing firms is $72,160.8m, suggesting that the announcements are mostly from large-scale firms.

### 3.2 Long-term event study method

We employ the long-term event study method to quantify the performance impact of 3DP implementation in terms of stock returns (Kothari and Warner, 2007). We choose to focus on stock returns rather than accounting-based operating performance indicators such as sales growth and cost reduction (De Jong et al., 2014; Orzes et al., 2017) for several reasons. First, the implementation of 3DP varies greatly across industries such as healthcare, automotive manufacturing, fashion, consumer products and aerospace, so it is difficult to determine appropriate operating performance measures that fit in all the contexts of different types of implementation. Moreover, operating performance indicators such as sales and costs focus

| Panel A: distribution of 3DP implementation announcements across years
<table>
<thead>
<tr>
<th>Year</th>
<th>Frequency</th>
<th>Percentage</th>
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<tbody>
<tr>
<td>2010</td>
<td>4</td>
<td>2</td>
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<td>2011</td>
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<td>18</td>
</tr>
<tr>
<td>2016</td>
<td>61</td>
<td>26</td>
</tr>
<tr>
<td>2017</td>
<td>45</td>
<td>19</td>
</tr>
<tr>
<td>Total</td>
<td>232</td>
<td>100</td>
</tr>
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</table>

| Panel B: distribution of 3DP implementation announcements across industries
<table>
<thead>
<tr>
<th>Industry</th>
<th>SIC</th>
<th>Frequency</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, mining, construction</td>
<td>0100-1999</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>Food, textiles, furniture, paper and chemicals</td>
<td>2000-2999</td>
<td>34</td>
<td>15</td>
</tr>
<tr>
<td>Rubber, leather, stone, metals, machinery and equipment</td>
<td>3000-3569, 3580-3659, 3800-3999</td>
<td>57</td>
<td>25</td>
</tr>
<tr>
<td>Computers, electronics, communications and defense</td>
<td>3570-3579, 3660-3699, 3780-3789</td>
<td>37</td>
<td>16</td>
</tr>
<tr>
<td>Automobile, aircraft and transportation manufacturing</td>
<td>3700-3759, 3790-3799</td>
<td>24</td>
<td>10</td>
</tr>
<tr>
<td>Transportation, communications, wholesaling and retailing</td>
<td>4000-5999</td>
<td>22</td>
<td>9</td>
</tr>
<tr>
<td>Services and non-classifiable</td>
<td>6000-9999</td>
<td>53</td>
<td>23</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>232</td>
<td>100</td>
</tr>
</tbody>
</table>

| Panel C: characteristics of 3DP implementation announcing firms
<table>
<thead>
<tr>
<th>Firm characteristics</th>
<th>Mean</th>
<th>SD</th>
<th>Max.</th>
<th>Min.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market value ($ million)</td>
<td>72,160.8</td>
<td>108,860.4</td>
<td>647,506.9</td>
<td>20.2</td>
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<tr>
<td>Total assets ($ million)</td>
<td>34,618.8</td>
<td>150,870.0</td>
<td>751,216</td>
<td>15.8</td>
</tr>
<tr>
<td>Sales ($ million)</td>
<td>37,442.5</td>
<td>46,791.1</td>
<td>233,715</td>
<td>0.38</td>
</tr>
<tr>
<td>Net income ($ million)</td>
<td>3,235.9</td>
<td>6,491.83</td>
<td>53,394</td>
<td>-6,127</td>
</tr>
</tbody>
</table>

Table I. Descriptive statistics
on a firm’s tangible value, which may fail to account for the impact of 3DP implementation on the firm’s intangible value. Stock returns, on the other hand, represent a firm’s overall value, taking both tangible and intangible components into account (Joshi and Hanssens, 2010; Sorescu et al., 2017) and thus more likely to capture the overall performance impact due to 3DP implementation. In addition, accounting-based performance indicators are lagging measures, representing a firm’s performance over a specific period (e.g. a fiscal year). This suggests that it may take a relatively long time period for the impact of a firm’s strategy to be reflected in the accounting-based performance measures, especially when technology implementation is involved. For example, Hendricks et al. (2007) examined the impact of the implementation of enterprise systems on accounting-based performance measures over a five-year period. Such an approach is not feasible for our research as 63 percent of the 3DP implementation were announced in 2015–2017, suggesting that our sample size will drop drastically if a five-year investigation period is applied. On the other hand, stock returns are a forward-looking measure (Sorescu et al., 2017), which indicates investors’ expectation of a firm’s future performance and better suits our research context.

We prefer quantifying the impact of 3DP implementation in terms of long-term rather than short-term stock returns (Ding et al., 2018) as stock markets may fail to reveal the true intrinsic value of 3DP implementation within a short time period. Specifically, immediately after the announcements are made, investors possibly over-react to the 3DP implementation due to over-optimism and limited knowledge. In an investigation of e-commerce, Ferguson et al. (2010) argued that stock market may overprice the added value of technologies which are regarded as innovative, exciting and glamorous. Similarly, we believe that there could also be an upward bias in investors’ valuation of 3DP, which is perceived as a groundbreaking technology to disrupt conventional manufacturing. As Hendricks and Singhal (2001) indicated in a study of TQM, the market may wait for more information to incrementally acquire knowledge about new innovation and judge its effectiveness. Therefore, we adopt the long-term event study method to examine the stock returns due to the implementation of 3DP which is a pioneering technology with relatively little knowledge of its value.

For the long-term event study, we calculate the abnormal stock returns as the buy-and-hold return (BHR) of the sample firms less the BHR of an appropriate benchmark (Barber and Lyon, 1997; Lyon et al., 1999). The buy-and-hold abnormal return (BHAR) is:

$$BHAR = \prod_{t=1}^{T} (1 + R_{it}) - \prod_{t=1}^{T} (1 + R_{bt}),$$

where $R_{it}$ is the monthly stock return of the sample firm $i$ in month $t$; $R_{bt}$ the monthly stock return of the control firm paired with sample firm $i$ in month $t$; and $T$ the length of the event window. Monthly stock returns were retrieved from the Center for Research in Security Prices (CRSP) database. In developing the benchmark, we follow the standard procedures proposed in previous research (Barber and Lyon, 1997; Hendricks and Singhal, 2001) and match each sample firm to a control firm based on different combinations of three widely accepted characteristics, namely industry, size and market-to-book (MTB) ratio. The control firm approach has advantages in eliminating new listing bias, rebalancing bias and the skewness problem compared with the portfolio approach (Barber and Lyon, 1997). As the maturity level and magnitude of sustainability benefits of 3DP vary across industries (Thomas-Seale et al., 2018), we emphasize industry as an important matching criteria to control for industry heterogeneity (Hendricks and Singhal, 2001). We use all the NYSE, NASDAQ and AMEX listed firms without 3DP implementation announcements as the benchmark pool[2]. Industry is indicated by the firm’s primary SIC code, size is measured as the market value of equity and MTB ratio is calculated as market value of equity divided by book value of equity. All the accounting data are in the most recent fiscal year prior to the announcement year and were retrieved from the Compustat database. To enable us to check the sensitivity of our results, we
take three different matching approaches to identify the control firm for each firm-year observation: first, for the industry-size match, we first match a sample firm to control firms with the same four-digit SIC code, then the control firm closest in size is identified. If the control firm is not found, we match the sample firm to control firms with the same three-digit SIC code. The control firm must have at least same two-digit SIC code as the sample firm and is closest in size. Second, for industry-MTB match, we follow similar procedures as in the industry-size match, but the control firm closest in MTB ratio is identified. Third, for industry-size-MTB match, we follow similar procedures as in the industry-size match, but the control firm closest in the absolute percentage difference between size and MTB ratio is identified. As a robustness test, we adopt propensity score matching (PSM) as an alternative matching approach to control for other factors besides industry, size and MTB ratio, as discussed in Section 4.

We set the calendar month when the announcement was made public as the event month 0. The month before and after the event month are denoted as month \(-1\) and 1, respectively. In reality, it usually takes several months for firms to finish the implementation of 3DP, suggesting that the effectiveness of 3DP implementation may not manifest until a few months after the announcement month. However, as there is little guidance in the literature regarding the appropriate time period for 3DP implementation, we determine the length of implementation period based on the evidence provided in our sample announcements. For example, Mattel Inc. announced on April 20, 2016 that they start a collaboration with Autodesk Inc. to power the Mattel toy line with cutting-edge 3DP technology. Ten months later, Mattel introduced their 3DP eco-system named ThingMaker to enable consumers to design, create and print their own toys (Business Wire, 2015). Based on the information in the announcements and previous long-term event studies (Hendricks and Singhal, 2001), we set month (1, 12) as the time period required for implementation. A long post-implementation investigation period may capture the effect of 3DP implementations more extensively but also reduce our sample size substantially as most of our announcements were released between 2014 and 2017. To strike a balance, we set the post-implementation period as month (13, 24). We measure the effect of 3DP implementation over both implementation and post-implementation periods, i.e., month (1, 12) and month (1, 24), to fully capture the market reactions. Month \((-24, -1)\) is set as the pre-implementation period. We conduct t-test, Wilcoxon-signed rank (WSR) test, and sign test to determine the significance of the BHARs over different periods but mainly focus on the non-parametric test results due to their better ability to account for possible extreme values of BHARs. Moreover, as the multiple event windows used in our research might increase the possibility of false positive results, we follow Orzes et al. (2017) and adopt the approach proposed by Benjamini and Hochberg (1995) to control the false discovery rate and address the multiple testing concern.

3.3 Cross-sectional regression

We construct a cross-sectional regression model as shown below to investigate the moderating role of environmental factors including industry munificence, dynamism and competition. Table II presents the measures, data sources and references of the variables in the regression analysis:

\[
BHAR_i = \beta_0 + \beta_1 \text{Firm size}_i + \beta_2 \text{MTB ratio}_i + \beta_3 \text{R&D intensity}_i \\
+ \beta_4 \text{Prior performance}_i + \beta_5 \text{Capital structure}_i + \beta_6 \text{Momentum}_i \\
+ \beta_7 \text{Velocity}_i + \beta_8 \text{Manufacturing}_i + \text{Year dummies}_i + \beta_9 \text{Munificence}_i \\
+ \beta_{10} \text{Dynamism}_i + \beta_{11} \text{Competition}_i + \epsilon_i.
\]

The dependent variable is the BHAR calculated for each sample firm over a specific event window. As to the independent variables, we control for several firm-specific, industry-specific
<table>
<thead>
<tr>
<th>Variable type</th>
<th>Variable name</th>
<th>Measurement</th>
<th>Data source</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable</td>
<td>BHAR</td>
<td>Abnormal buy-and-hold stock return calculated with monthly return</td>
<td>CRSP</td>
<td>Lyon et al. (1999)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$BHAR = \prod_{t=1}^{T} \left(1 + R_{it}\right) - \prod_{t=1}^{T} \left(1 + R_{it}\right)$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Explanatory variables</td>
<td>Industry munificence</td>
<td>Slope coefficient obtained by regressing sales over the time period of 2010–2017/mean sales over the same time period</td>
<td>Compustat</td>
<td>Jacobs et al. (2015)</td>
</tr>
<tr>
<td></td>
<td>Industry dynamism</td>
<td>Standard error of the slope coefficient obtained by regressing sales over the time period of 2010–2017/mean sales over the same time period</td>
<td>Compustat</td>
<td>Jacobs et al. (2015)</td>
</tr>
<tr>
<td></td>
<td>Industry competition</td>
<td>$1 – \text{Herfindahl index} = 1 – \sum_{i} \left(\frac{\text{Sales}_i}{\text{Total sales of firms in the same industry}}\right)^2$</td>
<td>Compustat</td>
<td>Xia et al. (2016)</td>
</tr>
<tr>
<td>Control variables</td>
<td>Firm size</td>
<td>Natural logarithm of market value of equity in the most recent fiscal year before the announcement year</td>
<td>Compustat</td>
<td>Hendricks and Singhal (2001)</td>
</tr>
<tr>
<td></td>
<td>MTB ratio</td>
<td>Market value of equity/Book value of equity in the most recent fiscal year before the announcement year</td>
<td>Compustat</td>
<td>Lam (2018)</td>
</tr>
<tr>
<td></td>
<td>R&amp;D intensity</td>
<td>R&amp;D expenses/Sales in the most recent fiscal year before the announcement year</td>
<td>Compustat</td>
<td>Jacobs et al. (2015)</td>
</tr>
<tr>
<td></td>
<td>Prior performance</td>
<td>Sample firm ROA – Median ROA of firms with the same 3-digit SIC code</td>
<td>Compustat</td>
<td>Swink and Jacobs (2012)</td>
</tr>
<tr>
<td></td>
<td>Capital structure</td>
<td>Total liabilities/Sales in the most recent fiscal year before the announcement year</td>
<td>Compustat</td>
<td>Chari et al. (2007)</td>
</tr>
<tr>
<td></td>
<td>Momentum</td>
<td>Buy-and-hold return of sample firms from 6 months to 1 month prior to the announcement month</td>
<td>CRSP</td>
<td>Qian and Zhu (2017)</td>
</tr>
<tr>
<td></td>
<td>Velocity</td>
<td>Fast velocity industries (SIC = 284, 367, 737) = 1 Other industries = 0</td>
<td>Compustat</td>
<td>Jacobs et al. (2015)</td>
</tr>
<tr>
<td></td>
<td>Manufacturing</td>
<td>Manufacturing industries = 1 Service and other industries = 0</td>
<td>Compustat/Announcements</td>
<td>Swink and Jacobs (2012)</td>
</tr>
<tr>
<td></td>
<td>Year dummies</td>
<td>Years of 3DP implementation announcements</td>
<td>Announcements</td>
<td>Lam (2018)</td>
</tr>
</tbody>
</table>
and market-specific factors that have been commonly identified to potentially affect firms’ stock returns (Ding et al., 2018; Lam, 2018; Hendricks and Singhal, 2001; Qian and Zhu, 2017; Sorescu et al., 2017). We also include year dummies to account for unobservable time-specific effects (Jacobs et al., 2015). We rely on $\beta_9$, $\beta_{10}$ and $\beta_{11}$ to determine the effects of industry munificence, dynamism and competition, respectively.

4. Results

4.1 The stock returns of 3DP implementation

Table III presents the BHAR results based on three different matching approaches: industry-size match, industry-MTB match and industry-size-MTB match. To alleviate the concern that other factors rather than 3DP implementation might affect firm performance, we test the BHARs during pre-implementation periods (Yang et al., 2019). If significant BHARs are found even before 3DP is implemented, we might suspect that the significant BHARs, if any, detected during the post-implementation period are driven by other factors.

<table>
<thead>
<tr>
<th>Start month</th>
<th>End month</th>
<th>No. of observations</th>
<th>BHAR mean (%)</th>
<th>p-value</th>
<th>BHAR median (%)</th>
<th>p-value</th>
<th>BHAR positive (%)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry-size-matched control firms</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>−24</td>
<td>−1</td>
<td>184</td>
<td>−31.26</td>
<td>0.076</td>
<td>−4.52</td>
<td>0.393</td>
<td>46</td>
<td>0.338</td>
</tr>
<tr>
<td>−24</td>
<td>−13</td>
<td>184</td>
<td>−7.87</td>
<td>0.056</td>
<td>−0.80</td>
<td>0.493</td>
<td>49</td>
<td>0.941</td>
</tr>
<tr>
<td>−12</td>
<td>−1</td>
<td>192</td>
<td>−6.51</td>
<td>0.176</td>
<td>2.55</td>
<td>0.883</td>
<td>55</td>
<td>0.220</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>198</td>
<td>0.05</td>
<td>0.946</td>
<td>0.27</td>
<td>0.973</td>
<td>51</td>
<td>0.943</td>
</tr>
<tr>
<td>1</td>
<td>6</td>
<td>179</td>
<td>−1.71</td>
<td>0.429</td>
<td>−0.02</td>
<td>0.768</td>
<td>49</td>
<td>0.881</td>
</tr>
<tr>
<td>7</td>
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<td>145</td>
<td>3.36</td>
<td>0.122</td>
<td>2.80</td>
<td>0.158</td>
<td>56</td>
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<td>59</td>
<td>0.030**</td>
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<td>18</td>
<td>120</td>
<td>8.27</td>
<td>0.111</td>
<td>9.30</td>
<td>0.014*</td>
<td>61</td>
<td>0.022*</td>
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<td>94</td>
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<td>0.033</td>
<td>18.45</td>
<td>0.004**</td>
<td>63</td>
<td>0.017*</td>
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<td>Industry-MTB-matched control firms</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>−24</td>
<td>−13</td>
<td>161</td>
<td>−21.84</td>
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<td>2.08</td>
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<td>0.168</td>
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<tr>
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<td>112</td>
<td>8.88</td>
<td>0.001***</td>
<td>9.34</td>
<td>0.000***</td>
<td>66</td>
<td>0.001***</td>
</tr>
<tr>
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<td>63</td>
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<td>88</td>
<td>20.73</td>
<td>0.051</td>
<td>24.48</td>
<td>0.004**</td>
<td>66</td>
<td>0.004**</td>
</tr>
<tr>
<td>Industry-size-MTB-matched control firms</td>
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<td></td>
</tr>
<tr>
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<td>0.591</td>
<td>49</td>
<td>0.881</td>
</tr>
<tr>
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<td>0.941</td>
<td>52</td>
<td>0.863</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>198</td>
<td>0.14</td>
<td>0.883</td>
<td>−0.22</td>
<td>0.937</td>
<td>49</td>
<td>0.831</td>
</tr>
<tr>
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<td>182</td>
<td>−1.57</td>
<td>0.532</td>
<td>2.00</td>
<td>0.755</td>
<td>52</td>
<td>0.711</td>
</tr>
<tr>
<td>7</td>
<td>12</td>
<td>146</td>
<td>1.83</td>
<td>0.381</td>
<td>−0.05</td>
<td>0.646</td>
<td>50</td>
<td>1.000</td>
</tr>
<tr>
<td>1</td>
<td>12</td>
<td>146</td>
<td>0.13</td>
<td>0.973</td>
<td>2.35</td>
<td>0.718</td>
<td>53</td>
<td>0.563</td>
</tr>
<tr>
<td>13</td>
<td>18</td>
<td>121</td>
<td>7.74</td>
<td>0.002**</td>
<td>5.24</td>
<td>0.004**</td>
<td>62</td>
<td>0.011*</td>
</tr>
<tr>
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<td>18</td>
<td>121</td>
<td>9.54</td>
<td>0.049</td>
<td>7.17</td>
<td>0.084</td>
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<td>0.101</td>
</tr>
<tr>
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<td>20.26</td>
<td>0.015*</td>
<td>17.35</td>
<td>0.005***</td>
<td>65</td>
<td>0.007*</td>
</tr>
</tbody>
</table>

**Table III.**
Buy-and-hold abnormal returns of sample firms

Notes: ***,***Significant at 10, 5 and 1 percent levels, respectively (two-tailed tests; significance is adjusted using Benjamini and Hochberg’s, 1995 approach)
rather than 3DP implementation. The BHARs over three multi-month periods (i.e. month $(-24, -1)$, $(-24, -13)$, $(-12, -1)$) prior to 3DP implementation are not significant ($p > 0.1$) across the three matching approaches, indicating that the sample and control firms are comparable in terms of potential BHARs if the sample firms had not implemented 3DP.

We then look at the BHARs in the implementation periods within month (1, 12). In different time periods within month (1, 12), the BHARs are generally non-significant ($p > 0.1$) across the three matching approaches, except the BHAR over month (1, 12) with the industry-size-matched control firms, which is significant at the 10 percent level based on sign test. Overall, the non-significant test results confirm our expectation that it may take a few months for firms to implement 3DP and the value of 3DP implementation cannot emerge immediately following the announcement.

However, for longer time periods including the post-implementation periods of month (13, 24), there are significant positive changes in BHARs ($p < 0.1$) across the three matching approaches, especially when non-parametric tests are conducted. These positive results justify our choice of the long-term event study method and show the importance of focusing on 3DP’s post-implementation periods. As we find significant positive BHARs after the implementation of 3DP, $H1$ is supported.

4.2 The moderating effect of environmental factors

Table IV presents the correlations among variables to be included in the regression analysis. For brevity in presenting and discussing our results, the regression analysis with the dependent variable of BHAR over month (1, 18) calculated with the industry-size-matched group is shown in Table V. To check the sensitivity of the results, BHARs measured with alternative event window (1, 24) and matching approaches (industry-MTB match and industry-size-MTB match) are also tested and presented in Table VIII.

Model 1 is the basis model with a variety of control variables included. In Models 2–4, industry munificence, dynamism and competition are added gradually. The value of $R^2$ increases with additional variables added to the regression, showing that each environmental factor explains a significant amount of variation in the BHAR. Specifically, the coefficient of industry munificence is positive and significant ($p < 0.01$) across Models 2–4, suggesting that the stock returns of 3DP implementation is more positive for firms operating in more munificent industries. Thus, $H2$ is supported. The coefficient of industry dynamism is positive and significant ($p < 0.05$) in Models 3 and 4, indicating that the BHAR is higher for firms operating in more dynamic industries. Therefore, $H3$ is supported. The coefficient of industry competition is negative and significant ($p < 0.05$) in Model 4, showing that firms operating in more competitive industries benefit less from 3DP implementation. As a result, $H4a$ is rejected but $H4b$ is supported. The hypothesis test results based on both event study and regression analysis are summarized in Figure 2.

4.3 Sensitivity analyses

We conduct several sensitivity analyses to check the robustness of our findings and to account for alternative explanations.

Propensity score matching (PSM). We employ the PSM approach to match each sample firm with a control firm that had a similar probability or propensity as the sample firm to implement 3DP but eventually did not implement 3DP. This matching approach enables us to control for other factors that may influence 3DP implementation and address possible self-selection bias (Austin, 2011; Ding et al., 2018). To implement PSM, we first construct a logistic regression model with 3DP implementation as the dependent variable while the independent variables include industry dummies, firm size, MTB ratio, return on asset,
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<thead>
<tr>
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<th>2</th>
<th>3</th>
<th>4</th>
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<td>3. MTB ratio</td>
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<td>0.05</td>
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<td></td>
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</tr>
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<td>4. R&amp;D intensity</td>
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<td>-0.06</td>
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<td></td>
<td></td>
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</tr>
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<td>5. Prior performance</td>
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<td>0.09</td>
<td>-0.23***</td>
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</tr>
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<td>6. Capital structure</td>
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<td>-0.14</td>
<td>0.38***</td>
<td>-0.17*</td>
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<td>-0.05</td>
<td>0.00</td>
<td>-0.10</td>
<td>0.00</td>
<td>1</td>
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<td>8. Velocity</td>
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<td>0.10</td>
<td>-0.07</td>
<td>-0.03</td>
<td>0.57***</td>
<td>-0.19**</td>
<td>0.03</td>
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<td>9. Manufacturing</td>
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<td>-0.11</td>
<td>-0.19**</td>
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<td>-0.05</td>
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<td>0.25***</td>
<td>0.03</td>
<td>0.04</td>
<td>-0.25***</td>
<td>-0.09</td>
<td>-0.09</td>
<td>-0.01</td>
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<td>-0.24***</td>
<td>-0.04</td>
<td>-0.08</td>
<td>-0.08</td>
<td>-0.05</td>
<td>-0.18*</td>
<td>-0.21***</td>
<td>0.05</td>
<td>-0.08</td>
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<td>-0.22***</td>
<td>-0.13</td>
<td>0.09</td>
<td>0.16*</td>
<td>-0.14</td>
<td>-0.03</td>
<td>0.51***</td>
<td>-0.20**</td>
<td>-0.20**</td>
<td>0.32***</td>
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<td>10.14</td>
<td>5.05</td>
<td>0.23</td>
<td>0.04</td>
<td>1.03</td>
<td>-0.03</td>
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<td>0.71</td>
<td>0.01</td>
<td>0.01</td>
<td>0.74</td>
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<td>6.78</td>
<td>1.92</td>
<td>0.07</td>
<td>0.97</td>
<td>0.32</td>
<td>0.44</td>
<td>0.46</td>
<td>0.04</td>
<td>0.01</td>
<td>0.24</td>
</tr>
</tbody>
</table>

**Notes:** *,**,***,Significant at 10, 5 and 1 percent levels, respectively (two-tailed tests)
| Independent variables | Model 1 | | Model 2 | | Model 3 | | Model 4 | | VIF | VIF | VIF | VIF |
|-----------------------|---------|---|---------|---|---------|---|---------|---|---|---|---|
| **Intercept**         | 0.67 (0.96) | 0.68 (1.03) | 0.51 (0.78) | 1.11 (1.63) |
| **Control variables** |         |   |         |   |         |   |         |   |   |   |   |
| Firm size             | 0.09 (2.76)*** | 1.14 | 0.07 (2.13)*** | 1.14 | 0.09 (2.61)*** | 1.16 | 0.07 (2.05)*** | 1.18 |
| MTB ratio             | −0.01 (−0.71) | 1.04 | −0.01 (−1.41) | 1.05 | −0.01 (−1.25) | 1.05 | −0.01 (−1.17) | 1.05 |
| R&D intensity         | 0.03 (0.84) | 1.09 | 0.00 (0.14) | 1.10 | 0.01 (0.37) | 1.11 | 0.02 (0.79) | 1.11 |
| Prior performance     | −0.03 (−0.03) | 1.14 | 0.00 (0.06) | 1.14 | 0.15 (0.17) | 1.14 | 0.26 (0.30) | 1.14 |
| Capital structure     | −0.07 (−0.98) | 1.19 | 0.00 (0.06) | 1.22 | 0.01 (0.13) | 1.22 | 0.00 (0.03) | 1.22 |
| Momentum              | 0.16 (0.87) | 1.09 | 0.22 (1.26) | 1.09 | 0.32 (1.85)* | 1.11 | 0.36 (2.12)** | 1.11 |
| Velocity              | −0.52 (−3.64)*** | 1.13 | −0.45 (−3.33)*** | 1.13 | −0.41 (−3.04)*** | 1.14 | −0.20 (−1.26) | 1.25 |
| Manufacturing         | −0.31 (−2.27)** | 1.13 | −0.34 (−2.55)** | 1.03 | −0.34 (−2.64)*** | 1.13 | −0.33 (−2.60)** | 1.13 |
| Year dummies          | Included | 1.03 | Included | 1.07 | Included | 1.04 | Included | 1.04 |
| **Explanatory variables** |         |   |         |   |         |   |         |   |   |   |   |
| Munificence           | 4.06 (3.40)*** | 1.07 | 4.20 (3.60)*** | 1.07 | 3.80 (3.29)*** | 1.08 | 4.06 (3.40)*** | 1.07 |
| Dynamism              | 17.05 (2.46)*** | 1.09 | 24.88 (3.28)*** | 1.15 | 24.88 (3.28)*** | 1.15 | 17.05 (2.46)*** | 1.09 |
| Competition           | 1.19 | 119 | 119 | 119 | 36.85 | 1.23 
| No. of observations   | 21.49 | 119 | 119 | 119 | 119 | 119 | 119 |
| R² (%)                | 29.48 | 33.47 | 22.77 | 23.49 | 23.49 | 23.49 | 23.49 |
| Adjusted R² (%)       | 18.41 | 22.77 | 22.77 | 22.77 | 22.77 | 22.77 | 22.77 |
| F statistic           | 2.66*** | 3.24*** | 2.99*** | 3.24*** | 3.24*** | 3.24*** | 3.24*** |
| ΔR² (%)               | 7.99 | 3.38 | 4.00 | 3.38 | 3.38 | 3.38 | 3.38 |
| ΔF                    | 12.65*** | 5.25** | 6.33*** | 5.25** | 5.25** | 5.25** | 5.25** |

**Notes:** The dependent variable is the BHAR based on the industry-size matching approach with an event window of month (1, 18). t-statistics are in parentheses. ***,**,***Significance at 10, 5 and 1 percent levels, respectively (two-tailed tests).
R&D intensity, industry velocity, industry munificence, industry dynamism and industry competition. After running the logistic regression, the firms in the benchmark pool with the closest propensity scores to the sample firms are chosen as the control firms. The resulting BHARs based on the PSM approach shown in Table VI reveal a consistent pattern as that found in our main analyses.

Reduced sample size. The results shown in Table III suggest that our sample size drops significantly for longer event windows because about 45 percent of our announcements were made in 2016 and 2017. To check whether the decrease in sample size leads to biased estimation, we follow De Jong et al. (2014) and calculate the BHARs for the reduced sample across all the event windows. We focus on the subgroup of firms that have monthly stock return data over the longest time period of month (1, 24). The BHARs of this subsample generally follow a similar pattern as those of the firms in the full sample, as shown in Table VII. Specifically, the BHARs over three multi-month periods (i.e. month (−24, −1), (−24, −13), (−12, −1)) prior to the implementation are not significant (p > 0.1). However, over the post-implementation periods, especially for month (13, 18), (1, 18) and (1, 24), we find significant positive BHARs across all three matching approaches. In addition, the results show that this subsample enjoys greater gains in BHARs and earlier in time (e.g. month (7, 12), (1, 12)) compared with the full sample. One possible explanation is that these firms are early 3DP adopters, thus achieving greater benefits due to the first-mover advantage (Hendricks et al., 2007).

Alternative dependent variable. We also examine whether the results of regression analysis are consistent if BHAR with alternative event window and benchmark is used as the dependent variable. Table VIII presents the regression results with the BHAR calculated over

<table>
<thead>
<tr>
<th>Start month</th>
<th>End month</th>
<th>No. of observations</th>
<th>BHAR mean (%)</th>
<th>p-value (t-test)</th>
<th>BHAR median (%)</th>
<th>p-value (WSR)</th>
<th>BHAR positive (%)</th>
<th>p-value (sign test)</th>
</tr>
</thead>
<tbody>
<tr>
<td>−24</td>
<td>−1</td>
<td>158</td>
<td>−0.48</td>
<td>0.915</td>
<td>−1.77</td>
<td>0.942</td>
<td>48</td>
<td>0.691</td>
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<tr>
<td>−24</td>
<td>−13</td>
<td>158</td>
<td>3.84</td>
<td>0.259</td>
<td>2.71</td>
<td>0.241</td>
<td>53</td>
<td>0.474</td>
</tr>
<tr>
<td>−12</td>
<td>−1</td>
<td>170</td>
<td>−6.60</td>
<td>0.085</td>
<td>−3.60</td>
<td>0.325</td>
<td>44</td>
<td>0.145</td>
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<tr>
<td>0</td>
<td>0</td>
<td>174</td>
<td>1.24</td>
<td>0.072</td>
<td>0.37</td>
<td>0.228</td>
<td>51</td>
<td>0.820</td>
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<tr>
<td>1</td>
<td>6</td>
<td>172</td>
<td>0.82</td>
<td>0.692</td>
<td>0.96</td>
<td>0.447</td>
<td>53</td>
<td>0.402</td>
</tr>
<tr>
<td>7</td>
<td>12</td>
<td>171</td>
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<td>0.861</td>
<td>1.61</td>
<td>0.536</td>
<td>54</td>
<td>0.359</td>
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<tr>
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<td>12</td>
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<td>2.34</td>
<td>0.405</td>
<td>5.64</td>
<td>0.218</td>
<td>60</td>
<td>0.014*</td>
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<td>10.32</td>
<td>0.015*</td>
<td>63</td>
<td>0.002**</td>
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<td>128</td>
<td>8.58</td>
<td>0.107</td>
<td>9.97</td>
<td>0.017*</td>
<td>61</td>
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</tbody>
</table>

Notes: *, ** Significant at 10 and 5 percent levels, respectively (two-tailed tests; significance is adjusted using Benjamini and Hochberg’s, 1995 approach)
Table VII.

Buy-and-hold abnormal returns of subsample firms

<table>
<thead>
<tr>
<th>Start month</th>
<th>End month</th>
<th>No. of observations</th>
<th>BHAR mean (%)</th>
<th>( p )-value (t-test)</th>
<th>BHAR median (%)</th>
<th>( p )-value (WSR)</th>
<th>BHAR positive (%)</th>
<th>( p )-value (sign test)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry-size-matched control firms</td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>−24</td>
<td>−1</td>
<td>88</td>
<td>−49.43</td>
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<td>−0.83</td>
<td>0.631</td>
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<td>0.590</td>
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<td>0</td>
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<td>−0.58</td>
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<td>Industry-MTB-matched control firms</td>
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<td>0.000***</td>
<td>69</td>
<td>0.000***</td>
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<td>24.48</td>
<td>0.004***</td>
<td>66</td>
<td>0.004***</td>
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<tr>
<td>−24</td>
<td>−1</td>
<td>85</td>
<td>−45.74</td>
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<td>4.67</td>
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<td>−24</td>
<td>−13</td>
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<td>−7.92</td>
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<td>0.633</td>
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<td>−1</td>
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<td>−9.44</td>
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<td>−2.08</td>
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<td>18</td>
<td>94</td>
<td>11.01</td>
<td>0.000***</td>
<td>10.31</td>
<td>0.000***</td>
<td>67</td>
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<td>20.26</td>
<td>0.015*</td>
<td>17.35</td>
<td>0.008**</td>
<td>65</td>
<td>0.007**</td>
</tr>
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</table>

Notes: ***,***Significant at 10, 5 and 1 percent levels, respectively (two-tailed tests; significance is adjusted using Benjamini and Hochberg’s, 1995 approach).

Table VIII.

Regression analysis with alternative BHAR as dependent variable

<table>
<thead>
<tr>
<th>Models</th>
<th>Munificence</th>
<th>Dynamism</th>
<th>Competition</th>
<th>Adjusted R(^2) (%)</th>
<th>F-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry-size-matched group; event window = (1, 24)</td>
<td>3.49 (2.07)**</td>
<td>19.25 (1.70)*</td>
<td>−0.91 (−2.39)**</td>
<td>93</td>
<td>20.65</td>
</tr>
<tr>
<td>Industry-MTB-matched group; event window = (1, 18)</td>
<td>3.99 (2.80)**</td>
<td>28.57 (3.02)**</td>
<td>−0.75 (−2.06)**</td>
<td>109</td>
<td>23.88</td>
</tr>
<tr>
<td>Industry-size-MTB-matched group; event window = (1, 18)</td>
<td>4.69 (4.23)**</td>
<td>11.75 (1.67)*</td>
<td>−0.64 (−2.25)**</td>
<td>120</td>
<td>19.69</td>
</tr>
</tbody>
</table>

Notes: \( t \)-statistics are in parentheses. ***,***Significant at 10, 5 and 1 percent levels, respectively (two-tailed tests)
month (1, 24) and with industry-MTB-matched and industry-size-MTB-matched benchmark groups. The coefficients of the three environmental factors are significant and consistent across different regression models, demonstrating the robustness of our regression results.

5. Discussion and conclusions
Based on 232 announcements of 3DP implementation made by US-listed firms from 2010 to 2017, we employ the event study method to examine the stock returns of 3DP implementation over two years after the announcements. The event study results show significant higher BHARs of sample firms compared with their non-implementation industry peers over the two-year post-implementation period. Our cross-sectional regression analysis further suggests that the stock returns due to 3DP implementation are more pronounced for firms operating in more munificent, more dynamic and less competitive industry environments. Those findings are consistent with our CDC perspective which integrates the dynamic capabilities view with contingency theory. The empirical evidence documented and theoretical perspective adopted in our study provides important implications for practice and research, as discussed below.

5.1 Managerial contribution
Although 3DP has received extensive public attention in recent years, the current level of adoption of the technology is still relatively low. Such a low adoption rate is partly due to practitioners’ lack of the knowledge of 3DP and difficulties to quantify its impact (Ernst & Young, 2016). Our study represents one of the first research efforts examining the impact of 3DP implementation in terms of stock returns. We employ the event study method to provide an objective documentation of the positive stock returns due to 3DP implementation, which helps resolve the controversy over the business value of 3DP and encourage firms to implement 3DP to reap the financial benefits. The positive stock returns documented in our research also enable firms to convince their shareholders or investors to support their 3DP implementation. However, firms should realize that 3DP is not a “quick fix” solution as we cannot find significant positive stock returns in the first few months following the announcements of 3DP implementation. This can be attributed to the fact that 3DP implementation is a complex process and it takes time for firms to overcome various barriers (e.g. technical issues, human resources, quality concerns) in order to implement 3DP (Shukla et al., 2018; Thomas-Seale et al., 2018). Instead, our research suggests that the positive stock returns become more significant in the long run (about two years after the announcements of 3DP implementation). Therefore, managers (and also investors) should be patient with 3DP implementation, allowing 3DP’s value to emerge in the post-implementation periods.

While we encourage firms to implement 3DP based on the positive stock returns documented in our research, we also urge them to pay attention to the industry environments in which the 3DP is implemented. This is because our research shows that the stock returns due to 3DP implementation vary across different industry environments. In particular, our research suggests that firms can benefit more from 3DP implementation in munificent and dynamic industries. Munificent industries are characterized by their sufficient resources to support firms’ growth, which are important to 3DP implementation. Various critical barriers such as “education, cost, software, material, mechanical properties, validation and finishing” (Thomas-Seale et al., 2018, p. 108) have limited the broader applications of 3DP. The resources available in munificent industries can help firms overcome those barriers and support the effective implementation of 3DP. On the other hand, in dynamic industries with fluctuating market demands and changing customer preferences, 3DP enables firms to gain a competitive advantage due to its ability to help firms improve manufacturing flexibility and product variety (Dong et al., 2017; Shukla et al., 2018). For example, in the highly dynamic apparel industry, Nike was able to implement
3DP to slash the time required for manufacturing and testing and better accommodate the ever-changing fashion (Jopson, 2013). Therefore, we urge firms operating in munificent and dynamic industries to take advantage of their operating environments to reap more benefits from 3DP implementation.

However, our research suggests that firms operating in competitive industries with a large number of competitors may not benefit from 3DP implementation. Although implementing 3DP can enable a firm to differentiate itself from its competitors in competitive industries, it is difficult for the firm to gain sufficient resources to support its 3DP implementation due to the intensive competition for resources among firms in such industries. Our research shows that the negative effect due to weak support for 3DP implementation overweighs the positive effect arising from strong demand for 3DP implementation, resulting in lower benefits gained from 3DP implementation in competitive industries. This finding provides important implications for policy makers. In particular, for industries with strong demand but weak support for 3DP implementation, governments can provide better financial (e.g. tax incentives) and non-financial resources (e.g. education and trainings) to support 3DP implementation, enabling 3DP adopters to gain competitive advantage in such industries.

5.2 Theoretical contribution
Our CDC perspective provides a comprehensive and complementary theoretical explanation of the 3DP implementation–stock returns relationship. On the one hand, we deploy the dynamic capabilities view (Barreto, 2010; Schilke et al., 2018) to theorize how 3DP implementation enhances firms’ manufacturing capabilities through broadening their operational scopes without cost penalties, ultimately leading to improved competitive advantage and resulting in positive stock returns. This theorization enables us to link firms’ practices or strategies such as 3DP implementation to their performance in terms of stock returns. On the other hand, we adopt contingency theory (Reinking, 2012; Sousa and Voss, 2008) to reject the one-size-fits-all assumption and explore the possible fit between 3DP-enhanced manufacturing capabilities and firms’ operating environments in terms of industry munificence, dynamism and competition. We theorize how these industry variables represent different levels of environmental support and environmental requirement for 3DP implementation, thus moderating the impact of 3DP implementation on stock returns. Taken together, this CDC perspective advances our understanding of the 3DP implementation–stock returns relationship as it considers not only the direct impact of 3DP implementation on stock returns but also the indirect moderating role of firms’ operating environments. We believe this CDC perspective can serve as a useful theoretical foundation for future 3DP research. In particular, it urges researchers to shift their focus from the discussion of 3DP’s technological features and industrial applications (Lam et al., 2002; Ventola, 2014; Williams et al., 2010) to a more strategic view on 3DP implementation, exploring its ability to enhance firms’ manufacturing capabilities and its potential to contribute to firms’ competitive advantage. Moreover, it also reminds researchers about the importance of taking firms’ operating environments in which the 3DP is implemented into account. While our research is focused on industry munificence, dynamism and competition, future research can adopt the CDC logic to further explore other environmental characteristics that may exhibit varying levels of alignment with 3DP implementation and thus affect its performance impact.

Our research contributes to the literature on dynamic capabilities and contingency theory in several ways. First, we extend the dynamic capabilities view to consider the role of other dimensions of firms’ operating environments beyond environmental dynamism. In addition to confirming the dynamic capabilities view that stresses the importance of developing dynamic capabilities to satisfy the requirements arising from “rapidly changing environments” (Teece et al., 1997, p. 516) or dynamic environments, our research suggests it is also crucial for
the environments to provide sufficient support for firms to develop such capabilities in order to gain a competitive advantage. Specifically, our research shows that munificent environments with sufficient resources and support available for firms to implement 3DP enable them to gain higher stock returns. Moreover, our research on industry competition further suggests that environmental support may be even more critical than environmental requirement when there is a conflict between them. Specifically, although competitive environments exhibit the requirement or demand for developing dynamic capabilities, such environments with a large number of competitors may not possess sufficient resources to support firms to develop the required dynamic capabilities, thus preventing them from gaining competitive advantage in such environments. Therefore, our research highlights the limitations of focusing only on environmental requirement in general and environmental dynamism in particular and encourages future dynamic capabilities research to explore the roles of other dimensions of firms’ operating environments.

On the other hand, while the contingency literature has considered many different environmental variables that may moderate the performance outcomes of firms’ practices or strategies, it has been criticized for relying too much on the “it all depends” notion without more theoretical classifications of those external factors (Reinking, 2012). Our research helps address this concern by characterizing firms’ operating environments in terms of environmental support and environmental requirement. We believe such classifications should be beneficial to future contingency research for explaining the performance variation due to the fit between other firm strategies beyond 3DP implementation and other environmental variables beyond munificence, dynamism and competition. In particular, researchers can adopt our classifications to theorize whether the specific environmental variables considered in their research indicate different levels of environmental support and/or environmental requirement for the specific firm strategies concerned, thus affecting the extent to which such strategies impact on firm performance.

Finally, our research sheds some light on the structure-conduct-performance framework that has been frequently adopted in the operations management literature to study manufacturing capabilities (Terjesen et al., 2011). In particular, prior research has relied on this framework to view environmental conditions as a driver of firms’ manufacturing strategies and capabilities, which in turns lead to firm performance (Mellor et al., 2014; Ward and Duray, 2000). Although we do not reject this causal sequencing explanation, our CDC perspective stresses the overlooked moderating role of environmental conditions in the manufacturing capabilities–firm performance relationship. To put it another way, our research suggests that structure can be viewed not only as a driver but also as a moderator in the conduct–performance relationship. Our research thus enriches the structure-conduct-performance framework by encouraging future research to consider the multiple roles that structure plays in the conduct–performance relationship.

5.3 Limitations and future research
Our research suffers from several limitations which in turn create new opportunities for future research. First, our research is focused on US publicly listed firms, which may limit the generalizability of our findings to private firms and firms located in other counties. Indeed, private firms should possess less resources compared with publicly listed firms, which may affect their 3DP implementation. Similarly, firms located in different counties may receive different levels of environmental support to implement 3DP, thus reaping different benefits from 3DP implementation. Therefore, it would be interesting for future research to examine the benefits of 3DP implementation for other firms (e.g. private firms) and in different contexts (e.g. developing countries).

Moreover, we study the impact of 3DP implementation in terms of stock returns. Although stock returns represent overall firm value and better capture the full performance...
impact due to 3DP implementation (Joshi and Hanssens, 2010; Sorescu et al., 2017), it is unclear whether 3DP implementation influences stock returns “through top-line impact, bottom-line impact, or both” (De Jong et al., 2014, p. 131). It thus is worth investigating how 3DP implementation may affect other dimensions of firm performance such as sales growth, cost reduction and profitability improvement (De Jong et al., 2014; Orzes et al., 2017) in order to gain a more comprehensive understanding of the performance implications of 3DP implementation. Such investigations can also help verify the conclusions drawn in our research based on abnormal stock returns.

Finally, following contingency theory that emphasizes the fit between firm strategies and external environments (Reinking, 2012; Sousa and Voss, 2008), our research considers the moderating role of several factors at the industry level rather than at the firm or individual level. However, firm-level and individual-level factors may also affect 3DP’s implementation and thus its performance impact. For example, firms with larger sizes may possess more resources to implement 3DP while CEOs with technical backgrounds may be more likely to support 3DP implementation, both of which may affect the effectiveness of 3DP implementation. Therefore, future research on 3DP implementation can explore the moderating role of other non-industry-level factors.

Acknowledgments
The authors thank the handling Guest Editor and two anonymous reviewers for their insightful comments and useful suggestions, which help improve the quality of this paper. The authors also thank Chen Liang (Zhejiang University) for assistance in verification of the sample and control firms used in the research. Lam was partly supported by the EC Project 777742 (GOLF-H2020-MSCA-RISE-2017) and the University of Liverpool’s ECR and Returners Fund. Cheng was supported in part by The Hong Kong Polytechnic University under the Fung Yiu King – Wing Hang Bank Endowed Professorship in Business Administration.

Notes
1. To verify whether our sample is representative in terms of industry distribution, we included the keyword “service” and “manufacturing”, and searched the announcements of 3DP implementation made by both publicly listed and private firms in Factiva between 2010 and 2017. About 68 percent of the announcements were found when the keyword “manufacturing” was included, corresponding with our sample distribution.

2. We further verified whether the matched control firms have implemented 3DP. Specifically, we searched a combination of 3DP-related keywords and the names of the matched control firms in Factiva between 2010 and 2017. We could not identify any control firm that had implemented 3DP in this time period, confirming the appropriateness of the control firms used in our research.

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Impact of 3DP implementation on stock returns


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Leveraging open-standard interorganizational information systems for process adaptability and alignment

An empirical analysis

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Abstract

Purpose – The purpose of this paper is to understand the value creation mechanisms of open-standard interorganizational information system (OSIOS), which is a key technology to achieve Industry 4.0. Specifically, this study investigates how the internal assimilation and external diffusion of OSIOS help manufactures facilitate process adaptability and alignment in supply chain network.

Design/methodology/approach – A survey instrument was designed and administrated to collect data for this research. Using three-stage least squares estimation, the authors empirically tested a number of hypothesized relationships based on a sample of 308 manufacturing firms in China.

Findings – The results of the study show that OSIOS can perform as value creation mechanisms to enable process adaptability and alignment. In addition, the impact of OSIOS internal assimilation is inversely U-shaped where the positive effect on process adaptability will become negative after an extremum point is reached.

Originality/value – This study contributes to the existing literature by providing insights on how OSIOS can improve supply chain integration and thus promote the achievement of industry 4.0. By revealing a U-shaped relationship between OSIOS assimilation and process adaptability, this study fills previous research gap by advancing the understanding on the value creation mechanisms of information systems deployment.

Keywords Supply chain integration, Industry 4.0, Open standards, Process adaptability, Inter-organizational information systems

1. Introduction

The rapid growth and development in digital technology have provided great opportunities to evolve traditional businesses and industries. Although most of the attention has been paid on the transformation of the digital economy, many of these advanced technologies are also re-shaping traditional manufacturers. Driven by the aforementioned new technologies, many have viewed the next phase of industry development to have higher levels of operational efficiency and productivity due to supply chain integration and automation (Lu, 2017). This new phase of industry development is coined as Industry 4.0, and it is characterized by digitization, optimization and production customization, automation and
adaptation, human machine interaction, value-added services and businesses and autonomous data exchange and communication (Posada et al., 2015; Roblek et al., 2016).

Industry 4.0 aims to address traditional manufacturers’ supply chain deficiencies that have resulted in high costs and poor quality of product and service. One of the pillars to achieve Industry 4.0 is the interoperability and transparency of data, which enables manufacturers to achieve supply chain integration, exchange timely and accurate data and automate supply chains and smart factories (Lasi et al., 2014). Despite the recent advent of computing and, in particular, internet technologies, achieving Industry 4.0 is still some way off because of reported challenges faced by manufacturers (Gold, 2018). Notable among these challenges is the ability for manufacturers to implement the concept of a “virtual single factory” that vertically integrates supply chain partners’ systems to share information with each other (Kobusch, 2015). Despite the importance of supply chain integration for achieving Industry 4.0, organizations have undergone slow, struggling experiences or even failures to develop an integrated supply chain (Mustafa Kamal and Irani, 2014; Vanpoucke et al., 2017). To transform the concept of virtual single factory into reality, open-standard inter-organizational information systems (OSIOS) is attracting attentions from both scholars and practitioners (Sodero et al., 2013). OSIOS refers to the kind of inter-organizational systems that uses open standards that are the technical specifications to support, automate and coordinate the “interrelated, sequential tasks” such as inventory management, product development and logistics (Bala and Venkatesh, 2007). These open standards are typically developed and approved by consortia of firms based on the negotiation, communication and coordination among the participants (Zhu, Kraemer, Gurbaxani and Xu, 2006), and they are freely available for all potential adopters. Being used to create, sustain and develop inter-organizational relationships (Hagel and Brown, 2005), OSIOS provides the electronic enablement of extended enterprise by synchronizing and integrating inter-organizational relationships and processes (Dyer, 1997; Dyer and Singh, 1998).

Despite the optimistic attitude toward OSIOS in helping to achieve Industry 4.0, it remains an unsettled question that to which extent can supply chain integration be improved through deploying OSIOS. In the field of operations management, numerous studies have made efforts to understand the factors facilitating OSIOS deployment (e.g. Nurmilaakso, 2008; Chong et al., 2009; Liu et al., 2010; Chan et al., 2012; Sodero et al., 2013). In these studies, they shared a common assumption that OSIOS deployment will improve supply chain integration with very little challenges. However, contradictory findings on the influence of OSIOS deployment have been reported (Saeed et al., 2011), which suggest that the value creation mechanism of OSIOS requires careful studies driven by relevant theories in operations management. To unveil the “black box” between OSIOS deployment and supply chain integration (Liu et al., 2016), this paper proposes that the key is to exploit the “plug-and-play” competency of OSIOS to generate process adaptability, such that companies can reconfigure their IT resources and business processes (Gosain et al., 2004; Rai and Tang, 2010). In volatile market environments, companies need to continuously restructure their supply chain procedures, processes, activities and inter-organizational relationships to adapt to external changes. OSIOS permits the flexibility to tune the parameters related to business processes, which produces process adaptability to prevent existing business processes from being too rigid or even obsolete by dynamically adjusting and restructuring supply chain patterns (Gosain et al., 2004; Malhotra et al., 2007). Thus, companies can continually facilitate the coordination and joint optimization of activities with supply chain partners, making it possible to exploit process alignment. Although adaptability per se does not directly generate relational or operational value for companies (Saraf et al., 2007), it serves as an intermediate value creation mechanism between OSIOS deployment and process alignment. To establish and test the important role
of process adaptability in connecting OSIOS deployment and process alignment, this study will fill in the current knowledge gap in the operations management literature by enhancing the understanding of how to achieve an integrated supply chain.

Apart from the knowledge gap in understanding the link between OSIOS deployment and supply chain integration, previous literature does not provide sufficient guidance on how to effectively deploy OSIOS to garner the most benefits (Saeed et al., 2011; Liu et al., 2016). Past research primarily employed linear models to investigate the performance impacts of OSIOS (Bala and Venkatesh, 2007; Malhotra et al., 2007; Saldanha et al., 2013), which may not adequately capture the complexity of OSIOS deployment and thus could not accurately reflect the exact nature of the relationship between OSIOS and supply chain performance. To fully exploit the potential of OSIOS and to facilitate supply chain integration to the greatest extent, it is imperative to investigate the optimized strategy of deploying OSIOS by employing nonlinear models (Liu et al., 2016). Although electronic connections can improve supply chain performance through enhancing collaboration (Croom, 2005), it might possibly erode a firm’s ability to make effective decisions and induce partner opportunism when the level of collaboration reaches extremes. This calls for a better understanding of the conditions where OSIOS may positively (or negatively) affect supply chain operations (Crosno and Dahlstrom, 2008; Villena et al., 2011). The current study, thus, aims to reveal the nonlinear impact of OSIOS deployment by suggesting the possibility of an inverted U-shape relationship between OSIOS deployment and adaptability. When OSIOS is deployed to digitalize inter-firm activities and relationships, it will contribute to process adaptability to a certain level, but beyond that level, a negative relationship will appear, as system complexity and information redundancy become overwhelming for firms to manage and control, resulting in reduced process adaptability.

Furthermore, OSIOS deployment requires a firm to make strategic decisions to determine how to assimilate OSIOS solutions internally across their supply chain activities and also, at the same time, diffuse them externally among the partners in the supply chain networks (Ranganathan et al., 2004). However, scholars have pointed out that most studies neglected the differences between the use of technology for internal and external activities, thereby generating confounding results on this topic (Zhang et al., 2011). To address this research gap, we distinguish internal assimilation and external diffusion as two focuses of technology use. Internal assimilation is defined as the extent to which OSIOS and related technological solutions have been deployed in the key supply activities to support inter-organizational relationships. External diffusion refers to the degree to which OSIOS and related technological solutions have been utilized to integrate supply chain partners and to conduct inter-firm transactions (Ranganathan et al., 2004; Zhang and Dhaliwal, 2009). After implementation, a technology will be deployed to support organizational routines and activities as well as the exchange of knowledge and technology across organizational boundaries. Internal assimilation and external diffusion, therefore, work together to contribute to the infusion stage of the overall diffusion process for a typical OSIOS technology (Premkumar et al., 1994; Ramamurthy and Premkumar, 1995). This research, therefore, attempts to answer the following research question:

**RQ1.** How can the internal assimilation and external diffusion of OSIOS create values for manufacturers in achieving process adaptability and process alignment?

The study contributes to extant literature on operations management and, particularly, toward the research of Industry 4.0 on three fronts: it contributes to the research stream of supply chain integration by showing that process alignment can be enhanced by OSIOS through improving process adaptability to continuously adjust to external changes; it advances the understanding of how to use OSIOS to generate the most benefits for supply chain operations by exploring the U-shaped relationship between OSIOS deployment and
process adaptability; by categorizing OSIOS deployment into internal assimilation and external diffusion, it provides a nuanced lineation of the relationship between OSIOS deployment and process adaptability.

2. Research and theoretical background

2.1 Industry 4.0 and OSIOS

The fourth industrial revolution – Industry 4.0 – promotes changes in production systems and networks through IT advancement beyond industrial automation, so as to achieve greater potentials and values in operations management (Lasi et al., 2014). In this new paradigm shift, digitalization is the key, fundamental requirement, and it will be achieved through integrating internet technologies (incorporated with artificial intelligence, such as machine learning capability) and relevant objects (e.g. machines, products and humans) with associated production processes (Marr, 2016).

In order to achieve digital transformation, data standardization is the key (Dallasega et al., 2018). A recent report by the US National Institute of Standards and Technology (Lu et al., 2016) emphasized that standards are fundamental for achieving smart manufacturing systems. For example, standards for product and engineering information enable data exchanges between computer-aided design software from different vendors. The report also pointed out that one of the key attributes of smart manufacturing is the agility of supply chains. Such agile manufacturing relies heavily on supply chain integration and flexibility, which are enabled by interorganizational standards. Similarly, Grangel-González et al. (2017) stated that interoperability among actors, sensors and heterogeneous systems is an important factor for realizing the Industry 4.0 vision, that is the creation of smart factories by enabling intelligent human-to-machine and machine-to-machine cooperation. In order to empower interoperability in smart factories, standards and reference architectures have been proposed by various organizations. Among these, OSIOS is an exemplary technology for enabling the modularized interoperability between supply chain partners (Bala and Venkatesh, 2007; Rai and Tang, 2010).

Similar to information systems based on proprietary standards such as electronic data interchange (EDI), OSIOS enables the digital exchange of structured information between firms (Chong and Ooi, 2008). However, the key difference between EDI and OSIOS is that the latter defines the structure and content of e-exchanges based on a common agreed language. However, EDI allows only for a customized one-to-one exchange of information; the quasi-open, multilateral nature of OSIOS (e.g. open source development and access) allows for the alignment of international standards (Malhotra et al., 2007), which is the key to harmonize multi-platform transactions for realizing smart manufacturing. An example of open standards would be RosettaNet, which consists of three core components including the Partner Interface Processes (PIP), the RosettaNet implementation framework (RNIF) and the RosettaNet business and technical dictionaries. In a smart manufacturing environment involving different organizations and platforms, transactions will be conducted through a PIP connection. A PIP is a specialized system-to-system XML-based dialog that depicts the activities, decisions and interactions to fulfill business transactions among supply chain partners (Chong and Ooi, 2008). Each PIP specification contains a business document template and a diagram of the business process (Malakooty, 2005). The standardized PIP messages are then sent to the trading partners via network connections. The RNIF, however, provides the exchange protocols for implementing RosettaNet standards such as the security, transfer and routing information. Once again, trading partners’ transactions are harmonized through these standardized exchange protocols. The RosettaNet dictionaries specify the common vocabularies and semantics for conducting transactions, thus eliminating confusions that may occur in the trading process due to the idiosyncratic terminology by each organization (Chong and Ooi, 2008).
Compared to the advances achieved in comprehending the technical properties of OSIOS, much less progress is being made in recognizing the wider implications of OSIOS deployment. Due to a paucity of studies on the applications of OSIOS, researchers have debated much on the extent to which value can be appropriated from OSIOS. On the one hand, there are researchers who regard OSIOS as the key technology that will pave the way for achieving Industry 4.0, centered on its ability to help supply chain network partners achieve automation and decentralization of business processes (Dallasega et al., 2018). On the other hand, there are also researchers who claim that it is too challenging to implement OSIOS, as the current implementation roadmap and strategies are too simplistic (Damodaran, 2005), and the cost of investing in the technology bears little return on investment (Chang and Shaw, 2009; Sodero et al., 2013). To address the preceding knowledge gap, our study attempts to shed light on the value creation mechanism of internal assimilation and external diffusion of OSIOS.

2.2 Internal assimilation and external diffusion of OSIOS
As OSIOS is deployed to support a wide spectrum of internal supply chain functions and cross-boundary processes, it is important to consider internal assimilation and external diffusion at the same time to provide a complete delineation of its permeation process. After a technology is adopted and adapted, it will progressively be integrated into supply chain processes to support activities and knowledge transfers within and beyond organizational boundaries (Ranganathan et al., 2004). While internal assimilation concerns the intensity and scale of OSIOS assimilation, external diffusion concerns the diversity and scope of OSIOS diffusion (Zhang, Xue and Dhaliwal, 2016). These concepts can provide valuable insights about the post-adoption stages (Fichman, 2000), which have seldom been studied in the current literature, as a majority of studies have focused on the single adoption stage, which essentially treated innovation diffusion process as a one-shot behavior (Zhu, Kraemer and Xu, 2006).

Internal assimilation refers to the extent to which the use of OSIOS permeates organizational processes and becomes routinized in the relevant activities (Chatterjee et al., 2002; Ranganathan et al., 2004). External diffusion refers to the extent to which OSIOS is used across organizational boundaries to integrate various trading partners (Ranganathan et al., 2004; Wu and Chang, 2012). By aligning IT assets with internal and external resources, internal assimilation and external diffusion of OSIOS can fully leverage the technological value and improve and develop a firm’s capabilities (Nevo and Wade, 2010). However, the full value of OSIOS can only be leveraged when it is appropriately deployed to support internal and external processes (Zhang, Xue and Dhaliwal, 2016), which entails the importance to understand the risks and challenges involved in assimilation and diffusion processes to gain a more complete picture of the value creation mechanisms of OSIOS.

Although internal assimilation is the key to exploit the full business value of a technology (Liang et al., 2007), practitioners may encounter difficulties in assimilating new technologies into their business processes very often, a phenomenon that is referred to as the “assimilation gap” (Fichman and Kemerer, 1999). To routinize a new technology within a firm after the initial adoption stage, a company needs to develop sufficient knowledge to leverage and adapt the technology to align it with relevant processes (Zhu, Kraemer and Xu, 2006). Bridging the assimilation gap for OSIOS will require a considerable amount of investment in the form of hardware, software and personnel training. Moreover, relevant cross-boundary processes should be redesigned to satisfy the requirements of the new technical standards (Sodero et al., 2013). Weighing the business value and the substantial investment, the performance implication of internal assimilation of OSIOS remains undetermined.
By diffusing OSIOS to connect with supply chain partners, the focal firm can exploit network effects (Sodero et al., 2013) with enhanced information processing capability and a larger knowledge base (Church and Gandal, 1992; Venkatesh and Bala, 2012). However, the diffusion process is complex, dynamic and contingent on various technological and contextual factors, which entails a long time lag before the full attainment of the benefits (Wu and Chang, 2012). Moreover, the widespread diffusion of technology might create inconsistency across different adopters regarding technical documents and managerial procedures due to discrepancies in understanding. Therefore, it remains challenging to conclude the influence of external diffusion of OSIOS.

Past studies investigating the outcomes of OSIOS deployment generally assume a linear relationship between them wherein an increased assimilation and diffusion of OSIOS will indefinitely enhance the postulated benefits. For example, Venkatesh and Bala (2012) found that there is a negative linear relationship between OSIOS assimilation and cycle time; the study of Malhotra et al. (2007) suggested a positive association between OSIOS deployment and mutual adaptation. Although these studies expanded our knowledge frontier in understanding the performance outcomes of OSIOS adoption, they might have used an oversimplified lens by assuming an invariant, linear impact on a firm’s capabilities and performance. This ignores the possibility of negative effects when OSIOS is assimilated or diffused to a certain level. Scholars also doubted this positive linear effect by claiming that the use of IT might hurt supply chain performance (e.g. ineffective decision making) when a company collaborates too closely with its partners (Crosno and Dahlstrom, 2008; Villena et al., 2011). Accordingly, our study proposes that to maximize the benefits enabled by OSIOS, there should be an appropriate level of OSIOS assimilation and diffusion, such that an inflection point will be achieved where the users can be benefitted the most. Developing and testing non-linear models to study technology adoption and use has been suggested to be an important contribution to fill the research gap in current literature where oversimplified linear models have been essentially used to understand the phenomenon (Venkatesh and Goyal, 2010).

2.3 The relational mechanisms of OSIOS

The relational view of the firm, employing an inter-organizational theoretical lens, explains how relational resources and capabilities can form the foundation of strategic advantages (Kanter, 1994; Dyer and Singh, 1998). It is contended that a firm’s critical resources will span across organizational boundaries and can be generated from inter-organizational processes and routines (Dyer and Singh, 1998). Therefore, this theoretical view extends beyond the resource-based view, which, based only on a single firm’s view, asserts that competitive advantages fully originate from the resources housed internally (Wernerfelt, 1984; Barney, 1991). With the evolution of inter-firm relationships from arm-length short-term transactions to collaborative partnerships over the last few decades (Corsten and Felde, 2005), increasingly, inter-organizational information systems (IOS), including OSIOS, are being used to create, sustain and develop inter-organizational relationships (Hagel and Brown, 2005). OSIOS could be the major source of competitive advantage, as it is embedded in inter-organizational processes and routines to develop relational capabilities (Powell and Dent-Micallef, 1997; Bharadwaj, 2000). Therefore, following the logic of relational view, OSIOS, through promoting information sharing and inter-firm communication, can serve as an important embedding mechanism to generate relational rents that promote long-term success in supply chains (Paulraj et al., 2008).

Relational rents are conceptualized as the economic rents generated from inter-organizational linkages when companies uniquely configure and combine the complementary relation-specific resources emerging from external partnerships (Dyer and Singh, 1998; Saraf et al., 2007). The framework of Dyer and Singh (1998) identified a wide
range of determinants of relational rents (drivers of organizational performance), which provides the theoretical generalizability to study various inter-organizational relationships such as scientific alliances, marketing alliances and supply chain collaborations (Malhotra et al., 2005). In our study, some of the strategic determinants of relational rents such as complementary capabilities, effective governance mechanisms, partner scarcity and institutional environment, however, are excluded because they are more relevant with joint ventures and R&D collaborations, which are out of the scope of this study. In the context of digital supply chain relationships, this study will focus on relation-specific assets, knowledge exchange and joint learning and interfirm assets interconnectedness identified by Dyer and Singh (1998) as the key sources of relational rents (Saraf et al., 2007; Wang et al., 2014). As a firm’s core infrastructure to communicate and transact with supply chain partners, OSIOS can perform as a platform enabling the combination of these resources and producing relational rents (Bensaou and Venkatraman, 1996; Bala and Venkatesh, 2007).

It is suggested that OSIOS could have a significant impact on an organization’s process adaptability by transforming and shaping interfirm connectedness and knowledge exchanges (Malhotra et al., 2007). Process adaptability connotes a firm’s ability to accommodate new functions and reduce the costs associated with reconfiguring resources to support the emerging requirements to adapt supply chain activities and operational processes in inter-organizational relationships (Young-Ybarra and Wiersema, 1999; Gosain et al., 2004; Rai and Tang, 2010), which can be enabled by OSIOS by developing flexible and responsive IT assets and processes. Based on modular interdependent processes, structured data connectivity and standardized interfaces (Gosain et al., 2004), OSIOS allows a firm to quickly and economically adapt its IT assets to both the evolutionary and revolutionary changes in business requirements and processes (Kumar, 2004; Langdon, 2006). Users of OSIOS explicitly or implicitly agree on the common specifications at both syntactic and semantic levels, which not only improves multilateral information processing capability and knowledge exchange but also resolves the interpretive differences in the information transmitted (Malhotra et al., 2007). Supply chain partners, thus, can learn and adapt to the needs of each other better without the extensive coordination efforts in clarifying and conveying the uncertainty and ambiguity in the messages they send or receive (Gosain et al., 2003). At the same time, the modular architecture of OSIOS allows for the disaggregation and reconfiguration of systems to accommodate new functions, which enables adaptation at system level (Rai and Tang, 2010). Therefore, the common templates and standardized interfaces of OSIOS will not constrain information diversity, as the users are allowed to customize parameters to flexibly adapt to the requirements of partner-specific process (Malhotra et al., 2007).

However, process adaptability per se does not create direct performance gains (Saraf et al., 2007). Companies must develop process alignment that integrates, coordinates and jointly optimizes interfirm activities with partners (Rai and Tang, 2010). A major source of process alignment is suggested to be asset interconnectedness, which is created when supply chain partners closely link their business processes, thereby increasing relationship specificity (Dyer and Singh, 1998). Through process alignment, a focal firm can coordinate and interweave the interdependent supply chain activities with its business partners, which can ensure that business processes spanning across the supply chain network are operationally integrated (Saraf et al., 2007; Rai and Tang, 2010). A company can achieve process alignment by deploying its IT assets to work as a “functional whole” with that of its partners (Saraf et al., 2007, p. 324), which requires supply chain partners to resolve their differences at both the syntactic and semantic boundaries (Malhotra et al., 2007). With the standardized interfaces of OSIOS, companies can quickly respond to the idiosyncrasies in the interfirm processes of their partners (Saraf et al., 2007), enabling information sharing,
activity coordination and process alignment (Grover and Saeed, 2007). In doing so, OSIOS provides firms with valuable bonding mechanisms that allow firms to transform from traditional, weakly connected supply chains to closely aligned collaborative networks for joint success (Whipple and Russell, 2007).

3. Hypothesis development

3.1 Curvilinear relationships between OSIOS and process adaptability

Internal assimilation and external diffusion are the two underlying building blocks for the strategies to deploy OSIOS (Zhang and Dhaliwal, 2009). Internal assimilation of OSIOS provides companies with the ability to coordinate and synchronize interfirm processes (Bala and Venkatesh, 2007). When OSIOS is deployed to digitalize more supply chain processes, companies can standardize more information exchange, which can reduce the time and effort spent in interpreting and completing supply chain activities. By assimilating OSIOS with internal processes, the clarity of exchanged information is improved, which prevents information distortion and errors during information transfer (Venkatesh and Bala, 2012). This increased operational efficiency and information visibility will enhance a company’s flexibility to adapt its business operations to external environments (Stevenson and Spring, 2007).

However, excessive internal assimilation of OSIOS may restrict the level of adaptability OSIOS can enable. To internally assimilate OSIOS, a company needs to spend a large amount of resources and make substantial adjustments to its supply chain processes (Venkatesh and Bala, 2012). Therefore, over-assimilation of OSIOS may present a major disruption in a company’s existing processes that are already embedded in its operational routines (Porter, 2001), which will increase the difficulty to control interfirm processes, reducing a firm’s ability to reconfigure current supply chain activities and adapt to the external environment. In addition, OSIOS may not be compatible with a firm’s existing IT infrastructure, which requires specialized IT investment and personnel to support the operations of OSIOS (Gosain et al., 2003). When OSIOS is deployed to complement numerous supply chain activities, it will become increasingly challenging for a company to develop an adequate IT capability to maintain the systems and to adapt the systems and functions to the changing requirements. The discussion leads to the following hypothesis:

**H1.** An inverted U-shaped relationship exists between OSIOS internal assimilation and the level of process adaptability enabled by OSIOS, such that internal assimilation improves process adaptability at first and impedes process adaptability after reaching a certain level.

When OSIOS is externally diffused to connect more partners, the users can exploit network effects that may expand the scope and range of information exchanged (Zhu, Kraemer, Gurbaxani and Xu, 2006). The more the partners are connected in the OSIOS network, the more diverse will be the knowledge accessed and integrated by a company, through which a company can absorb knowledge to enhance adaptability (Malhotra et al., 2005). To adapt to the changes in the external environment, a company should develop knowledge of the environment, understand and improve its existing capabilities and skills and restructure relevant business processes to build new capabilities. External diffusion of OSIOS generates a rich knowledge base by accessing diverse external knowledge sources, which enables companies to receive and respond to signals in the market and adapt to the changes in the business environment by precisely capturing and fulfilling market needs (Malhotra et al., 2005).

When OSIOS is excessively diffused and connected with too many external partners, the problem of information overload will be created (Hiltz and Turoff, 1985; Gulati et al., 2012), which reduces a firm’s ability to organize the information in the supply chain and also
creates obstacles for interfirm collaboration. The information flow might have a curvilinear relationship with the level of adaptability enabled by OSIOS, because there can be an inflection point at which it becomes overwhelming for an organization to deal with more information or coordinate with more partners (Huber, 1991). In the meantime, the information shared in the OSIOS network will become increasingly homogenous, as the number of partners increases, which diminishes the informational value accessed from OSIOS because the knowledge circulated among the partners will become increasingly redundant. This declined value of external knowledge might induce rigidity to deal with market changes (Gulati et al., 2012). In addition, as the number of participants increases, free-riding behaviors and unexpected spillover effects are highly possible due to the misuse of proprietary information and resources (Wu, 2008). To deal with this threat, additional efforts of security control and institutional mechanisms should be implemented to manage OSIOS, which further complicates business processes and impedes the level of adaptability that can be attained by a company from OSIOS (Lee and Lim, 2003; Valdés-Llaneza and García-Canal, 2006). Based on our discussion, we propose the following hypothesis:

H2. An inverted U-shaped relationship exists between OSIOS external diffusion and the level of process adaptability enabled by OSIOS, such that external diffusion improves process adaptability at first and impedes process adaptability after reaching a certain level.

3.2 Process adaptability and process alignment

To effectively manage supply chain relationships and leverage external resources, alignment and adaptability are highly correlated together (Bharadwaj, 2000; Langdon, 2006). However, researchers argue that there exists a trade-off between these two capabilities. To exploit benefits of alignment, a firm must forgo most of the benefits of adaptability (Kambil et al., 1999; Saeed et al., 2005). Therefore, it has been challenging for companies to maintain both process alignment and adaptability. This intuition is rooted in the context of traditional EDI where a firm must make chunky infrastructure investments, develop rigid and complex X12 formats and create highly relation-specific EDI connections, which will result in a minimal level of flexibility to adjust and reconfigure IT assets (Hart and Estrin, 1991; Gosain et al., 2004). Based on recent developments in open standards, modular design and extensible markups, OSIOS can resolve the contradictory requirements between alignment and adaptability (Zhu, Kraemer, Gurbaxani and Xu, 2006; Malhotra et al., 2007; Saraf et al., 2007). There is going to be a greater degree of IOS flexibility after the deployment of OSIOS, which, in turn, can enhance supply chain integration (Hagel and Brown, 2005).

Allowing firms to flexibly adjust their IT infrastructures and extend IT functionalities, OSIOS enables supply chain partners to rapidly respond to the changing needs in business processes and adapt to inter-organizational activities and plans (Rai and Tang, 2010), which can facilitate the dynamic alignment of processes with supply chain partners (Gosain et al., 2004). Although in a stable environment, a firm can only choose to create highly partner-specific connections and invest in process-specific IT assets that forgo flexibility and adaptability, in a more dynamic environment, a company must establish linkages and develop IT infrastructures that are more robust and reconfigurable. Otherwise, the company may develop sticky patterns with entrenched partners over time, resulting in resistance to change (Van Den Bosch et al., 1999). Through obtaining process adaptability from OSIOS, firms can bridge the information gaps in markets and quickly respond to the changes in external environments using various strategies and actions (Gosain et al., 2004), which can reduce of risk of the aforementioned “rigidity traps” and can promote the restructuring of
supply chain processes and lead to greater process alignment in the long term (Bharadwaj, 2000). Therefore, we formulate the following hypothesis:

\[ H3. \text{ OSIOS-enabled process adaptability is positively associated with OSIOS-enabled process alignment.} \]

The overarching research model of this study is depicted in Figure 1.

4. Methodology
To test the hypotheses, this study collected data from manufacturing companies operating in China using a self-report survey instrument that was carefully developed following existing guidelines and exemplars (Sethi and King, 1994). China is considered as an ideal environment to study IOS and supply chain management because of several reasons. First, China is currently one of the foremost global manufacturing centers and is an attractive place for companies throughout the world to set up a manufacturing base (Flynn et al., 2010). Second, the Chinese Government has made significant efforts in the drive toward achieving Industry 4.0, with many resources being invested into areas such as smart and intelligent manufacturing (Zhong et al., 2017). Lastly, the Chinese Government also places great emphasis on its efforts to achieve the “Made in China 2025” project, and as a result, there are growing efforts devoted by Chinese companies in deploying IOS to integrate partners within their global supply chains (Huo et al., 2014; Liu et al., 2016). To collect data from the existing adopters of OSIOS, the respondents were asked to identify the type of IOS implemented by their companies before they were provided with the questionnaire to fill in.

4.1 Measurement development
The survey instrument employed in this study was designed on the basis of a comprehensive review of the literature on IOS, inter-organizational relationship management and supply chain management. Whenever possible, existing measurements in the literature were adapted from past studies to safeguard the content validity of the constructs and their fit in the research context, and to ensure that the overlap among the constructs was minimal (Cronbach, 1971).

The key variables in this study were operationalized as multi-item reflective and formative constructs. To decide whether a construct should be modeled as formative or reflective, four major criteria should be examined: the direction of causality between constructs and their indicators, the interchangeability of indicators, the covariation among indicators and the nomological net of constructs (Jarvis et al., 2003). A latent variable should be constructed as formative when the direction of causality is from the indicators to the constructs (i.e. the indicators create the constructs), the indicators are not interchangeable and do not necessarily covary and the nomological net of the indicators can differ (Chin, 1998). In contrast, reflective constructs should be created when the opposite conditions hold.
Suggested by the decision rules, OSIOS enabled process alignment and internal assimilation, which were modeled as formative constructs; it also enabled process adaptability and external diffusion, which were modeled as reflective constructs. The response formats and specific items for all measures are shown in Table III.

Internal assimilation measures the extent to which OSIOS has been used to support internal supply chain operation practices (Zhang, Xue and Dhaliwal, 2016). Following Zhu, Kraemer and Xu (2006), Zhang and Dhaliwal (2009) and Zhang, Xue and Dhaliwal (2016), a three-item, formatively measured construct was adapted to assess the degree of OSIOS usage in different key upstream supply chain activities: supplier selection, purchase-order processing, procurement from suppliers and invoicing and payment processing.

External diffusion refers to the degree to which OSIOS has been used to facilitate inter-organizational activities with supply chain partners. In total, three reflective items were adapted from Premkumar et al. (1994), Premkumar and Ramamurthy (1995), Zhang, Xue and Dhaliwal (2016) and Zhang and Dhaliwal (2009) to measure the breadth and volume of the transactions that a firm has conducted through OSIOS (Zhu and Kraemer, 2002; Zhang and Dhaliwal, 2009; Zhang, Xue and Dhaliwal, 2016), which includes the number of partners a firm has been interacting with, the volume of transactions with partners and the overall interactions with partners that have been handled via OSIOS.

OSIOS-enabled process alignment measures the extent to which OSIOS enables the coordination and joint optimization of activities between a firm and its supply chain partners, and it was measured with four formative items adopted from Tang and Rai (2012) and Rai and Tang (2010). The capabilities of OSIOS to enhance bonding among supply chain partners were assessed by the four items through coordinating interdependency, improving process visibility, optimizing supply chain processes and handling operational exceptions and errors efficiently.

OSIOS-enabled process adaptability was assessed with three reflective items adapted from Gibson and Birkinshaw (2004) and Im and Rai (2008), which measured the extent to which OSIOS promotes organizational responsiveness to adapt to the variations in the external environment through reconfiguring and adjusting supply chain relationships and activities.

4.2 Control variables
To control for unobserved heterogeneity caused by industry effects in value creation analysis, following China’s industrial classification guide (National Bureau of Statistics, 2017), eight industry dummies were created to represent the industries of the following: automobiles and components, electrical goods and electronics, materials and chemicals, energy, healthcare and healthcare machinery, machinery and equipment, consumer durables and apparel and others. Ownership was also controlled by creating dummy variables to indicate whether a firm was state owned, privately owned, or foreign controlled. In addition, performance was also controlled for the influence of firm size by measuring the yearly turnover and the number of employees of a firm. Larger firms tend to enjoy more abundant resources to deploy OSIOS compared with smaller firms. We also controlled for the number of years a firm has been operating because the older a firm is, the more likely it has invested legacy systems that might not be compatible with OSIOS. In addition, we measured IT department size as the number of technical personnel hired to control for the IT capability of a firm. Also, two additional control variables – relationship duration and number of suppliers – were also accounted for the possible effects of supplier portfolio characteristics (Tang and Rai, 2012). Relationship duration measured the average relationship length (in years) between a firm and its major suppliers, which is consistent with Im and Rai (2008). The number of suppliers measures the number of major suppliers a firm has been routinely interacting with.
We further controlled for the effects of market and technological turbulence. Market turbulence describes the heterogeneity and the rapid variations in a firm's customer portfolio and the preferences of its customers (Kandemir et al., 2006), which was assessed by three reflective items adapted from Calantone et al. (2003), Kandemir et al. (2006) and Trkman and McCormack (2009). Technology turbulence refers to the speed of changes in technology over time in the principal industry that a firm operates in and the consequences these changes induce to the industry (Chatterjee, 2004). To measure technology turbulence, three reflective items adapted from Kandemir et al. (2006), Koo et al. (2006) and Trkman and McCormack (2009) were employed.

4.3 Data collection
To facilitate the data collection process, a survey research company specialized in helping researchers distribute survey in China was hired to collect data. The role of the data collection firm was to help distribute the survey as well as following up by phoning the companies and conversing with them in Chinese to remind them to fill in the questionnaire if they were willing to participate in our research. The use of data collection to distribute surveys has grown substantially in recent years across a variety of academic disciplines, but specific examples in supply chain operations and management research include Autry et al. (2010), Cai et al. (2010) and Schoenherr et al. (2015). Previous researchers have addressed the concerns with regards to the quality of data collected from survey research firms by confirming that the responses do not differ from those collected via random mail samples as long as the target population is knowledgeable regarding the subject matter (Autry et al., 2010; Schoenherr et al., 2015). It is argued that despite the potential challenges faced by survey research firm recruitment, employing it for data collection can provide a viable alternative to traditional self-administered surveys (Schoenherr et al., 2015). In order to avoid potential bias in our data collection process, one of the co-authors of the research was present at the survey research company when the follow-up phone calls were made to the respondents. We also followed the guidelines recommended by Schoenherr et al. (2015) to avoid potential bias in our data such as having clear procedures with the survey research company to ensure only qualified respondents took part in the survey, as well as having screening questions to provide assurance of reliability and validity of responses. In this study, the list of manufacturing firms with the Chinese Industrial Classification codes 1311 – 4290 (National Bureau of Statistics, 2017) was decided to be the sampling frame to ensure that the sample could span a comprehensive spectrum of manufacturing industries. Following Cai et al. (2010), the target companies were randomly selected on the basis of the stratified probability proportional to sizes method, which could ensure good representation of the sample in terms of industry, firm size and ownership. A list of 3,400 firms was selected as the target samples.

The surveys were conducted through computer-aided phone interviews by the employees of the professional research company. Based on standard practice (Flynn et al., 2010; Zhou et al., 2014; Liu et al., 2016), our survey collected data from senior executives holding titles such as the chief executive officer, chief technology officer and senior operations managers. These individuals were identified to be the key informants because they confirmed their involvement with supply chain technology as part of their job role, and they had strong knowledge about their companies’ overall operational and IT capabilities. The data collection professionals first identified whether a firm has adopted OSIOS or not before administrating the questionnaire to the respondents. We screened our data by following the procedure by Schoenherr et al. (2015). We were able to monitor the time respondents took to complete the survey. Surveys that were answered in less than 15 min were eliminated. This 15-min benchmark was the average completion time incurred by the authors when carefully reading and thoughtfully answering the survey.
Following Schoenherr et al. (2015), we deemed these “speeders” as unreliable respondents. After discarding the responses with missing data, the final sample consisted of 308 valid responses from OSIOS current adopters. The sample demographics and respondent profile are shown in Table I.

5. Data analysis and results
5.1 Measurement validation

Confirmatory factor analysis was conducted to validate the measurement. Because reflectively measured constructs and formatively measured constructs are based on different concepts, they must be distinguished when evaluating the measurement models by using different assessment measures (Ringle et al., 2009). Reflective constructs were assessed regarding their internal consistency reliability and construct validity following Hair et al. (2014), whereas formative constructs were evaluated following guidelines suggested by Petter et al. (2007).

The internal consistency reliability of the reflective constructs was established by assessing composite reliabilities. The results in Table II showed that the composite reliabilities of all constructs were greater than the recommended benchmark of 0.70, suggesting satisfactory internal consistency of the reflective measurement model (Barclay et al., 1995).

Construct validity assesses whether the items can actually capture the concepts that the constructs intend to measure (Bagozzi, 1980), which is evaluated by convergent and discriminant validity, respectively. As shown in Table II, the reflective measurement models

<table>
<thead>
<tr>
<th>Sample demographics</th>
<th>Frequency</th>
<th>Percentage</th>
<th>Turnover</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Automobiles and components                                                         21</td>
<td>6.82</td>
<td></td>
<td>&lt; 25m</td>
</tr>
<tr>
<td>Electronic and electronics                                                          71</td>
<td>23.05</td>
<td></td>
<td>25–100m</td>
</tr>
<tr>
<td>Materials/metals/chemicals                                                          93</td>
<td>30.19</td>
<td></td>
<td>100–300m</td>
</tr>
<tr>
<td>Energy</td>
<td>13</td>
<td>4.22</td>
<td>&gt; 300m</td>
</tr>
<tr>
<td>Health Care</td>
<td>28</td>
<td>9.09</td>
<td>Employee</td>
</tr>
<tr>
<td>Equipment and machinery</td>
<td>46</td>
<td>14.94</td>
<td>&lt; 160</td>
</tr>
<tr>
<td>Consumer durables and apparel</td>
<td>22</td>
<td>7.14</td>
<td>160–1,000</td>
</tr>
<tr>
<td>Others</td>
<td>14</td>
<td>4.55</td>
<td>&gt; 1,000</td>
</tr>
<tr>
<td>Years of operation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≤ 5 years</td>
<td>15</td>
<td>4.87</td>
<td></td>
</tr>
<tr>
<td>6–10 years</td>
<td>127</td>
<td>41.23</td>
<td></td>
</tr>
<tr>
<td>≥ 10 years</td>
<td>166</td>
<td>53.90</td>
<td></td>
</tr>
<tr>
<td>Organization type (ownership)</td>
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<td></td>
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<tr>
<td>State-owned (fully/partly owned)</td>
<td>36</td>
<td>11.69</td>
<td></td>
</tr>
<tr>
<td>Privately owned</td>
<td>145</td>
<td>47.08</td>
<td></td>
</tr>
<tr>
<td>Foreign controlled</td>
<td>127</td>
<td>41.23</td>
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<tr>
<td>Size of IT department</td>
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<tr>
<td>≤ 5</td>
<td>58</td>
<td>18.83</td>
<td></td>
</tr>
<tr>
<td>6–10</td>
<td>90</td>
<td>29.22</td>
<td></td>
</tr>
<tr>
<td>≥ 16</td>
<td>67</td>
<td>21.75</td>
<td></td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Respondent profile</th>
<th>Frequency</th>
<th>Percentage</th>
<th>Years of working</th>
</tr>
</thead>
<tbody>
<tr>
<td>Position</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CEO/President</td>
<td>3</td>
<td>0.97</td>
<td></td>
</tr>
<tr>
<td>Senior executive/Vice President</td>
<td>122</td>
<td>39.61</td>
<td>6–10 years</td>
</tr>
<tr>
<td>IT Manager/CIO/CTO</td>
<td>72</td>
<td>23.38</td>
<td>≥ 11 years</td>
</tr>
<tr>
<td>Supply chain/Operations</td>
<td>111</td>
<td>36.04</td>
<td></td>
</tr>
</tbody>
</table>

Table I. Sample demographics and respondent profile

Note: n = 308
### Construct and items

<table>
<thead>
<tr>
<th>Construct and items</th>
<th>Standardized loadings</th>
<th>Composite reliability</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>OSIOS-enabled process alignment (ALM)</strong> Adapted from Tang and Rai (2012) and Rai and Tang (2010)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Through implementing OSIOS…</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ALM1: we can closely coordinate interdependent processes with specific partners</td>
<td>0.851</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>ALM2: we can make interdependent operating procedures and routines (e.g., manufacturing, bar coding, packaging, shipping, etc.) to be highly visible among specific partners and us</td>
<td>0.688</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>ALM3: we can jointly optimize related operating processes with specific partners</td>
<td>0.714</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>ALM4: we can closely coordinate interdependent processes with specific partners</td>
<td>0.866</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td><strong>OSIOS-enabled process adaptability (ADP)</strong> Adapted from Gibson and Birkinshaw (2004) and Im and Rai (2008)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Through implementing OSIOS…</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ADP1: we can adapt current supply chain relationships to respond quickly to changes in our markets</td>
<td>0.838</td>
<td>0.868</td>
<td>0.686</td>
</tr>
<tr>
<td>ADP2: we can adapt existing business processes rapidly to respond to shifts in our business priorities</td>
<td>0.821</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>ADP3: we can facilitate reconfiguration of activities to respond to changes in the external environments</td>
<td>0.827</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td><strong>Internal assimilation (INT)</strong> Adapted from Zhu, Kraemer and Xu (2006), Zhang and Dhaliwal (2009) and Zhang, Xue and Dhaliwal (2016)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Please rate the extent to which your firm has been using OSIOS to conduct the following supply chain activities…</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INT1: supplier selection (getting quotes, bid, etc.)</td>
<td>0.928</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>INT2: purchase order processing</td>
<td>0.907</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>INT3: procurement from suppliers (distribution, warehouse, shipping, logistics, etc.)</td>
<td>0.944</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td><strong>External diffusion (EXT)</strong> Adapted from Premkumar et al. (1994), Premkumar and Ramamurthy (1995), Zhang, Xue and Dhaliwal (2016) and Zhang and Dhaliwal (2009)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Please indicate the percentage of total transactions or inter-firm interactions that your firm has performed through OSIOS…</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EXT1: percentage of total supply chain partners who interact with your organization through the system</td>
<td>0.968</td>
<td>0.983</td>
<td>0.949</td>
</tr>
<tr>
<td>EXT2: percentage of total supply chain partner transactions done through the system</td>
<td>0.983</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>EXT3: percentage of overall interactions with supply chain partners carried out through the system</td>
<td>0.973</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td><strong>Market turbulence (MT)</strong> Adapted from Galantone et al. (2003), Kandemir et al. (2006) and Trkman and McCormack (2009)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Please indicate the extent to which you agree with the following statements regarding the principal market your company is operating in…</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MT1: we continuously cater many new customers</td>
<td>0.804</td>
<td>0.803</td>
<td>0.577</td>
</tr>
<tr>
<td>MT2: our customers tend to look for new products all the time</td>
<td>0.681</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>MT3: new customers tend to have product-related needs that differ from our existing customers</td>
<td>0.788</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td><strong>Technological turbulence (TT)</strong> Adapted from Kandemir et al. (2006), Koo et al. (2006) and Trkman and McCormack (2009)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Please indicate the extent to which you agree with the following statements regarding the principal market your company is operating in…</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TT1: it is very difficult to forecast where the technology in our industry will be in the next 2–3 years</td>
<td>0.883</td>
<td>0.876</td>
<td>0.704</td>
</tr>
<tr>
<td>TT2: in our principal industry, the modes of production and service often change</td>
<td>0.887</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>TT3: the rate of product/service obsolescence in our industry is very high</td>
<td>0.737</td>
<td>–</td>
<td>–</td>
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</tbody>
</table>

**Note:** *Formative constructs*
exhibit sufficient indicator reliability because the standardized factors loadings ranged from 0.681 to 0.983 (Flynn et al., 2010). Meanwhile, the average variance extracted (AVE) ranged from 0.577 to 0.949, greater than the suggested 0.50 threshold (Koufteros, 1999). These results, thus, provided strong evidence of convergent validity. To establish discriminant validity of the reflective measurements, the Fornell–Larcker criterion and cross-loadings were used as two measures. The Fornell–Larcker criterion (Fornell and Larcker, 1981) proposes that a construct should share more variance with its indicators than the variance shared with other constructs in the same model, which is statistically expressed as the rule suggesting that the square root of a construct’s AVE should exceed its highest correlation with any other construct. As shown in Table III, the square roots of the AVEs (figures on the diagonal) were all greater than the correlations among the constructs (figures off the diagonal), providing evidence for discriminant validity. In addition, the results in Table IV demonstrate that no indicators loaded higher on other constructs than on their assigned constructs (Petter et al., 2007), which further lends support for discriminant validity.

For OSIOS-enabled process alignment and internal assimilation, which are formative measures, the statistical assessment criteria for reflective measurements, such as composite reliability and AVE, are not applicable. Content validity of formative measures, which ensures that all the formative indicators capture all, or at least a major part of, the facets of the construct domain (Nunnally, 1978), must be established before data collection and estimation. Because all of the measures for formative constructs were adapted directly from the previous literature in prestigious IS and OM journals, the theoretical grounding of the indicators is well supported. In addition, as described in the data collection section, the questionnaire items were reviewed cautiously by a panel of eight academics and five practitioners to ensure the content validity of the formative indicators.

Similar to reflective measurements, cross-loadings of formative indicators are employed to evaluate their discriminant validity (Petter et al., 2007). As shown in Table IV, no formative indicators loaded greater on the constructs they are not intended to measure, which provides support for discriminant validity of the formatively measured constructs.

5.2 Hypothesis testing
Conventional analytical methods such as ordinary least squares (OLS) and general least squares (GLS) might not be appropriate for this study, because the endogenous variable – OSIOS-enabled process adaptability – is also specified as an explanatory variable in another equation in the system of equations (Hamilton and Nickerson, 2003). In addition, problems may arise from correlated error terms due to the possible omission of variables that are correlated with the dependent variable and any of the independent variables in the model (Zaefarian et al., 2017). Correlation among error terms could also arise because each case is based on data obtained from a single respondent (Kuruzovich et al., 2008). Therefore, the three-stage least squares (3SLS) estimation, which combines the features of two-stage least squares (2SLS) and seemingly unrelated regression estimation, was employed to analyze the data to simultaneously address the problems of dependent repressors and correlation of error terms (Kuruzovich et al., 2008). In addition, 3SLS is recommended to be a more efficient approach (compared with OLS and GLS) to solve triangular structural models (Lahiri and Schmidt, 1978), just as the research model proposed in this study. When estimating models involving latent variables, 3SLS also has the advantage of being more robust to model specification errors, for example, omitted paths or incorrect structures, compared with the commonly used maximum likelihood-based structural equation modeling (SEM) method (Bollen et al., 2007). Furthermore, as our research model involves quadratic effects, using 3SLS can cater for
<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Process alignment</td>
<td>4.698</td>
<td>0.780</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>2. Process adaptability</td>
<td>4.925</td>
<td>0.758</td>
<td>0.696**</td>
<td>0.828</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Internal assimilation</td>
<td>3.961</td>
<td>0.980</td>
<td>0.577***</td>
<td>0.532**</td>
<td>0.695**</td>
<td>0.693**</td>
<td>0.974</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. External diffusion</td>
<td>4.518</td>
<td>1.800</td>
<td>0.638**</td>
<td>0.532**</td>
<td>0.691**</td>
<td>0.693**</td>
<td>0.760</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Market turbulence</td>
<td>5.190</td>
<td>0.645</td>
<td>0.439**</td>
<td>0.303**</td>
<td>0.303**</td>
<td>0.453**</td>
<td>0.760</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Technological turbulence</td>
<td>5.447</td>
<td>0.647</td>
<td>0.407**</td>
<td>0.281**</td>
<td>0.322**</td>
<td>0.486**</td>
<td>0.711**</td>
<td>0.839</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Number of suppliers</td>
<td>119.344</td>
<td>119.350</td>
<td>0.062</td>
<td>0.034</td>
<td>0.161**</td>
<td>0.217**</td>
<td>−0.118*</td>
<td>−0.092</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Relationship duration</td>
<td>6.107</td>
<td>2.653</td>
<td>0.258**</td>
<td>0.208**</td>
<td>0.271**</td>
<td>0.289**</td>
<td>−0.017</td>
<td>0.005</td>
<td>0.342**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9. Turnover</td>
<td>na</td>
<td>na</td>
<td>0.388**</td>
<td>0.287**</td>
<td>0.375**</td>
<td>0.454**</td>
<td>0.077</td>
<td>0.008</td>
<td>0.376**</td>
<td>0.423**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10. Ownership</td>
<td>na</td>
<td>na</td>
<td>0.105</td>
<td>0.096</td>
<td>0.191**</td>
<td>0.285**</td>
<td>0.113**</td>
<td>0.045</td>
<td>−0.201**</td>
<td>−0.003</td>
<td>0.042</td>
<td></td>
</tr>
<tr>
<td>11. Industry</td>
<td>na</td>
<td>na</td>
<td>−0.056</td>
<td>−0.060</td>
<td>−0.100</td>
<td>−0.145**</td>
<td>−0.006</td>
<td>−0.033</td>
<td>−0.094</td>
<td>−0.190**</td>
<td>−0.146*</td>
<td>−0.001</td>
</tr>
</tbody>
</table>

**Notes:** The square roots of the AVEs were shown as figures on the diagonal. *p < 0.05; **p < 0.01
interacting variables more easily compared with SEM. The following system of equations was developed to test the proposed hypotheses:

\[
\text{Process Adaptability}_i = \beta_0 + \beta_1 \text{External Diffusion}_i + \beta_2 \text{Internal Assimilation}_i + \beta_3 \text{Internal Assimilation}^2_i + \beta_4 \text{Market Turbulence}_i + \beta_5 \text{Technological Turbulence}_i + \beta_6 \text{Turnover}_i + \beta_7 \text{Employee}_i + \beta_8 \text{IT Department}_i + \beta_9 \text{Operation Years}_i + \beta_{10-15} \text{Ownership Dummies}_i + \beta_{13-18} \text{Industry Dummies}_i + \epsilon_i.
\]

(1)

\[
\text{Process Alignment}_i = \gamma_0 + \gamma_1 \text{Process Adaptability}_i + \gamma_2 \text{No. of Suppliers}_i + \gamma_3 \text{Relationship Duration}_i + \gamma_4 \text{Market Turbulence}_i + \gamma_5 \text{Technological Turbulance}_i + \gamma_6 \text{Turnover}_i + \gamma_7 \text{Employee}_i + \gamma_8 \text{IT Department}_i + \gamma_9 \text{Operation Years}_i + \gamma_{10-15} \text{Ownership Dummies}_i + \gamma_{12-18} \text{Industry Dummies}_i + \nu_i.
\]

(2)

As specified in the equations, we controlled the effects of market and technological turbulence on process adaptability. In addition, relationship duration and number of suppliers, as two network properties, were included as control variables for process alignment in the model.

5.3 Results

Table V details the main estimation result of the system of equations, wherein Models (1), (2) and (3) list estimate for the various specifications of Equation (1), whereas Models (4) and (5) detail the result for Equation (2). Among the control variables, it was found that the effect of number of suppliers was negative on process alignment, which reflects the difficulty in
managing a wide variety of inter-organizational relationships. A company is constrained to
tain high levels of process alignment when there are many partnerships to cater for (Madhok, 2002). Relationship duration, however, was positively associated with process alignment, which lends support to the notion that tie strength can facilitate supply chain integration (Tang and Rai, 2012).

In Model (1), the main linear effects of both OSIOS deployment constructs were entered. Consistent with our earlier discussion that OSIOS can provide relational mechanism to enable process adaptability, results showed that external diffusion ($\beta_1 = 0.265$, $p < 0.01$) and internal assimilation ($\beta_2 = 0.241$, $p < 0.01$) were predictive for the creation of process adaptability. In Model (2), quadratic terms of the two OSIOS deployment constructs were entered. Only the nonlinear term of internal assimilation was significantly predictive for process adaptability ($\beta_3 = -0.075$, $p < 0.01$), which lent support for $H1$. However, $H2$ was not supported, as the nonlinear effect of external diffusion was not significant ($\beta_4 = -0.06$, ns). External diffusion, thus, only had a positive linear effect on OSIOS-enabled process adaptability. To corroborate the nonlinear effect in the case of internal assimilation, Figure 2 illustrates the graph of the quadratic relation. $H3$ posits that OSIOS-enabled process adaptability positively affects OSIOS-enabled process alignment. Model (3) represents the corresponding result: the positive effect of process adaptability was statistically significant ($\gamma_1 = 0.501$, $p < 0.01$), offering support to $H3$.

Although not explicitly suggested in the hypotheses, the research model implies a mediation effect of process adaptability on the relationship between OSIOS deployment and process alignment. As external diffusion was shown to have no significant relationship with
process adaptability, we only tested the mediating role of process adaptability. Due to the involvement of nonlinear effect, we performed a bootstrapping test \( n = 5,000 \), following the procedure of Hayes and Preacher’s (2010), to calculate the instantaneous indirect effects of internal assimilation on process alignment through process adaptability at different values of internal assimilation (i.e. mean and mean ± SD). The instantaneous indirect effect was significant at low internal assimilation \( (\theta_x = -1.04 = 0.288, \text{bias-corrected bootstrap 95% CI = [0.167, 0.397], not including 0}) \), mean \( (\theta_x = -0.11 = 0.227, \text{bias-corrected bootstrap 95% CI = [0.145, 0.307], not including 0}) \) and higher \( (\theta_x = 0.82 = 0.167, \text{bias-corrected bootstrap 95% CI = [0.085, 0.259], not including 0}) \). The result provides evidence that increasing internal assimilation can enable more process alignment through the effect on OSIOS-enabled process adaptability. However, the return from internal assimilation is diminishing, as its marginal effect on process alignment is larger for companies low in internal assimilation compared with those have moderate or high levels of internal assimilation.

As OSIOS internal assimilation and external diffusion could be endogenously affected by the level of process adaptability, the results might be biased and inconsistent (Guide and Ketokivi, 2015). We conducted a 2SLS regression with instrumental variables and a Durbin–Wu–Hausman postestimation test of endogeneity (Davidson and MacKinnon, 1993) to deal with the potential endogeneity concern (Liu et al., 2016). The results (see Appendix 1) showed that the findings in our original model were unlikely to be unduly influenced by endogeneity.

Several additional tests were conducted to check the robustness of our results. We tested our hypotheses using SEM with FIML estimation to estimate simultaneously the effect of OSIOS adoption on process adaptability and process alignment. The model leads to the same statistical conclusions as 3SLS (see Table AII). Additionally, a 2SLS analysis with LIML estimation was performed, which also showed consistent results with 3SLS (see Table AIII). 2SLS was recommended for system of equations where there might be endogeneity due to potential reverse causality between the independent and dependent variable (Baron and Kenny, 1986). The consistent results from 2SLS, thus, minimize concerns about endogeneity.

6. Discussion and implications
OSIOS technology is an important fundamental IT artifact to help achieve Industry 4.0. It has the potential to provide the standards for business processes and data exchanges that
can create an autonomous, decentralized supply chain network, thus helping firms to achieve better supply chain integration. As found in Flynn et al. (2010), supply chain integrations can be described in three dimensions, namely, internal, customer and supplier integration. OSIOS technology is important in helping firms improve their supply chain integration (Chong and Ooi, 2008). However, OSIOS deployment is still in its infancy stage, given that the technology is still elusive to most manufacturers. Most manufacturers understand the potential values of OSIOS, but at the same time, they are taking a cautious approach in investing in OSIOS. Our research advances contemporary knowledge of the values brought by the assimilation and diffusion of OSIOS. Drawing on the theoretical lens of the relational view of the firm, we examined how manufacturers can achieve process adaptability and alignment by deploying OSIOS. Through collecting surveys from a large group of manufacturers, we were able to examine the non-linear impact of OSIOS assimilation and diffusion on process adaptability and alignment, thus shedding light on how manufacturers should optimize their deployment of OSIOS to achieve the best outcomes. As such, our research bears significant implications for both theory and practice.

6.1 Implications for theory
By conducting an empirical examination on the research model proposed, this research contributes to extant literature on three fronts. First, supply chain alignment and integration is one of the most important topics studied by the scholars of operation management. In particular, the success of Industry 4.0 is very much dependent on achieving integration and alignment in supply chains. Our study extends extant literature on the topic by focusing on an important enabler of supply chain integration and alignment – OSIOS. Although the importance of supply chain integration is widely recognized, it remains a considerable challenge for organizations to reap the benefits of an integrated supply chain because of the complexities in SCM strategies (Mustafa Kamal and Irani, 2014; Vanpoucke et al., 2017). Given the inconsistent results of OSIOS deployment in different industries (Saeed et al., 2011), the relationship between OSIOS deployment and supply chain integration remains a black box (Liu et al., 2016). Our study, thus, enriches this stream of research by exploring the relationship between OSIOS deployment and process alignment. Through enabling process adaptability, OSIOS can indirectly generate process alignment to integrate inter-firm supply chain processes and activities. This finding is of particular interest and importance to achieve Industry 4.0, given that OSIOS has the ability to address the potential tradeoffs between OSIOS integration and flexibility (Saraf et al., 2007; Rai and Tang, 2010). Although a company achieves process alignment without process adaptability, it will not be able to reconfigure its supply chain activities to adapt to the changing environments. The company will end up facing the risks of rigidity, such that the existing business processes that were once aligned will become obsolete or misaligned when relevant supply chain activities or relationships change. This rigidity has been pertinent in the application of EDI because of its inflexibility and costs that have restrained its ability to transform inter-organizational relationships (Hart and Estrin, 1991). OSIOS overcomes the disadvantages of EDI by affording companies with the flexibility to tune the parameters related to business processes, thus allowing them to adapt to the emerging alignment requirement (Malhotra et al., 2007; Saraf et al., 2007). Therefore, our research empirically confirmed that OSIOS enables companies to enjoy close coordination and inter-firm integration and to pursue higher order performance by developing adaptability to continually restructure supply chain processes and respond to external changes.

Second, despite the critical role of OSIOS in determining the extent to which an organization can attain supply chain integration, there is little understanding of how OSIOS can be deployed effectively (Saeed et al., 2011; Liu et al., 2016). In order to fill this
research gap, it is imperative to go beyond linear models to identify an ideal way of deploying OSIOS for supply chain collaboration (Liu et al., 2016). Therefore, a key contribution of this research is the examination of the curvilinear effects of OSIOS internal assimilation and external diffusion on enabling process adaptability and process alignment. This facilitates the identification of the optimal level of OSIOS deployment that will most effectively manage supply chain integration. Our study found that relationship between internal assimilation and OSIOS-enabled process adaptability followed an inverted U-shaped pattern. The findings ascertain that by deploying OSIOS to support key supply chain activities, the utility of OSIOS to enhance process adaptability and alignment will drop after a certain degree. This could be due to the fact that as more functions and processes are integrated in OSIOS, the whole system will become complicated to use and difficult to learn, which reduces the flexibility of the system and thus constrains the level of process adaptability that can be enabled by OSIOS. External diffusion only showed a positive linear relationship with process adaptability, which confirms with the network externalities of OSIOS, where once there are more supply chain partners using OSIOS, the value of OSIOS increases (Zhu, Kraemer and Xu, 2006). This supports why OSIOS such as RosettaNet needs manufacturers in the industry to buy into the technology and co-adopt it in order to maximize the collaboration and alignment in the supply chain.

Lastly, this study further contributes to the supply chain management literature by categorizing OSIOS deployment into internal assimilation and external diffusion, which provides a nuanced understanding about the linkage between OSIOS deployment and supply chain performance. This endeavor echoes the call in the operations management literature to investigate the influencing mechanisms exerted by different approaches of implementing information systems (Zhang et al., 2011). Distinguishing internal assimilation and external diffusion of OSIOS can enhance the assessment of the operational improvement generated by OSIOS deployment (Zhang, Van Donk and van der Vaart, 2016). The different impact mechanisms between internal assimilation and external diffusion explored by this research, thus, provide valuable insights to understand how IT can create value when deployed to support different integration needs.

6.2 Implications for practice
Our research informs practice in two ways. First, although Industry 4.0 provides numerous opportunities for many countries to digitalize manufacturing industries, contemporary applications of Industry 4.0 technologies still exist at an experimental stage. This study offers an overview of how OSIOS can be deployed to help create value to supply chain processes. Furthermore, we separate deployment of OSIOS into internal assimilation and external diffusion, thus offering a richer understanding of how applying OSIOS within a firm’s business process and its integration with its partners can help create values to a manufacturer. In this sense, our study informs practitioners who are planning or are in the process of deploying OSIOS, to gain a comprehensive view of the value offered by OSIOS.

Second, given that organizations may have limited resources to invest in OSIOS, our study provides valuable insights into how to deploy IT assets internally and externally to maximize the relational outcomes from OSIOS. In particular, we showed that manufacturers should not blindly increase assimilation of OSIOS into their business processes, as more does not necessarily mean better in our U-shaped result. Manufacturers should instead focus on key business processes to implement OSIOS, while other business processes internally can function using existing systems. However, within the supply chain network, manufacturers should ensure that the business processes that have assimilated OSIOS should be fully integrated with their supply chain partners, as this is shown to increase the process adaptability of manufacturers.
7. Limitations and future research

Despite the contributions of this study in both theory and practice, there are several limitations. First, this study could not show the value creation of OSIOS over time. Future studies can consider the dynamism of time when evaluating the relationship between OSIOS and relational capabilities. This study used cross-sectional data, which might be subject to the risk that the influence of OSIOS on organizational outcomes is only temporal. The quasi-open attribute of OSIOS makes imitation easy, which will reduce the uniqueness of OSIOS and erode a firm’s competitive advantage over time. It is important to ensure that performance gains from OSIOS can be sustained in the long term. Future study can conduct longitudinal research to understand whether and how OSIOS deployment can promote long-term advantages. The use of cross-sectional data also restricts us from exploring whether the capabilities developed from OSIOS deployment, in the long run, will, in turn, affect the extent to which OSIOS are deployed. With improved adaptability and alignment, a firm might be more capable of assimilating and diffusing OSIOS to support inter-firm activities.

Although our research model in terms of OSIOS-enabled process adaptability and alignment has the advantage of parsimony, the explanatory breadth and richness can be improved. Future study, thus, can include other outcomes of OSIOS such as relationship flexibility (Rai and Tang, 2010) or even first-order value such as operational and financial performance that could potentially yield from OSIOS deployment. In addition, the moderation effects of inter-organizational relationships, for example, trust and information sharing, can be explored in the future. In addition, we also acknowledge the limitation of measuring internal assimilation as the extent to which OSIOS is deployed to support internal activities. Due to the differences in downstream and upstream supply chain activities, assimilation of IT to integrate customers and suppliers should be measured as separate variables (Frohlich, 2002). Future research can investigate internal assimilation of OSIOS in downstream activities to provide more insights into the phenomenon.

Furthermore, the data were collected from China where there is a collectivist cultural environment; therefore, the respondents may have a tendency to agree regardless of the content of the questions (Liu et al., 2010). Thus, there might be a slight chance of acquiescence bias in our data. Despite these limitations, we believe that this study provides compelling evidence showing that OSIOS can be leveraged as importance value creation mechanisms to lead to the roadmap of Industry 4.0.

References


Appendix 1. Endogeneity test

It is possible that OSIOS deployment, that is, internal assimilation and external diffusion, is endogenously affected by the level of process adaptability, which may cause biased and inconsistent results (Greene, 2003; Guide and Ketokivi, 2015). A 2SLS regression with instrumental variables was used to deal with the potential endogeneity concern (Liu et al., 2016). The variables that were not significantly associated with process adaptability (i.e. market turbulence, technological turbulence, relationship duration, turnover, number of employees, IT department size and years of operations) (see Table V) were identified as the instrumental variables for internal assimilation and external diffusion (Bellamy et al., 2014; Liu et al., 2016).
To conduct 2SLS estimation, internal assimilation and external diffusion should be regressed on all the instrumental variables and control variables at the first stage. The $R^2$ values for internal assimilation and external diffusion are 0.342 (Model 1) and 0.570 (Model 2), respectively. These values are significantly higher than the $R^2$ of the regressions with only the control variables ($R^2_{\text{Internal Assimilation}} = 0.72$ and $R^2_{\text{External Diffusion}} = 0.175$), which lends support for using the aforementioned variables as effective instrumental variables (Liu et al., 2016). At the second step, the predicted values of internal assimilation and external diffusion were applied to test the relationship between them and process adaptability. As shown in Models 3 and 4, the effects of the predicted values of internal assimilation ($\beta = 0.260, \ p < 0.01$) and external diffusion assimilation ($\beta = 0.642, \ p < 0.01$) were significantly positive.

After performing the 2SLS, a Durbin–Wu–Hausman postestimation test of endogeneity (Davidson and MacKinnon, 1993) was conducted by testing an augmented regression, which included additional error terms of internal assimilation and diffusion obtained from the first stage of 2SLS. The coefficients of the error terms ($\beta_{\text{Internal Assimilation}} = 0.051, \ p = 0.746; \beta_{\text{External Diffusion}} = -0.054, \ p = 0.385$) were shown to be insignificantly related to process adaptability. The result suggests that the endogeneity test associated with internal assimilation and external diffusion was insignificant. Thus, the null hypothesis that internal assimilation and external diffusion are exogenous cannot be rejected (Bellamy et al., 2014; Liu et al., 2016). Therefore, we can conclude that the findings in our original model were unlikely to be unduly influenced by endogeneity.

![Table AI](image-url)
## Appendix 2. Robustness test

<table>
<thead>
<tr>
<th></th>
<th>Process adaptability</th>
<th>Process alignment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Market turbulence</td>
<td>0.042 (0.80)</td>
<td>0.052 (0.99)</td>
</tr>
<tr>
<td>Technological turbulence</td>
<td>0.042 (0.76)</td>
<td>0.053 (0.95)</td>
</tr>
<tr>
<td>Internal assimilation</td>
<td>0.242** (4.59)</td>
<td>0.218** (4.00)</td>
</tr>
<tr>
<td>External diffusion</td>
<td>0.228** (4.70)</td>
<td>0.235** (4.75)</td>
</tr>
<tr>
<td>Internal assimilation²</td>
<td>0.012 (0.22)</td>
<td>0.005 (0.09)</td>
</tr>
<tr>
<td>No. of suppliers</td>
<td>-0.127** (-2.70)</td>
<td></td>
</tr>
<tr>
<td>Relationship duration</td>
<td>0.0371 (0.79)</td>
<td>0.110** (3.08)</td>
</tr>
<tr>
<td>Turnover</td>
<td>-0.047 (-0.81)</td>
<td>0.157** (3.59)</td>
</tr>
<tr>
<td>No. of employees</td>
<td>0.034 (0.55)</td>
<td></td>
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<tr>
<td>IT department size</td>
<td>0.042 (0.72)</td>
<td></td>
</tr>
<tr>
<td>Years of operation</td>
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<td></td>
</tr>
<tr>
<td>Ownership</td>
<td>0.022 (0.17)</td>
<td></td>
</tr>
<tr>
<td>Ownership (private)</td>
<td>0.183* (2.14)</td>
<td></td>
</tr>
<tr>
<td>IND1</td>
<td>0.334 (1.74)</td>
<td></td>
</tr>
<tr>
<td>IND2</td>
<td>0.054 (0.74)</td>
<td></td>
</tr>
<tr>
<td>IND3</td>
<td>0.03 (0.65)</td>
<td></td>
</tr>
<tr>
<td>IND4</td>
<td>0.010 (0.19)</td>
<td></td>
</tr>
<tr>
<td>IND5</td>
<td>0.054 (1.28)</td>
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</tr>
<tr>
<td>IND6</td>
<td>-0.017 (-0.58)</td>
<td></td>
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<tr>
<td>IND7</td>
<td>0.011 (0.51)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>4.977** (139.87)</td>
<td>5.013** (82.16)</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.334</td>
<td>0.343</td>
</tr>
</tbody>
</table>

**Notes:** *p < 0.05; **p < 0.01

Table AII. Structural equation modeling with FIML estimation
<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Market turbulence</td>
<td>0.042 (0.75)</td>
<td>0.052 (0.96)</td>
<td>0.064 (1.22)</td>
<td>0.146** (2.79)</td>
<td>0.107 (1.91)</td>
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<td>Technological turbulence</td>
<td>0.042 (0.82)</td>
<td>0.052 (1.00)</td>
<td>−0.008 (−0.13)</td>
<td>−0.0142 (−0.27)</td>
<td>0.00875 (0.15)</td>
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<td>Internal assimilation</td>
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<td>0.218** (4.51)</td>
<td>0.295** (5.57)</td>
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<tr>
<td>External diffusion</td>
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<td>0.235** (4.87)</td>
<td>0.207** (3.89)</td>
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<td></td>
</tr>
<tr>
<td>Internal assimilation²</td>
<td>−0.056* (−2.03)</td>
<td>−0.056*** (−1.93)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>External diffusion²</td>
<td>0.011 (0.22)</td>
<td>0.005 (0.09)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Process adaptability</td>
<td></td>
<td></td>
<td></td>
<td>0.838** (11.27)</td>
<td>0.918** (8.99)</td>
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<tr>
<td>No. of suppliers</td>
<td>−0.127*** (−2.66)</td>
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<td>−0.010 (−0.21)</td>
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<td>Relationship duration</td>
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<td>0.0356 (0.71)</td>
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<td>Turnover</td>
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<td>0.100 (1.68)</td>
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<tr>
<td>No. of employees</td>
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<td>−0.154* (−2.37)</td>
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<tr>
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<td>0.032 (0.51)</td>
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<tr>
<td>Years of operation</td>
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<td>Ownership (state)</td>
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<td>0.248 (1.88)</td>
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<tr>
<td>Ownership (private)</td>
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<td></td>
<td>0.0418 (0.51)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IND1</td>
<td>0.334 (1.90)</td>
<td></td>
<td>−0.366 (−1.78)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IND2</td>
<td>0.0543 (0.84)</td>
<td></td>
<td>−0.0189 (−0.24)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IND3</td>
<td>0.0310 (0.75)</td>
<td></td>
<td>−0.0138 (−0.26)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IND4</td>
<td>0.0103 (0.20)</td>
<td></td>
<td>−0.0722 (−1.28)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IND5</td>
<td>0.0538 (1.28)</td>
<td></td>
<td>0.00739 (0.17)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IND6</td>
<td>−0.0166 (−0.65)</td>
<td></td>
<td>0.0339 (1.12)</td>
<td></td>
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<tr>
<td>IND7</td>
<td>0.0116 (0.62)</td>
<td></td>
<td>−0.0258 (−1.09)</td>
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<td></td>
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<tr>
<td>Constant</td>
<td>4.711** (136.59)</td>
<td>4.713** (126.19)</td>
<td>4.728** (34.27)</td>
<td>4.711** (136.59)</td>
<td>4.728** (34.27)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.334</td>
<td>0.343</td>
<td>0.381</td>
<td>0.399</td>
<td>0.336</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.325</td>
<td>0.330</td>
<td>0.336</td>
<td>0.393</td>
<td>0.316</td>
</tr>
</tbody>
</table>

Table AIII. 2SLS analysis with LIML estimation

Notes: *p < 0.05; **p < 0.01; ***p < 0.1

Corresponding author
Alain Yee Loong Chong can be contacted at: alain.chong@nottingham.edu.cn

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Abstract

Purpose – The purpose of this paper is to investigate the effects of Blockchain on the customer order management process and operations. There is limited understanding of the use and benefits of Blockchain on supply chains, and less so at processes level. To date, there is no research on the effects of Blockchain in the customer order management process.

Design/methodology/approach – A twofold method is followed. First, a Blockchain is programmed and implemented in a large international firm. Second, a series of simulations are built based on three scenarios: current with no-Blockchain, 1-year and 5-year Blockchain use.

Findings – Blockchain improves the efficiency of the process: it reduces the number of operations, reduces the average time of orders in the system, reduces workload, shows traceability of orders and improves visibility to various supply chain participants.

Research limitations/implications – The research is based on a single in-depth case that has the scope to be tested in other contexts in future.

Practical implications – This is the first study that demonstrates with real data from an industrial firm the effects of Blockchain on the efficiency gains, reduction on the number of operations and human-processing savings. A detailed description of the Blockchain implementation is provided. Furthermore, this research shows a list of the resources and capabilities needed for building and maintaining a Blockchain in the context of supply chains.

Originality/value – This is the first study that demonstrates with real data from an industrial firm the effects of Blockchain on the efficiency gains, reduction on the number of operations and human-processing savings. A detailed description of the Blockchain implementation is provided. This paper contributes to the resource-based view of the firm, by demonstrating two new competitive valuable capabilities and a new dynamic capability that organisations develop when implementing and using Blockchain in a supply–demand process. It also contributes to the information processing theory by highlighting the analytics capabilities required to sustain Blockchain-related operations.

Keywords Supply chain, Digital technology, Resource-based view (RBV), Blockchain, Information processing theory (IPT)

1. Introduction

Inaccuracy of specifications, volume variability, frequent change requests, a lack of clarity and diverse safety specifications are among the most common customer order management problems in supply chains. These problems are generally intensified by other resource-based problems such as multiple information systems, manual input, numerous customer communication channels, and varied cultural and human practices and behaviours. The combination of problems consequently leads to lack of traceability of orders, lack of visibility for customers and supply chain participants together with lack of reliability, ultimately leading to trust shortages and inefficient operations and transactions (Carter and Koh, 2018).

Traceability is becoming a fundamental differentiator in many supply chain industries including the agri-food sector (Feng, 2016; Aitken, 2017), the health and pharmaceutical sector (Rotunno et al., 2014; Eklab et al., 2016) and high-value goods (Maurer, 2017). The lack...
of traceability leads to a lack of transparency and visibility, affecting the reliability and trust of operations. For instance, the Salmonella outbreak linked to raw chicken products affected nearly a hundred people in more than eight states of the USA. If only the producer and its supply chain could have been traced and disclosed, it could have saved many people from falling ill and being hospitalised (Centers for Disease Control and Prevention, 2018). This situation urgently calls for a better information-sharing and verifiability (Saberi et al., 2019).

Safety of the data is another issue: the majority of supply chains rely on centralised information systems such as enterprise resource planning. Centralised information systems like these leaves the entire system exposed to error, hacking or attack (Dong et al., 2017).

Blockchain – a distributed digital ledger technology – ensures traceability, transparency and security; it is showing some potential promises in terms of easing some supply chain problems (Mendling et al., 2018).

Blockchain is one of the top 5 digital technologies forecast to change the way we operate and live (Brennan et al., 2015; Tapscott and Tapscott, 2017). By 2027, 10 per cent of the global GDP will be stored on Blockchain (World Economic Forum, 2015). At the World Economic Forum in Davos, Blockchain stood out as a priority technology with significant implications for people, businesses and the wider society (Carter and Koh, 2018). Countries such as Germany and China have placed Blockchain as at the core of their 2020 and 2025 national action plans (respectively) to become digital industry leaders (Xu et al., 2018; Sartor et al., 2014). Tapscott and Tapscott (2017) argue that “Blockchain allows companies to eliminate transaction costs and use resources on the outside as easily as resources on the inside”. Carson et al. (2018) highlight that the value of Blockchain will eventually shift from driving cost reductions to enabling entirely new business models and revenue streams. Power Ledger is an example of a decentralised energy-sharing company built on Blockchain technology, where energy producers (such as solar-panel owners) trade their extra electricity, generated locally, to neighbours in exchange for real-time payment carried out transparently on Blockchain (Ethereum). Implementations in Australia and New Zealand resulted in savings of up to $900 on users’ yearly electricity bills and doubled the savings of solar-panel owners (Powerledger, 2017).

Blockchain is a public and incorruptible platform where users upload self-executing programmes and can verify all past and current states of the system. There is great interest in Blockchain because of its architecture of traceability, transparency (visibility), security (resilience) and anonymity, requiring neither trust between the participants nor a regulating intermediary (Yli-Huumo et al., 2016; Saberi et al., 2019). The information track record is held in a tamper-proof database that is available for inspection on demand by interested parties (Swan and de Filippi, 2017). Blockchain has four important attributes that can benefit a business application (Palfreyman, 2016; Carter and Koh, 2018):

1. immutability: transactions, once validated, cannot be altered by malicious actors;
2. traceability: there is a complete and transparent audit trail of transaction history;
3. consensus: there is a single record agreed upon by all participants to prevent disputes; and
4. automation: commands and transactions can execute themselves on previously set conditions.

Some scepticism around this relatively new digital technology is observed. While some argue that Blockchain is nothing more than a mere data structure with multiple user ownership and control (Karafiloski and Mishev, 2017), others suggest that “Blockchain is an innovative technology in search of use cases” (Glaser, 2017). One plausible explanation is that the early applications of Blockchain – from 2008 to 2014 – were devoted to cryptocurrencies (Miau and Yang, 2018). Despite criticism, the popularity of Blockchain is
growing exponentially and applications of Blockchain are broadened to different contexts. In 2015, fewer than 100 documents were found in the Scopus Database; in the subsequent year, this figure doubled; by the end of 2018, more than 750 documents were found; and, finally, by early 2019, more than 820 documents had been identified.

To date, there are not academic studies or industrial cases demonstrating the effects of Blockchain implementations on punctuated processes of the supply chain, particularly in customer order management. Moreover, existing studies lack of an understanding of the capabilities and effects of Blockchain’s implementations on already existing operations, systems and capabilities:

The objective of this study is to identify the effects of Blockchain on the operations of the customer order management process of a supply chain. A parallel objective, is to provide a detailed implementation of Blockchain in a customer order management process.

The following sections discuss the theoretical foundations of the study. This continues with the research design taken to answer these questions including the selection of methods. The results lead to a set of findings that shows how Blockchain implementation could advance management of the theory and practices in the supply chains of industrial firms. Finally, this paper concludes with contributions to the advancement of the Blockchain theory, implications for practice and limitations.

2. Theoretical foundations
2.1 Blockchain applications
Blockchain is a revolutionary technology that is largely applied in the financial sector particularly in cryptocurrencies such as Bitcoin (Glaser and Bezzenberger, 2015; Holottuk et al., 2017; Yermack, 2017, Miau and Yang, 2018) and smart contracts (Alharby and Moorsel, 2017). Outside cryptocurrencies, a limited understanding of the uses of Blockchain is evident (Avital et al., 2016; Risius and Spohrer, 2017).

Nowiński and Kozma (2017) foresee a trend that the research body on applications will explode in the coming years. Applications could include services in supply chain management, insurance, digital knowledge management and e-commerce (Glaser, 2017).

The majority of applications of this digital technology are at a nascent stage. Several cases demonstrate the use of Blockchain; nonetheless, learning from these applications has changed the way that companies operate. The impact of Blockchain on business models remains extremely interesting to both industrialists and scholars (Risius and Spohrer, 2017).

Beyond the financial applications (Brown, 2018), Blockchain has been recently implemented and tested in a few other contexts such as health (Eklab et al., 2016), energy (Naudin, 2017), land registry (Lantmateriet, Chromaway, SBAB, Landsbygden Bank, Telia Company, & Kairo Future, 2017; Vorick and Champine, 2014; Bocovich et al., 2017), automotive (Shieber, 2017), education (Duran and Trachy, 2017), high-value assets (Everledger), data management (Zyskind et al., 2015), land administration, (Conoscenti et al., 2016), food (Steiner and Baker, 2015) and other marketplace economic models (Sun et al., 2016; McConaghy and Holtzman, 2015). However, the majority of these implementations are reduced to early Blockchain implementation stages, with little information disclosed about the effects of Blockchain on their operations, performance and outcomes. Only a few successful cases show the impact of the Blockchain technology on business performance.

For instance, Ripple orchestrated one of the earliest Blockchain implementations in the financial sector (Nowiński and Kozma, 2017). Partnering with Apple and Santander, Ripple facilitates inter-bank payments in real time at lower fees. It leverages the Blockchain to create a frictionless fiat currency transfer across entities and borders. The system is implemented and operates transfers, with more than thirty banks involved and more than a hundred institutional customers worldwide. The results of Ripple’s Blockchain show a more
efficient cost structure for money transfers, resulting in transaction fees that are lower than those associated with traditional systems. The first pilot test saw savings of 40–70 per cent on the entire operation compared to traditional foreign exchange providers. Moreover, an average transfer took a little over 2 min, as opposed to the average of two to three days of traditional bank transfers (Ripple, 2018).

Provenance is another successful implementation case of Blockchain. The company facilitates retailers to provide customers with reliable data to track fresh produce (such as seafood, coconut, cotton, etc.) from origin to supermarket. In these cases, transparency and validity of sustainable practices are paramount for customers, producers and retailers (Steiner and Baker, 2015).

2.2 Blockchain in supply chains
Blockchain is an open platform that allows companies to build their own applications. Its versatility and vast array of applications recommend its use in the supply chain (Benkler, 2006). Companies are actively exploring how they can leverage Blockchain to innovate parts of their business operations in the form of “private” Blockchains (Davidson et al., 2016). Private Blockchains require neither cryptographic incentives nor proof-of-work as public ones, but access is restricted to the chosen network and its information. There is a fine balance between cost and effectiveness, private Blockchains offer are less expensive as tend to operate in regions within secure business networks, whereas public Blockchains are more expensive as they run their computational power in secure global networks. (Koetsier, 2017).

Public Blockchains are general adopted to operate cryptocurrencies and other valuable transactions (Kshetri, 2018). Reducing the complexity and lowering the technical barriers have contributed to the growing popularity of Blockchain. Thereby, it is foreseen that Blockchain will increasingly be in competition with the systems of existing organisations and could eventually pose a threat to them as a result of its potential to perform their tasks more efficiently or reliably (Davidson et al., 2016).

It is hypothesised that the value-added from Blockchains resides in the companies’ internal value chain (Government Office for Science, 2016). Blockchain could revolutionise the way supply chains work (Dickson, 2016). Kshetri (2018) claims that supply chains are believed to be one of the most promising and transformative non-financial applications of Blockchain. Bunger (2017) supports that an industrial use-case in supply chains can provide an early return on investment for Blockchain applications.

As information input into the Blockchain is immutable, trust amongst participants is solidified as they can keep track of shipments, deliveries and product quality during transport (Kshetri, 2018). Because of the potential of removing paperwork, middlemen and auditors, costs might be reduced, and efficiency and speed could be improved while broadcasting updated information in real time (Koetsier, 2017). Moreover, Blockchain promises to increase standardisation, automation and transparency based on data and code, and it has the potential to increase productivity and decrease transaction costs, errors and conflicts (Seebacher and Schüritz, 2017). Table I shows Blockchain implementations and outcomes in various industrial cases.

As most companies build and maintain their own supply chain management software, it is difficult to have a global view of goods’ status in today’s increasingly intricate supply chain networks. This appears to be a tantalising application for Blockchain, as a decentralised distributed database, to increase transparency and information integrity (Gao et al., 2018). In this field, the Blockchain could be used to facilitate the recording of orders and receipts of goods, and the tracking of goods in transport, and to support customer services. Combined with barcodes, GPS, radio-frequency identification (RFID), sensors and the emerging trend of the internet of Things, Blockchain can enhance goods
<table>
<thead>
<tr>
<th>Case</th>
<th>Industry</th>
<th>Use of Blockchain within supply chain processes</th>
<th>Level of implementation</th>
<th>Results and benefits achieved</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agri-food supply chain system (Feng, 2016)</td>
<td>Food</td>
<td>Blockchain implemented in the full supply chain, from growing, production, processing and distribution, to warehousing and retail. Blockchain and RFID technologies applied to an agricultural supply chain to track food from &quot;farm to fork&quot;. Blockchain oversees the quality, safety and transport conditions of food products at all stages of production.</td>
<td>Conceptual.</td>
<td>No results proved yet.</td>
</tr>
<tr>
<td>Walmart and IBM &quot;Food Trust&quot; (Aitken, 2017)</td>
<td>Food</td>
<td>Blockchain implemented in the full supply chain, from growing, production, processing and distribution, to warehousing and retail. Blockchain improves food safety, as contaminated food can be tracked to find its origin and path in order to remove products from sales and distribution and stop further spread.</td>
<td>Pilot Project (August 2017). Tracking products from South America to retailers in the USA. Also piloted from a Chinese farm to a Chinese retailer (Popper and Lohr, 2017)</td>
<td>From first pilot, numerous important pieces of information such as expiration date of produce, shipping details, farm of origin were recorded on the Blockchain and immediately made available to interested parties (Hackius and Petersen, 2017)</td>
</tr>
<tr>
<td>Bext360 (2017)</td>
<td>Food</td>
<td>Blockchain applied in the complete supply chain, from growing, production, processing, distribution and warehousing to retail. The software-as-a-service platform aims to increase the supply chain transparency of goods from producer to consumer to validate whether the raw material was correctly labelled, ethically sourced and the parties supported by the purchase.</td>
<td>Proof-of-concept demonstrated in November 2017 by tracking coffee supply chain from crops in Uganda to retail shops in Colorado, USA</td>
<td>Benefits include: end-customers had the visibility of the location of the harvest, farmers' identification, quality rating of beans, pay-outs at every stage of the handover and the identity of purchasers (Vu, 2018)</td>
</tr>
<tr>
<td>Skuchain (2018)</td>
<td>Goods</td>
<td>Blockchain applied to the inventory procurement and inventory finances of shipped goods across countries. Blockchain and smart contracts are implemented to increase information-sharing and control in inventory procurement for the participants to the supply chain without compromising the privacy of sensitive data.</td>
<td>Pilot Project (2016). Cotton shipment from Houston to China in a CMA CGM ship. This first used-case was concerned with Blockchain in the digitisation of the inventory finance (Johnson, 2016)</td>
<td>Suppliers obtained working capital relief by not having to take on expensive financing. Buyers obtained a lower cost of goods in addition to holding inventory off the books for longer. Improved transparency considering the trade's agreement terms (Besnainou, 2017)</td>
</tr>
</tbody>
</table>

(continued)
<table>
<thead>
<tr>
<th>Case</th>
<th>Industry</th>
<th>Use of Blockchain within supply chain processes</th>
<th>Level of implementation</th>
<th>Results and benefits achieved</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maersk and IBM (Popper and Lohr, 2017)</td>
<td>Perishables logistics</td>
<td>Blockchain applied in the distribution and shipment across continents involving border, customs and port authorities. Blockchain tracks perishable items as they are shipped across continents. Multiple agencies participated in the projects, from supply chain partners to border, customs and port authorities</td>
<td>Two pilots Project (2016 and 2017) with the aim of going into production in 2019 (Hackius and Petersen, 2017)</td>
<td>Successful pilots: accurate container tracking and digitising their information, resulting in potential significant cost savings when deployed at full scale. All partners obtained full visibility into the container status</td>
</tr>
<tr>
<td>Modum (2017)</td>
<td>Health and safety compliance</td>
<td>Blockchain in supply chain focussed on the use of policy enforcement (use verification and payments of the assets’ emissions when they exceed environmental standards). Blockchain verifies environmental conditions by placing sensors around assets in transit, and checks results against the limits set out in smart contracts, to make sure standards of health and safety are respected</td>
<td>First pilot with 55 shipments. Second pilot with 500 shipments</td>
<td>No benefits published</td>
</tr>
<tr>
<td>Everledger (n.d.)</td>
<td>High-value assets (diamonds)</td>
<td>Blockchain applied in the complete supply chain, from mining, processing and distribution to retailing. Everledger Blockchain is a platform designed to track the provenance of high-value assets – diamonds – using smart contracts and IoT. It provides supply chain partners with tamper-proof records of an asset’s history, authenticity and ownership in an attempt to increase transparency and minimise fraud</td>
<td>Mature/fully implemented in the business model. Since April 2014, Blockchain registry of over 2.2m diamonds and adds around 100,000 a month (Aaron, 2018).</td>
<td>Successful implementation. Blockchain is an important part of the business model sold to customers and end-users</td>
</tr>
<tr>
<td>Toyota Financial Services (Naumoff, 2018)</td>
<td>Automotive</td>
<td>Blockchain applied to the distribution and finances across countries. This Blockchain tracks the ownership and state of auto parts as they are being transferred across countries and factories, as well as helping to prevent and cope with supply chain disruptions</td>
<td>Conceptual</td>
<td>na</td>
</tr>
</tbody>
</table>
tracking from origin to customer; in fact, its applications in the supply chain focus on traceability and source tracking (Kim and Laskowski, 2018).

Our literature research shows that Blockchain is applied to a variety of dimensions on supply chains, ranging from designing (growing), making and using to distributing and selling within single or multiple markets. Table I summarises the Blockchain applications in supply chains.

Currently, the foods and goods supply chains are leading Blockchain implementation. Cases demonstrate the implementation of Blockchain on the mainstream supply chains of cotton, coffee and other goods, which use Blockchain from the growing, producing to the processing, distribution and retailing stages of the supply chain. Four out of eight applied cases reported in the literature have been used in the foods and goods supply chains. The rest are applications on diverse sectors such as health and safety compliance, high-value assets and automotive. Their Blockchain applications are limited to the front end of the supply chains, as in distribution and retailing.

With the exception of the Everledger case, the maturity level of these Blockchain implementations is at the proof-of-concept stage (see Table I). Most of these successful pilot cases are waiting to be scaled up to understand and study the full potential of the Blockchain in their industrial contexts. Unfortunately, the majority of these studies lack depth of understanding of Blockchain’s effects on individual supply chain processes and operations.

To date, no academic studies have demonstrated the effects of Blockchain implementation on punctuated processes of the supply chain. Moreover, existing studies lack an understanding of the behaviours and effects of Blockchain’s implementation on existing operations, systems and capabilities.

2.3 The resource-based view (RBV) and the information processing theory (IPT)
In pursuit of higher levels of visibility in customer order management, Blockchain is seen as a promising technology to drive competitive advantage—operational efficiency and/or the creation of new revenue models. Blockchain is considered to be a firm’s capability that requires intrinsic analytical skills to programme and process information. Koh et al. (2016) argue that the RBV of firms provides a good starting point for conceptualising resource efficiency. According to the RBV, valuable, rare, inimitable and non-substitutable resources, supported by tacit skills and socially complex organisational processes, give firms their competitive advantage (Barney, 1991). However, the competitive advantage described in the RBV is essentially a product of efficient and sustainable production and utilisation of resources. In this case, maximisation of the use of Blockchain opens up the traceability and visibility of the customer order management process.

The RBV theory explains the adoption of the capabilities, skills, processes, technology and networks required to implement this digital platform in organisations to enhance their competitive advantage. The analysis of Blockchain through the RBV lenses reflects on the importance of not only evaluating the requisite resources and capacity that underpin the implementation and use of this digital technology, but also more importantly understanding the existing and missing skills and capabilities and the bridge between them. In bridging current and missing capabilities, the RBV provides the theoretical foundation for understanding the dynamic re-adaption of current capabilities (Barney, 1991; Koh et al., 2016).

In rapidly changing environments as today, the dynamic capabilities equip companies with the ability to integrate, build and reconfigure competencies to provide fast response to changes in their ecosystems (Teece, 2007). Sensing, sizing and transforming are foundations that distinguish dynamic capabilities. Sensing is the ability to identify and filter opportunities, e.g. customer innovation. Sizing is ability to assess and manage complementsors and co-specialisation for reconfiguring assets and processes to respond to
chosen opportunities. Transforming is the ability to learn, manage knowledge and decompose/decentralise structures to assist reconfiguration (Teece, 2007).

Blockchain is ultimately an information technology; thus, the IPT complements the understanding of the effects of Blockchain on supply chain processes. The IPT focuses on the link between environmental uncertainty (collaboration and information-sharing in supply chains), information processing (analytics capability) and the adaptation needs of organisations (organisational flexibility and market volatility). The information processing (the analytics capability) of an organisation is complemented with organisational flexibility. Higher levels of supply chain transparency, measured by supply–demand visibility, require stronger information processing, hereafter referred to as “analytics capabilities” (Srinivasan and Swink, 2017; Zhu et al., 2018). Blockchain technology provides significant visibility (Swan and de Filippi, 2017; Karafiloski and Mishev, 2017) but requires more specialised analytics capabilities within a given context. The analytics capabilities are continuously learnt and further developed/improved until they evolved within a particular context and become dynamic capabilities through the evolution of operational routines. The operational routines evolve through three learning mechanisms – experience accumulation, knowledge articulation and knowledge codification process (Zollo and Winter, 2002).

While the RBV provides a framework to understand the capabilities, skills and processes that must be built and re-adapted to drive competitive advantage through Blockchain in supply chain processes, the IPT advances the RBV as a potential dynamic capability by evaluating the information processing needs in Blockchain implementation. For instance, the competitiveness of private vs public Blockchain technologies could be evaluated using IPT; similarly, the evaluation of the consequent analytical capabilities required for each Blockchain technology. Greater transparency requires the use of public Blockchain technologies and complex analytics capabilities to manage environmental uncertainty (public competitiveness, collaboration and information-sharing), whereas private Blockchain enhances private supply chain competitiveness and therefore requires less complex analytical capabilities. From the IPT, Saberi et al. (2019) call for more studies to understand how supply chain processes are affected by the implementation of Blockchain technology.

Our research enquiry is also prompted by hearing repeated problems from industrialists associated with the lack of understanding of this digital technology. Common problems include pressure to become more digital and a lack of understanding about the benefits, opportunities, short- and long-term investments and the consequences for existing technologies. There is still a (mis)conception about more digital capabilities leading to higher competitive advantage. One IT director of a multinational organisation pointed out: “[…] it is difficult to see how Blockchain will change the way WE operate in our context? The tasks, the skills, the processes, etc. At the end of the day, it is difficult to gauge if Blockchain would be worth the investment[…]”. One supply chain manager added: “[…]Blockchain vendors are very keen to come and sell you their solutions (generally at astronomical prices), but they rarely explain in detail the impact of blockchain – in our processes, changes in operations, systems and costs”. Looking at these industry problems from an academic perspective, the confusion and lack of understanding are not surprising. The literature sheds very little light on the effects of Blockchain in the operations of a supply–demand chain. In response to this series of problems, we set up an experimental study. The objective of this study was to identify the effects of Blockchain on operations in a supply–demand chain.

In setting up the research, the first set of premises was the lack of investment in, and credibility of, Blockchain in the supply chain of an international industrial manufacturer. In formulating our first research question, we took the RBV theory and assumed a lack of
budget to acquire the Blockchain technology and the necessary skills and expertise. Therefore, our first question was:

*RQ1.* How could a Blockchain programme be coded with basic in-house resources and capabilities?

This led us to a subsequent line of enquiry:

*RQ2.* What are the effects of a distributed ledger platform – Blockchain – on the customer order management operations?

### 3. Method

The emerging nature of research on Blockchains in supply chains was formalised not long after 2015; however, few studies have been conducted beyond smart contracts in a supplier–provider context (Dickson, 2016; Vorabutra, 2016; Miu and Yang, 2018). Given the emerging nature of knowledge on this topic, an exploratory research method was chosen as the right methodological fit to investigate our line of enquiry (Edmondson and McManus, 2007). The exploratory research based on case studies enables an in-depth understanding of the phenomenon that could lead to theory development through elaboration (Eisenhardt, 1989; Ketokivi and Choi, 2014; Gehman et al., 2018). An in-depth case study method was selected as the foundational method for this research because the close proximity to the phenomenon and access to the data (Eisenhardt, 1989).

The logic of this research design revolved around our two research questions. In answering the first research question (*RQ1*), we built a “Pilot” and by programming an in-house Blockchain system and an interface to enable the end-user to communicate with the Blockchain programme.

To answer the second research question (*RQ2*), we used the Blockchain system that developed in *RQ1* and then we developed a series of simulations based on three different scenarios: “as it is” (current scenario without blockchain); “as it could be”, with the use of blockchain in the first year; and “as it could be”, having used Blockchain for five years. Table II summarises the methods and correspondent steps to answer each individual question.

#### 3.1 Unit of analysis

To add a precise understanding to the existing body of literature and to control our study, we decided to focus on the implementation and use of Blockchain in a particular process of...
the supply chain – customer order management. Customer order management was chosen as it is a process that cuts across several internal functions, but also interacts with external agents, such as customers. It is considered to be a good representation of what Blockchain can do in the wider supply chain and it is a process that lends itself to be scaled up and join other processes. Additionally, this process is often seen as the bottleneck to all the information flowing from the early processes of supply chain stages. Methodologically, narrowing the research context to customer order management, “a contained process”, not only helps us to reduce complexity but can also increase the validity and reliability of this study.

3.2 Data collection
The single in-depth case study (Yin, 2009) was supported with direct data collection from primary sources at the company case: interviews, shadowing orders, mapping processes, skills and times, and a validation workshop. Secondary sources of data included: customer order reports, customer order modification reports and databases from the last 12 months, task descriptions, ERP reports, customer requirements and monthly/quarterly reports. Secondary data were used to complement and triangulate sources with primary data. The triangulation of data strengthened the validity and reliability of this research.

The primary data collection consisted of more than 63 h of direct contact:

1. Face-to-face interviews with four out of six account coordinators (ACs) for the customer order management department of the company, the head of supply chain and the head of digital transformation.

2. Shadowing customer orders by direct observation: the researchers followed a sample of orders through the process, mapping the activities and timing them.

The other data collection method that was used over 11 months of the study included:

1. Active remote dyadic (back-and-forth) interactions. For example, multiple questions and clarifications over phone, e-mail and Skype.

2. Two validation workshops with four ACs.

3.3 Simulation-based approach and theory elaboration
A simulation-based approach was adopted to obtain a closer, more significant and detailed understanding of the application and effects of this digital technology in the operations of this in-depth case study. Simulation provides an unparalleled experimentation platform to add realism through a dynamic and systematic set of experimentation (Weick, 1989).

To systematically elaborate theory, this research was guided by the seven-step roadmap for developing theory using a simulation method (Davis et al., 2007): it started with the definition of the research question (RQ2). Second, the RBV theory was selected to provide a theoretical ground to explain and compare the findings. Third, the discrete event simulation approach with Simul8 was chosen because it provides detailed analysis of transactions (which is core to answering RQ2). Fourth and fifth, to create and verify the computational representations and their correspondent logic, the individual process maps were developed to understand the customer order management process (the phenomenon under study). These include placing and amending orders maps for the current state “as it is” (without blockchain). Then, the maps were verified by every AC, and improvements were continuously made, until they reached a full consensus – in representations and logic. By using a simulation-based approach to build and elaborate theory, a strong emphasis
was placed on strengthening the rigour of these computational representations and their correspondent logic, which strengthened the internal validity of this research. Sixth, building on strong representations already verified, two further scenarios were developed and tested—“as it could be”, with the use of Blockchain in the first year, and “as it could be”, having used Blockchain for five years. Finally, these last scenarios were verified using precise empirical data (Davis et al., 2007). The findings of the simulation study are shown in the discussion section. The application of Davis, Eisenhardt and Bingham’s road map for developing theory into our simulation and case adds realism and strengthens the analytical generalisability of the findings and potentially elaborates or extends a theory (Ketokivi and Choi, 2014).

This is a theory-elaboration type of research. In elaborating theory, the focus is on the contextualised logic of a general theory. It reconciles the general with the particular, in our case Blockchain, in the light of the RBV and dynamic capabilities within a supply–demand context. Unlike theory-building, theory-elaboration does not anticipate the empirical findings—propositions or hypotheses—but elaborates them through the analyses of the findings (Ketokivi and Choi, 2014).

To get a complete understanding, analysis and evaluation of the development and implementation of Blockchain in a supply chain process, an in-depth case study is adopted. Differently from other methods such as surveys, in-depth cases could provide access to processes, orders, transactions and customers’ demands, among others (Eisenhardt, 1989). Welsh and Lyons (2001) add “outcomes from individual case studies are not statistically generalisable but analytically generalizable”. The case is a multinational company that has sites, customers and suppliers around the globe, therefore having interactions across parts of the supply chain in different cultural contexts.

4. FossorCo
4.1 Company background

Our study is set in an international industrial manufacturing company specialising in heavy-assets equipment.

At FossorCo (disguised name), an ERP, an in-house collaboration tool, an electronic data interchange (EDI), Excel sheets, customer portals, e-mails, fax and phone calls are all used to manage customer orders. The associated fragmentation and lack of standardisation result in a slow and inefficient system that is prone to frequent mistakes. Customer orders are highly manual and time-consuming; hence, there is a high investment and operating cost associated with human resources. Additionally, as a result of the laborious manual activities required for each order, processing and response times are long.

The scope of the study is limited to the stream of orders as follows:

- the internal customer transmits an order request to the order management department;
- the order management department checks for and resolves any problems and then approves the order request; and
- the order management department relays order specifications to the production team, which proceeds to assemble the components required into the desired product.

4.2 Process maps

The current customer order management typically starts with the customer placing an order. The supplier then either approves or declines the order and provides a response to the customer. If the order is approved, the customer may ask to modify the order and does so by submitting a request to the supplier. Thus, the supplier either approves or declines the modification requested depending on how well the modification meets a specific rule set
(e.g. the volume fluctuations). Finally, closing this loop, a response is provided to the customer. Often customers make more than one modification to their initial orders; hence, there is an iteration process called order amendment. To simplify the customer order mapping, this was split into two: first, a map for placing orders, and a subsequent one for amending orders.

The “current placing orders process map” has 36 steps (Figure 1), while the “current amend-orders process” consists of 20 steps. The process maps for placing orders are included as examples in this paper, but the whole study includes the quantification and analyses both – placing and amending orders.

An order can be modified by changing the quantity or the shipment date. To make these changes, there is an established three-rule process set by FossorCo: first, the frozen period: two weeks before the shipment date, when no further changes can be made. Second, the volume fluctuation allowance is the percentage by which a modified order quantity can deviate from the initial order quantity. Third, the recommended fluctuation threshold is the percentage deviation between the modified order quantity and initial order quantity that the supplier recommends. For instance, an order is approved if the new quantity falls within the volume fluctuation allowance.

4.3 Identified problems in the current processes

Looking into the problem further, several key issues are evident in mapping the scenario:

(1) Amending orders can take many days to be approved. Inefficient communication lines and inadequate scenario-handlers result in long periods of time elapsing before an amendment to an order is approved and modified.

(2) Multiple communication channels to place or amend an order, for example, fax, e-mail, phone. A lack of standardisation causes inefficiencies in the system, such as discrepancies in the data collected and the possibility of errors further down the line. This substantially increases customer frustrations and the likelihood of disputes between customer and supplier. For example, accuracy and traceability of modifications are highly unreliable.

(3) Multiple rule sets for different orders/customers: visibility is an issue, as customers do not see the rule sets that are in place when an order or modification goes through the approval process.

(4) Extensive manual work: multiple customers and a lot of manual work involved.

(5) Multiple external customers: they need to feel they are in control, which is impossible with the current process.

(6) Prolonged grief: grief refers to the inability to process an order as a result of incomplete or incorrect information. It is the source of many discussions and a significant drain of time for ACs.

5. Designing and implementing the FossorCo Blockchain

In preparation for programming and implementing the Blockchain for FossorCo, three foundational phases need to be developed. The first phase is the selection of technologies for the company’s and clients’ needs. Second, there is building the architecture. The third involves designing the Blockchain interactions or information flow for placing and amending orders. To secure the programming quality, the “test-driven development methodology” was followed (Dingsøyr et al., 2012). Table III summarises these three phases and explains the processes and results.
New order process

Other departments
Dispatch team
Production
MFG
ERP
Account coordinator (order management)
MRC collaboration tool

(Mirror of customer's MRP)
Internal customer

Ciprian  |  7 July 2018

Conference calls
to resolve grief

Conference calls
to resolve grief

Need for part arises
Customer places order in MRC or in customer portal

36 updates a week

MRC collaboration tool

Download and store excel file with data for audit purposes

Discrete
About 10 customers, 286 orders
EDI, Scheduled or Discrete Customer?

Customer?
EDl 1 customer, 60 orders

235 customers, 990 orders

MRC or customer portal/email?

20 customers
Access and check MRC 4–12 times a year

All others
Check
Copy data from MRC to prepare for input in MFG

Manual input in MFG

Customer acknowledgement required?

MFG ERP tool

Production receives order from MFG
Manufactures and assembles product

Receives order acknowledgement
Receives shipping notice
Receives part
Customer order fulfilled

Manual monitoring of finished goods
Manual customer that part is ready to ship
Ships part
2–8 weeks

95%
5%
No

Order confirmation sent as excel, together with any comments if necessary

No action required

Yes

1–3 hrs

Resolve grief

4–8 hrs

over 2 days

70%
30%
Daily
Weekly: check once a week

MRP of customer updated weekly or daily?

Check an additional 1 or 2 times a week

EDI failure?

Yes

5 min

20 min

No

Resolve grief

Manual input into MFG

Check MRC

Up to 5 min

About 30 min a day for 1–5 days

Figures 5–20 min

15 customers 1 min

Manual monitoring of finished goods

Manual customer that part is ready to ship
Ships part
2–8 weeks

95%
5%
No

Order confirmation sent as excel, together with any comments if necessary

No action required

Yes

1–3 hrs

Resolve grief

4–8 hrs

over 2 days

70%
30%
Daily
Weekly: check once a week

MRP of customer updated weekly or daily?

Check an additional 1 or 2 times a week

EDI failure?

Yes

5 min

20 min

No

Resolve grief

Email customer to acknowledge order

Conference calls to resolve grief

Check MRC

Up to 5 min

About 30 min a day for 1–5 days

Figure 1. Current placing orders process map
5.1 Coding the Blockchain

In maximising the accuracy and efficiency of coding, we used the “test-driven development” (TDD) methodology. By following a continuous cycle – coding, testing and refactoring – its unit testing verifies individual units of code to ensure that they work as intended. Thus, this methodology allows external developers to easily understand the codebase (Dingsøyr et al., 2012).

The final version of the Blockchain-enabled customer order management system for FossorCo (back-end and front-end applications) has more than 5,000 line codes and took 15 iterations. Two programmers were involved: one focussed on programming the Blockchain (back end) and the second on the customer interface (front end).

The customer interface (front end), coded in React, is designed as a straightforward dashboard for collecting customer data (place/modify orders), feeding the Blockchain (back end) and presenting the status of orders. This interface gives a complete overview
5.2 Using the Blockchain-enabled customer order management system

The integration of the back-end with the front-end programme builds the “Blockchain-enabled customer order management system”, from now on referred to as the “blockchain solution”. When a new customer organisation is added to the Blockchain solution, predetermined access rights for writing, viewing and/or accessing information to this Blockchain solution are set by the customer’s organisation and enabled (programmed) by FossorCo.

To achieve a fast and simple status of orders and their traceability history, we designed the dashboards (see Figure 2) with direct company input. The Blockchain solution allows FossorCo’s customers to have access to clear informative dashboards. The dashboards open the visibility of orders and their corresponding status. More importantly, they show the “tamper-proof” traceability history of orders, including: what changes were requested, when the changes were requested, who from the customer’s organisation placed/amended an order and the AC number. Traceability is a unique differentiator of the Blockchain among other databases; Figure 2 shows an example of the placed-order dashboard.

6. Findings

The Blockchain solution impacts the operations of the firm’s customer order management process. Thus, it is possible to draw the following findings:

(1) Improved the order management process efficiency: the Blockchain solution considerably improved processing time. While normally it would take two to four days for an order or modification to be processed and approved, the Blockchain solution leads to instantaneous, automatic approval times (including the verification time against set rules) and a reduction in the amount of griefs, which improved efficiency – from two to four days to less than 1 min.

![Figure 2. Placed order dashboard](image-url)
Improved traceability of order placed and amended: the Blockchain solution improved the traceability of orders placed/amended at FossorCo. The company never had this open and detailed traceability available for all its transactions in the past. This was achieved through the Access Control file, which secures the integrity of the data and controls and records the access of participants into the Blockchain solution. Now it is impossible for someone to alter previous transactions. Therefore, transactions displayed on a dashboard are traceable back to participants, with date/time and detailed modifications – quantities, specifications, approvals and confirmations (Figure 2).

Improved the visibility of the order management process: the visibility of data has been increased and safely opened to FossorCo employees, and its customers’ employees in the supply chain, by predetermined access rights for writing, viewing and/or accessing information. These rights were previously set by the customer’s organisation and enabled in the Blockchain solution of the firm.

It has been proved that the Blockchain solution can be programmed and used to solve real supply chain problems, particularly in the customer order management process, with relatively basic resources and capacity for further scalability. Coming back to our first research question, the Blockchain solution was programmed and built with simple resources (free-to-test applications) and basic programming skills. It is successfully working in the FossorCo scenario between provider and customers. This Blockchain solution was built with scope for scalability to accommodate more types of product and volumes within a large business context. With the front-end and back-end working seamlessly, it shows that Hyperledger Composer can be used to build a robust Blockchain network on the Hyperledger Fabric runtime, while React was used to create an aesthetically pleasing customer/user interface. The technology and programming choices, such as the use of the private type of Blockchain, Hyperledger Composer and Hyperledger Fabric, and the TDD methodology, among others, were made to lower learning entry barriers, reduce implementation costs, secure scalability and increase safety and usability.

From resources to dynamic capabilities: theory elaboration: during the development of Blockchain at the FossorCo’s customer order management, three types of resources emerged – Blockchain technology, knowledge and other resources (see Table IV). Our analysis shows that the more these resources interact and bundle with others, more they evolved into a competitive valuable resource. For instance, the “tacit and codified knowledge of customers consumption behaviours” formed a complementary bundle with the “Blockchain design – platform and subroutines”. Because these resources became intertwined and depended on each other, they resulted to be more specialised and rooted into the needs of the company. As a result, this bundled evolved and developed a new RVB competitive valuable capability, defined by Barney (1991) as rare, valuable, inimitable, non-substitutable. It is called “Blockchain logic & routines that identify and filter competitive opportunities based on customers consumption behaviours and supply chain flexibility knowledge”.

Later, this RBV competitive capability integrates and interacts with other emerging RBV competitive capability – called “Rules’ transformation process based on emerging customers’ demands”; as a result, these two evolved into a dynamic capability – called “Dynamic adaptation of rules and routines by active utilization of new/old learnings. This new dynamic capability has the ability to sense changes into customer consumption patterns through the monitoring of special customer’s
requests to their orders. Then, it seizes the opportunities according to the customer loyalty and supply chain flexibility to accommodate the customer’s requests. Finally, it transforms, adapts or creates an existing or new rule to deal with this type of customer’s requests like this in future. Therefore, a new Blockchain logic and subroutine are created to process the order (Teece, 2007). In a way, the rules and Blockchain’s logic and subroutines learn and adapt in response to new issues in the customer demand, similarly to Zollo and Winter’s (2002) deliberate learning through dynamic capabilities. This evolution from resources to dynamic capabilities is illustrated in Table IV.

### Table IV. Evolution from resources to dynamic capabilities

<table>
<thead>
<tr>
<th>Resources</th>
<th>Bundled resources: integration</th>
<th>RBV competitive valuable capabilities: rare, valuable, imitable, non-substitutable</th>
<th>Dynamic capabilities: sensing, sizing, transforming</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blockchain (BC)</td>
<td>• In-house Blockchain programming skills</td>
<td>• Blockchain flexible design: the platform surrounded by independent sub-routines for easy programming of new rules or deleting/freezing/unfreezing existing ones</td>
<td>• BC logic and routines that identify and filter competitive opportunities based on customers consumption behaviours and supply chain flexibility knowledge. This is the Blockchain analytics capability</td>
</tr>
<tr>
<td></td>
<td>• Blockchain technology: back-end and front-end</td>
<td></td>
<td>• Dynamic adaptation of rules and routines by active utilization of new/old learnings based on the evolution of customer demands – Dynamic learning. This leads to the evolution of more sophisticated rules and BC subroutines</td>
</tr>
<tr>
<td></td>
<td>• Tailored interactive Blockchain dashboards</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Knowledge</td>
<td>• Tacit and codified knowledge of customers’ consumption behaviours</td>
<td></td>
<td>• Rules’ transformation process based on emerging customers’ demands by restructuring and integrating existing rules, and building new ones, which make the process highly customised to a particular company and its customers. This is the organization’s analytics capability</td>
</tr>
<tr>
<td></td>
<td>• Customer knowledge</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Account coordinators’ experience: managing orders</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Knowledge of downstream supply chain’s flexibility</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other resources</td>
<td>• IT infrastructure</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Data storage</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Account coordinators</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>• COM manager</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

7. Discussions based on simulation analyses

7.1 Blockchain effects: a simulation-based approach

The Blockchain solution built for FossorCo improved the processing time for placing and amending orders. While the processing-time reductions are significant, we do not know exactly what the implications are for the operations in the customer order
management process. Furthering exploration of the effects of the Blockchain, our second research question is:

**RQ2.** What are these Blockchain effects on the operations of the customer order management process of FossorCo?

To answer this question, the simulation of the customer order management process was built in Simul8. Simul8 software was selected because it:

1. is accurate, robust and reliable;
2. requires basic analytical skills to interpret data;
3. is easy to programme for maintaining/updating and enhancing the rule sets to manage griefs; and
4. is not astronomically expensive.

These four selection criteria are particularly important for the purposes of capability-building, training and learning-transfer to the participating company’s employees. From the IPT theory, the simple information processing plays a key role in securing the sustainability of the Blockchain in the hands of employees.

In developing the simulation on the current-state (without Blockchain) scenario for placing and amending orders, we used four key parameters: the number of new orders by type (scheduled, discrete or EDI) and amended orders; the number of placed and amended orders entering the system; the average time for processing of each order’s task; and the average usage of ACs.

Using the process maps (Figures 1 and 2) and process specifications from interviews and shadowing, the list of assumptions to simulate scenarios was built. Assumptions include:

1. availability: ACs at 90 per cent efficiency, minus 20 per cent of their time spent on administrative tasks;
2. batching: orders arrive in batches of approximately equal size;
3. FIFO: orders are dealt with on a first-come, first-served basis;
4. switching time: 2 min between one order to another; and
5. fungibility: a job can be picked up by any AC.

The scenarios with the Blockchain solution implemented at one year and after five years in operation were simulated (Figure 3), as well as the current-state scenario (without Blockchain) (Figure 4).

The simulation ran for one business week, and a trial of 12 replications had its results aggregated to estimate an average value with a higher degree of statistical reliability. The results of the current-state scenario are shown in Table V (key results are highlighted).

The results of the current-state scenario show that the average time for placing an order in the system is 380.796 min, and for amending an order, it is 515.348 min. This analysis also shows that 5.25 ACs are needed to deal with the number of orders coming through, indicating the validity of the model, since, in reality, 6 ACs are employed. The discrepancy of 12 per cent between 5.25 and 6 can be attributed to the simplifying assumptions previously mentioned. The same analysis is performed for the initial Blockchain scenario at one year and for the mature Blockchain-state scenario at five years.

### 7.2 Simulation analysis

Table VI compares and contrasts the effects on operations in three scenarios: current-state (with no Blockchain) scenario, initial Blockchain state (one year) and mature Blockchain
The results of the simulation show that there is a 65 per cent reduction in the processing time for placing new orders and a 60 per cent reduction in the processing time for order amends from the current state to the mature Blockchain state.

The average time in the system for processing an order dropped from 515.3 to 22.1 min (493.3 min saved). Similarly, the average time for amending an order dropped from 380.8 to 132.9 min, saving 247.9 min.

Instead of the 5.2 (6) ACs required in the current (without Blockchain) scenario, the analyses of the Blockchain mature scenario recommend only 2.2. Assuming a similar discrepancy between the real world and the model of 12 per cent, as picked up for the current state, the number increases to 2.7, which can be rounded up to 3. Hence, there is a 50 per cent reduction in the workload of ACs.

The findings of this study show the significant impact of Blockchain on customer order management. It reduces the size of the department by 50 per cent, as well as the processing times for orders by 60–65 per cent.

Sensitivity analysis was carried out in the model and it was demonstrated that the system is robust to deal with variability in the number of orders processed, as well as their interarrival rate. The model is sensitive to the processing time of amending orders (as it would be expected).
Table V. Aggregated results of a trial of 12 one-week simulations of the current-state scenario

| Simulation object | Performance measure | Run 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | -2SD | Average | 95% |
|-------------------|----------------------|-----|---|---|---|---|---|---|---|---|----|----|----|-----|-------|-----|-----|
| Scheduled order   | Number entered       | 1   | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1   | 1     | 1   |
|                  | Number completed jobs| 25  | 37 | 31 | 27 | 32 | 34 | 33 | 40 | 34 | 35 | 31 | 29 | 26.88 | 32.333 | 34.978 |
| Discrete order    | Number entered       | 7   | 10| 3  | 6  | 5  | 7  | 8  | 10 | 11 | 6  | 7  | 5  | 5.4998 | 7.3333 | 9.1667 |
| Account coordinator | Minimum %            | 114.34 | 110.36 | 107.46 | 104.64 | 110.025 | 107.923 | 115.098 | 112.734 | 108.097 | 113.253 | 109.945 | 110.354 | 108.512 | 110.503 | 100 |
|                  | Maximum %            | 0.00912 | 0.00711 | 0.00816 | 0.00746 | 0.00898 | 0.00991 | 0.01053 | 0.01092 | 0.01116 | 0.01095 | 0.01094 | 0.01094 | 0.01179 | 0.01191 | 100 |
|                  | Minimum use          | 0   | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
|                  | Maximum use          | 5.42703 | 5.39117 | 5.10483 | 4.79115 | 5.24983 | 5.14501 | 5.02052 | 5.10352 | 5.13032 | 5.36318 | 5.22302 | 5.24052 | 5.16464 | 5.24946 | 5.34413 |
|                  | % in system less than time limit Maximum use | 97.2222 | 97.6 | 100 | 95.3236 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 95.969 | 100 |
|                  | % in system less than time limit Minimum use | 100 | 71.4599 | 100 | 95 | 100 | 100 | 97.15429 | 80 | 75 | 130 | 93.3033 | 100 | 88.894 | 92.7241 | 95.9501 |
| Average time in system | 32.2170 | 28.3576 | 23.5133 | 747.2298 | 304.304 | 218.435 | 399.246 | 233.247 | 598.417 | 357.491 | 401.496 | 337.246 | 296.305 | 385.796 | 403.382 |
|                  | Maximum time in system | 597.844 | 3,273.39 | 612.328 | 3,105.67 | 769.435 | 546.394 | 344.426 | 293.952 | 1,127.41 | 884.77 | 747.183 | 941.51 | 1,055.81 | 1,105.81 |
|                  | SD of                | 300.234 | 335.033 | 155.198 | 381.812 | 216.853 | 130.774 | 234.771 | 196.648 | 330.28 | 205.19 | 282.191 | 209.099 | 207.079 | 252.438 | 300.797 |
|                  | New order complete   | 18.778 | 120.831 | 69.3763 | 145.185 | 50.6999 | 152.971 | 135.175 | 77.1499 | 135.091 | 41.1831 | 84.4248 | 47.9202 | 73.5333 | 97.2704 | 120.709 |
|                  | Minimum time in system | 419.72 | 728.477 | 421.407 | 486.619 | 287.461 | 421.829 | 548.936 | 632.157 | 71.1309 | 532.418 | 489.008 | 457.339 | 420.74 | 515.348 | 603.909 |
| Average time in system | 899.074 | 1,382.15 | 751.974 | 97.489 | 697.174 | 751.462 | 1,018.49 | 1,463.42 | 1,815.73 | 571.749 | 1,075.73 | 952.967 | 637.181 | 1,069.61 | 1,097.72 |
|                  | Maximum time in system | 1,164.79 | 2,458.14 | 224.745 | 270.372 | 189.547 | 1,473.34 | 2,023.634 | 3,841.292 | 4,034.047 | 2,422,881 | 239.736 | 241.544 | 252.893 | 275.778 | 348.944 |
|                  | SD of                | 1,164.79 | 2,458.14 | 224.745 | 270.372 | 189.547 | 1,473.34 | 2,023.634 | 3,841.292 | 4,034.047 | 2,422,881 | 239.736 | 241.544 | 252.893 | 275.778 | 348.944 |

Note: The table includes performance measures such as number entered, number completed jobs, minimum/maximum times, and average time in system, among others, for different simulation objects like EDI customer, number in the system, and so on. The values areaveraged across the 12 simulations to provide a comprehensive view of the current-state scenario.
7.3 Effects of Blockchain on the customer order management operations
In response to our second research question, “What are the effects of Blockchain in customer order management?”, the evaluation of the simulation-based scenarios reveals a reduction in the number of operations. In the placing-an-order process, the current (without the Blockchain) scenario has 21 operations and 20 data storage. The data storage keeps orders waiting to be processed. Conversely, the Blockchain reduced the scenario from 21 to 6 operations and from 20 data storage to only 2. The process for placing a new order is simplified and lean.

Blockchain triggers major reductions in the number of operations and increases their speed. The process for placing a new order, from the moment the customer places the order until the order gets approved and the customer is notified, is analysed under two different scenarios – one without Blockchain, called the “current scenario”, and the other “with Blockchain scenario”:

1. In the current (without Blockchain) scenario: the process starts with the customer placing an order on the customer interface or on the MRC. Depending on the customer, the order could be an EDI, a scheduled or a discrete order. Each type follows a different sub-process: EDI processes 4.5 per cent of the total orders coming from only one customer (representing 2 per cent of total customers); scheduled processes 74 per cent of the total orders coming from 76 per cent of the total customers; and, finally, discrete processes 22 per cent of the total orders coming from 22 per cent of the total customers. These orders are managed following one of these sub-processes:

   - EDI orders: there is an activity question, “Is there an EDI failure?” If yes, the order goes to grief until the dispute has been resolved; generally, this activity takes 4–8 h over 2 days. For every 60 orders through EDI, up to 12 failures occur. Once the dispute has been resolved, it continues the normal process until no more actions are required, but the customer does not receive a notification.
   - Discrete orders: this process starts with the AC manually checking the MRC (the interface for customers to place orders), which generally takes between 5 and 20 min. If there is a grief (60 per cent of the discrete/scheduled orders have griefs), the AC e-mails the customer to acknowledge the order (approx. 10 min per order). Then the grief is resolved with a series of conference calls that
could last 30 min per day for up to five days. Once the griefs have been resolved or, in the absence of any griefs, there is a 5-min manual task per order for the AC to input the order into the MFG (a system used to communicate orders and specifications to the manufacturing department).

- Scheduled orders: this starts when the AC checks the orders coming to the MRC portal via e-mail (serves 20 customers) or the customer interface (serves 15 customers). Each check takes approximately 5 min. For those customers with MRC updated daily, the AC makes two extra checks per week. Once all the orders have been checked, the AC copies data from the MRC to prepare the input data that will go into the MFG. For discrete and scheduled orders, the AC continues to process the orders by manually recording the orders in the MFG. Once the order has been placed in the MFG, the next action is to ask if customer acknowledgement is required; the majority of times (95 per cent) the order confirmation is formalised in an Excel sheet, which takes approximately 1–3 h. Then the order confirmation is sent to the customer by e-mail. In parallel, the MFG orders are stored in the MRG ERP tool.

The analysis of this current (without Blockchain) scenario shows that processing an order continuously requires manual work/input from the AC, particularly in checking the order status, dealing with griefs and copying data from one system to another, or even to an Excel sheet. In addition, the process is extended by the numerous storage points. These recurring checks, multiple manual inputs and duplications of data explain why an order spends a long time in the system. As the simulation shows, the average time of an order in the system is 515.3 min.

(2) In the Blockchain scenario: the process starts with the customer placing the order in the customer interface (portal), and the entry interface automatically uploads the order in Blockchain. The following step questions whether the order contains a grief (e.g. missing data, incorrect data, unique requirement). If there is grief, a conference call is performed, and, as a result of the call, the dispute is resolved and finally the order is approved and stored in Blockchain. If there is no grief, the order is approved directly and stored in Blockchain.

The analysis of the Blockchain scenario shows that, as a result of the set of rules programmed in the Blockchain for processing orders, the responses are faster, and therefore the average time of an order in the system is reduced from 515.3 to 22.1 min.

This study shows that the Blockchain automatically processes the orders through a series of advanced rules already predefined and set in the Blockchain programme. The more advanced the rules are, the more griefs are automatically dealt with by the Blockchain, and, consequently, the less time an order spends in the system. Finally, customers receive a notification of the order recorded, “including the order’s traceable history”. Occasionally, griefs with unique customer requirements will need to be solved by the AC and then automatically accepted into the Blockchain.

The Blockchain dynamically incorporates new learning “capability” – from the solutions provided to new griefs – into the set of rules, which makes the Blockchain smarter and more customised, and, consequently, faster in its response time.

By comparing the simulations between the current and the Blockchain scenarios, the effects of Blockchain on customer order management show an overall increase in operational efficiency in the customer order management processes by:

- reducing the number of operations needed to place or amend orders, consequently making the customer order management process simpler and leaner: Blockchain reduced the process for placing orders from 21 to 6 operations.
• Reducing the average time of orders in the system: 493.3 min were saved for placing orders.
• Showing the traceability of orders through the user interface via dashboards.
• Improving visibility to various supply chain participants through the written rights set on Blockchain.
• Consolidating a single point of entry for placing and amending orders.
• Removing the multiple checkpoints such as MRC, EDI, customer portal and e-mails.
• Reducing manual input into the orders.
• Eliminating duplications of report status such as Excel sheets.
• Decreasing the number of storage points.
• Reducing the workload of ACs by 50 per cent: three instead of six ACs were required.
• Reducing the quantity of griefs.
• Enhancing the set of advanced rules for processing griefs. Continuous improvements in the set rules, maximising the active utilisation of new learning, therefore making the Blockchain operations more sustainable in future.

8. Conclusions
This paper has investigated the effect of Blockchain in the customer order management process of a supply chain. There is an emerging, fast-growing body of literature on Blockchain. The growing interest in Blockchain calls for more research, particularly on finances, cryptocurrencies and smart contracts (Avital et al., 2016; Risius and Spohrer, 2017; Nowiński and Kozma, 2017). McLannahan (2016) highlights the need to further understand the feasibility and benefits of this digital technology. This research demonstrates the effects of Blockchain on the efficiency gains, human-processing savings and major reductions in the number and speed of operations in the customer order management process.

Kim and Laskowski (2018), Brennan et al. (2015) and Carter and Koh (2018) argue that there is a need for Blockchain applications in the supply chain with a particular focus on traceability and source tracking. This research provides a detailed description of Blockchain implementation in an industrial supply chain context. The main benefits of a distributed ledger technology are traceability, visibility and security transactions (Palfreyman, 2016; Carter and Koh, 2018). This study contributes to the supply chain literature by demonstrating, from the technology and information systems' perspective, how traceability, visibility and security of transactions are designed and implemented. It demonstrates the selection of front-end to back-end technologies for programming the Blockchain, in addition to the interface used to display the traceability of orders and manage the visibility rights.

8.1 Theoretical contributions
First, this study observed that in order to avoid failure in the gathering and managing of customer orders, the company currently relay on the manual input, duplication of data and multiple checkpoints. This observation is important because of the focusses on the RBV theory particularly on the capabilities, resources and skills (Barney, 1991). The RBV theory applied to Blockchain reflects on the importance of setting the required resources and capacity that underpin an implementation and use of this digital technology. We demonstrated that the RBV provides a theoretical foundation to understand the required re-adaption of current capabilities in pursuit of a better competitive position (Carter and Koh, 2018).
Blockchain fundamentally changes the way people operate by emigrating from core manual capabilities to new core capabilities – e.g. data analytics, ruleset programming.

This research contributes to RBV theory (Barney, 1991) by demonstrating two RBV competitive valuable capabilities that an organisation develops when implementing and using Blockchain in a supply–demand process such as, the customer order management process (see Table IV). These two RBV competitive valuable capabilities – rare, valuable, inimitable, non-substitutable – are: first, “The Blockchain logic and routines” that identify and filter competitive opportunities based on customers consumption behaviours and supply chain flexibility knowledge. Second, “The Rules’ transformation process” based on emerging customers’ demands by restructuring and integrating existing rules, and building new ones, which make the process highly customised to a particular company and its customers’.

This study also contributes to the dynamic capability theory (Teece, 2007) by demonstrating a new dynamic capability – the dynamic adaptation of rules and routines by active utilisation of new/old learnings based on the evolution of customer demands. This is based on the two RBV competitive valuable capabilities and it leads to the evolution of more sophisticated rules and Blockchain subroutines.

In this way, the framework presented in Table IV proposes which resources are needed for a Blockchain implementation, how they can be combined (bundled) to create RVIN (logic and routines) resources and results in the dynamic capability.

This research demonstrates through the simulation analyses that these two new RBV competitive valuable capabilities and the new dynamic capability maximise the resource efficiency of “Blockchain customer order management operations” (Barney, 1991; Koh et al., 2016). These efficiency improvements include: a reduction in the processing time for placing orders by 65 per cent, a reduction for amending orders by 60 per cent from the current state to the mature Blockchain state and human-processing savings by around 50 per cent.

Second, this research argues that the two RBV competitive valuable capabilities identified in this research contribute to the IPT particularly, to the information processing “analytics capability” by contextualising the nature of the analytics in the intersection between Blockchain and supply chain processes. The first RBV competitive capability, “The Blockchain logic and routines” is, in principle, the ‘Blockchain’ analytics capability”. This identifies and filters competitive opportunities based on customers consumption behaviours and supply chain flexibility knowledge. The second RBV capability, “The Rules’ transformation process”, is the “Organization’s analytics capability”. It is based on emerging customers’ demands by restructuring and integrating existing rules, and building new ones. Both the Blockchain and the organisation analytics capabilities are continuously improved and evolve though three learning mechanisms – experience accumulation, knowledge articulation and knowledge codification process (Zollo and Winter, 2002).

From the IPT angle, Saberi et al. (2019) call for more studies to understand how supply chain processes are affected by the implementation of Blockchain technology. The analytics are critical capabilities to maximise the utilisation and integration of resources in supply–demand processes (Flynn et al., 2010). Swan and de Filippi (2017) highlight that Blockchain implementation increases information-sharing among supply chain partners. Srinivasan and Swink (2017) and Zhu et al. (2018) suggest that higher levels of supply chain transparency and visibility require a stronger analytics capability. Blockchain provides significant visibility. Finally, regarding resource efficiency, the efficient use of data from the Blockchain demonstrates faster and cheaper, more efficient and reliable traceable operations.

Third, this research contributes to the supply chain theory by taking the Blockchain principles – largely applied in the financial context (e.g. cryptocurrencies and Bitcoin) – and applying them to understand how they apply to operations and management processes, particularly in customer order management.
8.2 Managerial implications

As can be seen from the Blockchain implementation and the simulation analysis, this research has illustrated the path to Blockchain implementation for the customer order management process. This paper provides clear guidelines for managers to implement Blockchain in COM. The fact that the system was developed in-house, and at a relatively low cost, which shows managers that they can pilot the introduction of Blockchain to their processes without committing to large investments. The framework presented in Table IV guides managers to identify the resources needed and how to combine them to achieve a successful Blockchain implementation. Although the process tested in this case was the customer order management process, we argue that the approach can be extended to other supply chain processes (e.g. product development, order fulfilment, delivery) since they form part of the extended supply chain processes and there is interaction between the activities of these processes and the COM process.

Based on the dynamic fast-learning environment enabled by the Blockchain, there is much that management can do. As Teece (2007) suggests, “firms need to simultaneously design processes and structures to support the re-adaptation, innovation and transformation of business processes and structures designed for an earlier period”, particularly to accommodate the new learning from changing customer consumption behaviours in an increasingly digital era. Using the Blockchain platform and previous customer consumption behaviour analyses, managers could set advanced customised rules in the customer order management routines to provide faster responses to customers.

8.3 Limitations

This research is based on a single in-depth case that has the scope to be tested in future in different contexts. However, we argue that the results are generalisable to other processes in the supply chain since some of the activities will be common across processes (raising, amending and processing orders) Future research needs to confirm this by studying the impact of Blockchain visibility on different supply chain processes and actors – including customers and OEM, providers and others.

References


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