



Multistage implementation framework for smart supply chain management under industry 4.0



Xue-Feng Shao^a, Wei Liu^{a,*}, Yi Li^a, Hassan Rauf Chaudhry^b, Xiao-Guang Yue^c

^a Discipline of International Business, The University of Sydney, Sydney, NSW 2006, Australia

^b Suleman Dawood School of Business, Lahore University of Management Sciences, Lahore, Pakistan

^c Department of Computer Science and Engineering, School of Sciences, European University Cyprus, Nicosia 1516, Cyprus

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ABSTRACT

The true potential of the industry 4.0, which is a byproduct of the fourth industrial revolution, cannot be actually realized. This is, of course true, until the smart factories in the supply chains get connected to each other, with their systems and the machines linked to a common networking system. The last few years have experienced an increase in the adoption and acceptance of the industry 4.0's components. However, the next stage of smart factories, which will be the smart supply chains, is still in its period of infancy. Moreover, there is a simultaneous need to maintain a focus on the supply chain level implementation of the concept that industry 4.0 puts forth. This is important in order to gain the end to end benefits, while also avoiding the organization to organization compatibility issues that may follow later on. When considering this concept, limited research exists on the issues related to the implementation of industry 4.0, at the supply chain level. Hence, keeping in mind this lack of literature and research available, on a phenomenon that will define the future of business and industry, this study uses an exploratory approach to capture the implementation of industry 4.0 concepts across multiple tiers of the supply chain. Based on this research, the study proposes a multistage implementation framework that highlights the organizational enablers such as culture, cross-functional approach, and the continuous improvement activities. Furthermore, it also highlights the staged implementation of the advanced tools, starting from the focal organization with the subsequent integration with the partner organizations.

1. Introduction

One word that transcends most of the consumers, as well as the manufacturing topics being researched these days, is “digitization”. With the advent of the Covid-19 virus, that has taken over the world as one of the most devastating pandemics, all major industries, from education to manufacturing, are exploring novel ways to digitize their operations. Technology is now being seen as a robust strategic weapon (Chavarria-Barrientos et al., 2018) that is expected to ensure operational performance and continuity, through process integration (Srinivasan and Swink, 2015), by creating smart factories (Rashid and Tjahjono, 2016). This situation has given a much needed thrust to the adoption and implementation of smart technologies in various aspects of trade, business and organizational management. What started as a concept in Germany under the industry 4.0 revolution, by using smart ICT technologies, is now being acknowledged by all the segments of the society. Moreover, it is looking for ways to transform into this new

environment in the most seamless and successful manner.

Industry 4.0, or smart manufacturing, are the terms that are being used for digital transformation, using technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Cloud Computing (CC), Machine Learning (ML), and Data Analytics (DA), etc. These concepts have been built upon the interconnectedness of the machines and systems that are using the above-mentioned technologies, to self-correct and self-adapt according to environmental needs of time (Fatorachian and Kazemi 2020). Another term that is being used is of that of resilient systems that are capable of self-correction. Smart manufacturing signifies the working atmosphere, in which employees, machinery, enterprise systems, and devices are linked with other cyber-physical systems, as well as the internetwork (Öberg and Graham, 2016). The amount of data being generated by the industrial production systems has seen, and is also expected to experience, immense growth. Moreover, the increase in the computational power is now leading organizations to make more informed decisions. The use of

* Corresponding author.

E-mail addresses: xuefeng.shao@sydney.edu.au (X.-F. Shao), wei.liu2@sydney.edu.au (W. Liu), yi.li2@sydney.edu.au (Y. Li), hassan.rauf@lums.edu.pk (H.R. Chaudhry), x.yue@external.euc.ac.cy (X.-G. Yue).

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these technologies can be leveraged in order to integrate the data that is being generated, to make smarter and more calculated decisions. This fourth industrial revolution has brought about a new environment for industrial management and smart process management (Moeuf et al., 2018).

The concept of smart manufacturing is evolving from simple digitization and automation of individual machines, to connecting machines using IoT technologies and utilizing the data from the connected systems to make decisions on the go. Lean manufacturing, that focuses on improving the service that is provided to the customers, and reducing process waste (Womack and Jones 2003) is considered as one of the most widely adopted process management systems (Tortorella et al., 2017). However, implementing organizations have been able to reap benefits only when the internal improvement efforts were linked with the external stake holders, i.e. suppliers and the customers (Frohlick and Westbrook, 2001). Similar to the lean implementation across supply chains, digitalization of processes is obligatory for the supply chains, especially if they seek to reap the benefits in true terms (Pereira and Romero, 2017).

The extant literature available on the dynamics of industry 4.0 focuses more on the application of various technologies such as the IoT, AI, ML, and data analytics from a manufacturing standpoint. However, very limited research, particularly about the supply chain interaction of advanced technologies, exists in the literature (Müller and Voigt, 2018). Within the supply chain literature that has been written regarding the concept of industry 4.0, or smart manufacturing, the majority of the studies have been focused on the theoretical or conceptual models of implementation. Very few studies, however, capture the empirical perspective that pertains to this phenomenon (Buyukozkan and Gocer 2018). Since the industry 4.0 concept along the supply chain is still at its stages of infancy, within the supply chain literature, this exploratory study captures the stage-wise implementation of this concept across a multi-tiered supply chain.

The remainder of this paper is structured as follows. Section 2 represents the literature and the background of this research. Additionally, Section 2 has been further subdivided into smart manufacturing, components of smart manufacturing, and its application across supply chains. Moving on, Section 3 discusses the research methodology. Whereas, Section 4 captures the case data of industry 4.0 application, along with a three-tiered supply chain. Moving on, Section 5 presents the results of the exploratory study, and also proposes a framework of the industry 4.0 implementation across supply chains, while the last section looks at the contributions of this study, along with its limitations.

2. Literature review

2.1. Smart manufacturing

When it comes to analyzing the literature that has been written, it has been observed that different terms have been used interchangeably. These include, for instance, data driven or smart manufacturing, industry 4.0 technology, advanced manufacturing, factories of the future, and the fourth industrial revolution - all representing similar concepts (Buchi, Cugno, Castagnoli 2020). That is to say that all these terms are talking about the future of manufacturing, by utilizing the idea of connected and networked technologies, that will generate value for the organizations, as well as the society (Roblek et al., 2016). The broader concept here refers to the machines that are equipped with data capturing devices. These devices are designed so that they can communicate with other machines and systems, in order to fulfill certain predetermined objectives (Tang et al., 2016). The research carried out during the recent years has seen much emphasis on the advent of smart manufacturing. The integration and interoperability (Chen et al., 2008; Lu 2017), helps bridge the gap, and hence, create a connection between the physical and cyber world. This integration then creates the

connections between the external entities. In this context, enterprise integration can take place at multiple levels, i.e., physical, application and business level. Physical integration refers to the connection of physical devices and machines, whereas, application integration refers to the connectivity or integration of the software or database systems. Business integration involves the coordination among the business processes, which helps every aspect of the business to “gel in” together, so as to ensure the smooth transition of the work procedures (Chen et al., 2008). Also, interoperability creates the connections in the systems, in order to exchange knowledge and skills. It is defined as the ability of two separate systems to understand each other, and operate in other environments (Chen et al., 2008). That is to say that, in terms of the machines, it is considered to be the ability to access another machine's resources. Whereas, in a networked environment, it is the interaction between the various systems of the enterprise (Chen et al., 2008). The Initial research streams focused more on the component level application of this concept, which merely focuses on the individual technologies, such as the cloud services, big data, etc., (which will be discussed in the next section which refers to the enabling technologies). Whereas, some of the more recent papers have explored the integrative aspects of these technologies, such as the design, planning, manufacturing, human resource management, etc. (Osterrieder et al., 2020). The purpose of smart manufacturing is to utilize the data from the product lifecycle, into the intelligence systems, which improve the positive aspects of all the manufacturing processes (O'Donovan et al., 2015).

Frank et al. (2019) dissected and classified the concept of industry 4.0 into two main components. These included the front-end and the base technologies. The front-end technology dimension includes smart working, smart products, smart supply chain, and smart manufacturing initiatives. Whereas, the base technology elements include cloud services, the internet of things, big data, and analytics. Following in the same context, Wang et al. (2016) hypothesized that there are layers of activities taking place in the manufacturing environments. The physical layer consists of the shop floor, machines, and all the tangible activities taking place there. Whereas, the data layer consists of transferring the data captured from the physical layer, i.e., by using the sensors and other technologies, on to the cloud environment. The intelligence layer consists of the software and tools (analytical, prescriptive, etc.) that are needed to carry out the analysis, while the final layer comprises of the control layer forming the human supervision. According to Tao et al. (2018), the data driven smart manufacturing comprises of four modules. These include the real-time monitoring, problem processing data driver, and the manufacturing module. While the big data enables the companies to become more competitive, through intelligent tracking systems, and material assessment, energy efficiency management, and predictive maintenance.

Moving further, smart factories have the ability make timely decisions, with less human connection, which is managed via artificial intelligence (Wuest et al., 2016). Smart manufacturing can perform tasks such as the all-round monitoring, optimization of the manufacturing activities, and simulation through big data (Tao et al., 2018). Moreover, smart manufacturing utilizes the data that is extracted from the business processes, and in order to refine them further, it tends to improve the process efficiencies and the product performance. The first stage of this process is the collection of the data from the manufacturing environment. This includes the data on the inputs, i.e., the raw material characteristics, the data on the manufacturing variables, the data on the machine and human variables, and finally, the data on the output characteristics. The next step for smart manufacturing is to analyze the data that is stored at the cloud based data centers. This forms the core action point for the other subsequent activities, such as the monitoring and problem solving initiatives. In this regard, the monitoring stage acts as a quality controller, with any changes in process parameters resulting in the process readjustment. While the last stage, i.e., the problem processing, uses the data to predict emerging problems and the

possible solutions that can be suggested in this regard (Tao et al., 2018). Buchi et al. (2020) have indicated towards the increased production flexibility, improved performance, decrease in errors, higher efficiencies, and reduced set-up times due to the smart manufacturing initiatives. Moreover, Buchi and Castagnoli (2018) have pointed towards an increased efficiency factor, and a greater production capacity, as a result of smart adoption. Additionally, Tao et al. (2018) have further highlighted the characteristics of the data that is driven by smart manufacturing, which includes product development, self-organization (production planning), smart execution (raw material movement, processing), self-regulation and the self-learning within a system. Going deeper into the same context, it is observed that the product development, or the design uses rich consumer data (behavioral data, user-product interaction data), in order to identify the key product features and requirements. The manufacturing planning can be further enhanced, by using the data for the optimum resource allocation, and network optimization. Similarly, the machine data can also be used to predict any probable equipment faults, along with the diagnoses which will eventually lead to the proactive maintenance (Tao et al., 2018). Van Lopik et al. (2020) found that capabilities pertaining to augmented reality tend to enable the end-user, so that they can minimize the disruption to the workflow of the particular shop floor. Additionally, Oliff and Liu (2017) showed how data mining techniques could lead to an improvement of the production operations, in terms of the quality in small manufacturing organizations. Also, the internet of things helps to reduce the cost, improve quality, efficiency, and the predictive maintenance services (Ahleroff et al., 2020).

2.2. Enabling technologies

Many researchers have explained the phenomena of smart manufacturing, or industry 4.0 technologies, in terms of an augmented and virtual reality (Wu et al., 2013; Rüßmann et al., 2015; Kolberg and Zühlke, 2015), additive manufacturing (Huang et al., 2013; Chan et al., 2018), internet of things (Wu et al., 2017), big data analytics (De Mauro et al., 2015; Addo-Tenkorang and Helo, 2016; Lenz et al., 2018), and cyber-physical systems (Monostori, 2014; Lee et al., 2015; Zhong and Nof, 2015). Wu et al. (2013) have cited Azuma, (1997), in order to explain virtual reality as something which offers real time interactions, and three dimensional depiction of the objects in question. Additive manufacturing is a production technique, where the products are manufactured in a layer by layer manner, by using digital data, and special polymeric materials (Wu et al., 2013). Moreover, the Internet of Things (IoT) is a technology that lets autonomous objects and devices to be sensed or controlled remotely (Wu et al., 2017; Ketzenberg and Meters, 2020). Also, big data refers to the enhanced decision making capabilities, due to the collection and analysis of large data sets (Astill et al., 2020). Cloud computing is defined as the ability to access the data storage, and analyzing (computing) the relevant resources via the internet, while the resources are maintained by a third party (Zhong and Nof, 2015). In the same context, Adkil et al. (2018) highlighted the key technologies in industry 4.0, such as the (a) adaptive robotics, (b) data analytics and artificial intelligence, (c) simulation (d), embedded systems (e), communication and networking (f), cybersecurity (g), cloud (h), additive manufacturing (i), virtualization technologies (j), sensors and actuators (k), RFID and RTLS technologies, and finally, the (l) mobile technologies. Chiarello et al. (2018) explained the fourth industrial revolution in the form of enabling technologies. These included concepts such as 3D printing, augmented reality, additive manufacturing and virtual reality, digital transaction, big data, computing, programming languages, internet of things, protocols and architecture, communication networks and infrastructures, production and identification, including constituent technologies. Moreover, they also described them as well for the common knowledge about the industry 4.0 technologies. Furthermore, Osterrieder et al., 2020 have highlighted that the key eight perspectives, which primarily include

cyber physical systems, IT infrastructure, human machine interaction, cloud manufacturing and services, decision making, and data handling, are considered to be vital elements in smart manufacturing. According to Pacchini et al. (2019), eight enablers, such as artificial intelligence, additive manufacturing, the internet of things, cyber physical system, cloud computing, big data, augmented reality, and collaborative robots, have been empirically tested in the auto manufacturing sector in Brazil, so as to accelerate the adoption of industry 4.0. Moreover, Kusiak (2019) also described the characteristics of smart manufacturing, which included the prediction technology, the agent technology, the data storage technology, the cloud computing technology, the automation and process technology, and the digitization technology in depth.

In the same stride, Lee et al. (2015) defined Cyber Physical Systems (CPS) as a collection of technologies that further form a system that connects and manages the physical assets, with the computational system. Moreover, Lee et al. (2015) further explained that the cyber physical system consists of two major processes; (i) the acquisition of real time data, which comes with advanced connectivity through the information feedback from the cyber space and the physical world, and the (ii) smart data management, data analytics, and computing abilities that build and nurture the cyber space. Moreover, they also proposed a CPS structure with five levels, namely, the smart connection, data to information conversion, cyber, cognition and configuration. When we go further into the detail, the smart connection level provides plug and play, sensor work, and a tether-free communication mechanism. Moving on, the data to information conversion level provides the algorithms that are required for the data, in order to carry out the information conversion. With this in line, it helps the machines achieve a degree of self-awareness so as to account for the degradation, performance prediction and the multi-dimensional data correlation. Furthermore, the cyber level provides a central hub for the information that has been received, along with the analytical capability for the status of the other relevant components. Other than that, the cognition level provides the integrated simulation and synthesis, collaborative diagnostics and decision making, as well as the remote visualization capabilities for humans. Finally, the configuration level provides self-configuration capabilities for the resilience, self-adjustment and self-optimization of the model. Going further in the same context, Astill et al. (2020) have successfully shared the snapshots of precision poultry farming. This is a procedure that uses sensors to capture the data from various farm operations, while using the big data tools. This procedure is primarily used when making data driven decisions, and having a well-connected and networked farm equipment via the IoT technology, which will lead to the much needed automation and optimization in the farm operations.

In the recent years, there have been studies that have kept their focus on capturing the issues and the barriers that are related to the adoption of smart manufacturing technologies. In this regard, Raj et al. (2019) conducted an extensive review of the literature. This review was specifically targeted towards the adoption barriers that industry 4.0 technologies frequently come face to face with. Hence, through this analysis, Raj et al. (2019) experienced, and listed down high investment, lack of clarity on the economic advantage, issues in supply chain integration, risk of security breaches, technology risk, job threats, lack of standards, lack of skills, and the resistance to changes, as some of the common barriers that have been experienced (Kiel et al., 2017). Moreover, Raj et al. (2019) also argued that certain national policies regarding the technological infrastructure must be designed, with the support of the government regulations in both the developing and developed countries. Furthermore, Iyer (2018) argued that the governments should develop and implement a customized framework for industry 4.0, especially when it comes to the advent of employment opportunities and growth. At another instance, Backhaus and Nadarajah (2019) explained the concept of 4.0 technologies, by ranking them according to their impact, while also suggesting that

implementing the 4.0 technologies must initially be implemented on small scale pilot projects, which capture the organizational needs, which, in turn, will improve the competitiveness. Other than that, Ebrahimi et al. (2019) established the concept of the five pillars which are denoted by cost deployment, workplace organization, logistics and customer service, professional maintenance, and quality control. These pillars have the potential capability to reduce the costs and the rate of loss, as well as the three principles which include the real-time capability, decentralization, and virtualization, which will eventually help to overcome the barriers to revolutionize and skew the national economy towards industry 4.0. According to Kadir et al. (2019), there is now a need for empirical research, specifically based on the human factors and ergonomics approach, in order to completely understand, and break down the concept of the 4.0 opportunities and challenges on a tactical, operational, and strategic level.

2.3. Smart manufacturing and supply chains

Smart manufacturing explains the interconnected devices, within the Cyber Physical System, in order to reach a self-evolving environment that is equipped to manage the variations and suggest the optimum alternative and direct routes. However, given the critical role of multiple entities that contribute on an individual level, in order to shape the journey from raw materials to the end consumers, it is essential to realize that even if one entity does not effectively adopt the smart manufacturing concepts, the efforts of the rest of the members would not lead to a global optima point. In order for the supply chain to operate like a holistic entity, the smaller individual entities must work like interconnected platforms, just like the interconnected physical assets that exist within a smart environment. A change in one variable for a singular entity must initiate a counter and a collective response for the other interconnected entities (Nasiri et al., 2020).

Time and again, many scholars have highlighted the significance of the digital supply chain (Addo-Tenkorang and Helo, 2016; Scuotto et al., 2017; Crittenden et al., 2019; Riemer and Schellhammer, 2019). In this regard, the previous literature draws attention to the digital supply chain in the industrial sector (Büyükoğkan and Göcer, 2018). Smart technology is the extent to which the physical devices or processes are connected with the various digital platforms. The investment in smart technologies can exponentially improve the internal, and the external performance of the company, while incorporating such technologies within the current supply chain (Nasiri et al., 2020). Fig. 1 below can help the readers to understand the major differences between the traditional supply chains vs. the digital supply chains.

Grieco et al. (2017) conducted a case study in the fashion industry in Italy, and found that the decision support system facilitates the users to make better decisions about organizational activities, all over the supply chain. According to Ghadimi et al. (2019), a recent research on the fourth industrial revolution is taking into consideration several supply chain processes, such as the supplier selection, by applying the multi-agent technology. In the same context, Weking et al. (2019) developed a business model with three patterns such as integration, servitization, and expertization, for leveraging industry 4.0, and showed that the integration modernizes an existing business model with new procedures, and also integrates the parts of the supply chain simultaneously.

Moving on, Ralston and Blackhurst (2020) found that the smart systems may provide improved supply chain resilience, especially when owing to the new skills enhancement and capability development. The application of the 4.0 enabling technologies tends to enhance the entire supply chain performance, especially in terms of the procurement, manufacturing, inventory management, and trading, while also promoting the concept of information sharing and automation, digitization, and transparency across the supply network (Factorachian and Kazemi, 2020). Ghadge et al. (2020) emphasized the need to integrate the digital businesses, with digital supply chains, such as the incorporation and adoption of the (i) digital culture, (ii) new digital business models, (iii) optimized data management, (iv) connected processes and devices, (v) integrated performance management, (vi) synchronized planning and inventory management, (vii) supply chain transparency, (viii) integrated value chains, (ix) connected customers and channels, and the (x) collaboration and data sharing for fruitful adoption towards the concept of industry 4.0.

Preindl et al. (2020) demonstrated that the digital transformation, and industry 4.0, have the capability to accomplish a fully digital supply chain through higher transparency in terms of the centralization of the processes. However, this might not be achieved, if the firms do not have the appropriate information-sharing standards. While it is noteworthy that the decision making procedure is associated with the information exchange across the supply chain, for better efficiency and effectiveness of the processes. As a continuation of the same context, Ding's (2018) investigation revealed that the innovations and technologies related with the fourth industrial revolution, allow for the autonomous decision-making actions for the entire supply chain. Moreover, Machado et al. (2020) identified that the new technologies allow the industry 4.0 to leave a positive impact on the sustainable supply chains, and all the sustainability-related dimensions (e.g., sustainable circular production system and so on), in an integrated manner. In this

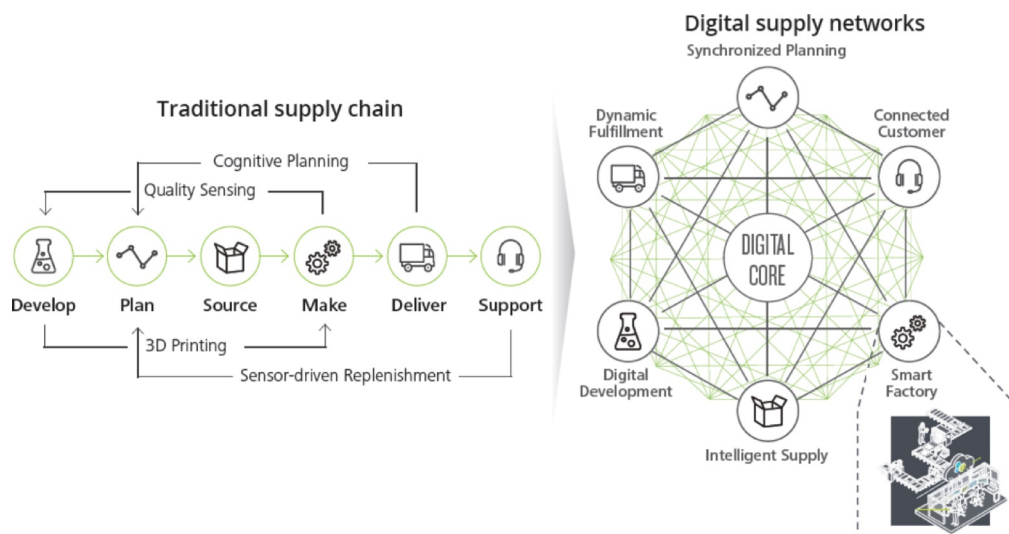


Fig. 1. Source The Smart Factories, Deloitte University Press.

regard, escalating the information exchange with the synchronization into the operations among supply chain partners, allows for the agility, efficiency, and total cost reduction throughout the entire supply network (Ghobakhloo and Fathi, 2019). The model suggested by Ghadge et al. (2020) found that the cloud technology and RFID enhanced the operational efficiencies through a reduction in the inventory levels and the costs. This was, however, made possible by an increased visibility through the data sharing that was taking place among the supply chain members.

In their study, De Sousa Jabbour et al. (2018) argued that choosing a method to resolve, identify the appropriate 4.0 technologies, embracing sustainable operations management decisions, creating collaboration in supply chain, and establishing performance enablers for small attainable targets, are still challenging issues that need to be tackled. Müller and Voigt (2018) argued that industry 4.0 is primarily concentrated on the basis of production, but the integration of the supply chain management in the context of industry 4.0, is still scarce in the contemporary research. Additionally, Manavalan and Jayakrishna (2019) analyzed that the research on the supply chain for the fourth industrial revolution is still lurking in its initial stages. The traditional supply chains must shift rapidly in order to effectively and efficiently adopt the industry 4.0 technologies' principles, in order to remain in the ever – changing and evolving markets, while the organizations are constantly finding ways to adopt to these new technologies (Ghadge et al., 2020). Also, in their study, Buyukozkan and Gocer (2018) have highlighted that, despite the advantages of industry 4.0 that are cited in the extant literature, the actual examples of empirical implementation across the supply chains are still scant. Similarly, Scuotto et al. (2017) have claimed that there is a lack of evidence based on the collaboration through the concept of digital transformation.

Thus, for the reasons that are cited above, we have essentially focused on how to integrate the cyber physical system with a digital supply chain, so as to assimilate the processes for better product quality, as well as system reliability.

3. Methodology

Given the lack of systematic studies on the implementation of the industry 4.0 concept across the supply chain, it was decided that for the purpose of this research, there was to be an exploratory case study model for the packaging supply chain in Pakistan. According to Eisenhardt, (1989), qualitative data tends to provide an understanding of the underlying dynamics of a particular phenomenon. In this regard, the case study research also helps in obtaining rich data to explore the management issues in the field of research (Yin, 2009; Eisenhardt and Graebner, 2007). It also helps to capture the emergent theories, by recognizing the design of the associations among the relevant constructs (Eisenhardt and Graebner, 2007). Moreover, the Inter-organizational liaisons are well studied in ways that are able to produce qualitative data, and permit the interpretive and explorative analysis as well (Maanen, 1998). Other than this, the explorative studies seem to concentrate on the new subject matter that sheds the spotlight on the research conducted (Brown and Brown, 2006). The purpose of this study is to use the explorative and qualitative research patterns to reveal the potential new approaches (Zikmund et al., 2013) regarding the integration of the supply chain and smart technologies, which provides further insight into the impact of such initiatives on smart organizations.

In order to explore the emerging phenomena of the implementation of industry 4.0 across the supply chain, a single case design has been adopted to unearth the dynamics that emerged during the course of the implementation (Siggelkow, 2001). In this regard, it also helped to describe the evolution of the firm or phenomena (Siggelkow, 2002). The single case study method is particularly useful, when the objective is to model the process that is adopted (Leonard-Barton and

Deschamps, 1988).

The organization for this study was selected using the theoretical sampling, as it provided the opportunity to capture the evolution of the industry 4.0 implementation across a supply chain that included the focal firm, along with its supplier and a downstream customer (Eisenhardt, 1989; Siggelkow, 2007).

In order to conduct the interviews for this exploratory data, a certain protocol was developed as a guide for the process (Eisenhardt, 1989). Semi structured interviews were then conducted at multiple levels, with the team members directly involved in the implementation process. The interviews were conducted in person at the plants of the collaborating organizations. Also, the interviews were transcribed and shared with the team for their further feedback. The interviews were then triangulated with the data on the projects carried out during the various implementation phases. Based on the analysis of the case data, an implementation framework was then proposed, which was shared with the implementing managers, plus the industry 4.0 researchers, in order to validate the findings.

4. Case data

The incorporation of the supply chain integration (digitization) for the purpose of problem solving, captures an example from a multinational corporation's Pakistan based factory (called as the focal firm from here onwards). The focal firm operates in the packaging business, serving clients that are mainly in the FMCG sector. The focal firm provides packaging material for liquid products, which are then filled and packaged at the focal firm's customer locations. The downstream customer in this case is a local FMCG company, with multiple divisions, and this particular case deals with a tea whitening product. The upstream part is a board factory, which provides the raw material for the focal firm. Both the supplier's and the customer's factories are located within a one hour driving distance from the focal firm.

The problem that cropped up was that there were dents observed in some of the randomly selected packages (the final product), after the filling and packaging stage. The objective was to find out the cause of the dents, in order to resolve the problem in real time at the customer's filling machines, focal firm process or at the process stage of the board supplier. Under the pre implementation scenario, whenever any issue or customer complaint is generated from the customer, it usually comes to the focal firm. The concerned team would then identify the problem at their end, by talking to the production team, or they would also talk to their supplier directly. It was observed that this process took at least two days to resolve any issue, which resulted in a loss of two business days which were dedicated to the production of the product. The objective of the supply chain digitization project was to integrate the processes, in order to have the relevant data available in real time, in order to resolve the issues more efficiently, and also to take corrective measures in a timely manner as well. In addition to this, the focal firm wanted to reduce the issue resolution time, and hence, improve their customer service score as well.

One reason cited by the team for not having taken up this initiative was that, the dents were not frequent, and the end consumers were also not overly demanding as well. However, they could foresee a change in this attitude, with the increasing competition in the industry. So they took it upon themselves to be proactive and solve the issue before it resulted in a loss of customers. When they started off, the team had no clue as to why the dents occurred in the final product. They also did not have any idea regarding the origin of these dents, or the cause for these dents. Moreover, there were multiple variables that could have resulted in the dents being formed at the end of the final process. For instance, these could have been possibly generated from the processes, at their suppliers' end, at the focal firm's end, or even at their customer's filling machine. Moreover, there could also be potential raw material issues, or a material issue in the focal firm's inputs, which may have created further issues at the focal firm's processing stage and so on.

A team was then formed around this dilemma, to investigate the probable causes of the dent formation at the final production stage. A cross functional team was formed consisting of the members from different the various sub divisions, such as the production, procurement, maintenance, IT and sales teams. This was a quick decision for the focal firm because of its experience of working in cross-functional teams, and the kaizen experience during its WCM journey. When the project was initiated, the data was only being captured at the focal firm's processes, and the idea was to collect data at three different legs (supplier, process in focal firm and process and customer end), to see if there were any possible product discrepancies which could lead to any potential problems at the last stage, so that those may be rectified in real-time. Furthermore, the team started discussing about the different variables that could be impacting the quality of the final product. Thus, they started off with exploring the issue from the supplier's end. The supplier was a paper and board mill, and had a long history of a healthy working relationship with the focal firm in question.

The first step of this investigation was to include the members of the supplier team in the problem-solving team. The paper rolls were then delivered with the quality assurance certificate, which is usually called the Certificate of Analysis. This contained the generic level parameters of the incoming roll. The team worked on the problem for approximately a little more than a year, in order to identify, capture and analyze the data from the supplier's process. The supplier being in the vicinity, helped the team's working processes, as they were able to plan frequent gatherings at the supplier's premises, so as to take a first-hand look at the identified areas.

When the team initially approached the supplier, they were met with an expected initial resistance from their side. The supplier's responded to this initiative by claiming that they had been sharing the quality certificate with every roll, and could also provide the data for this as evidence. However, the team shared their own lack of understanding of the causes, and explained that it was more of a proactive problem-solving initiative by them, and they were in the process of learning and wanted to understand the material usage and the process in order to explore the variables which could have been involved. Therefore, as there was a long working history with the supplier, they were able to bring the supplier on board. Moreover, the supplier's own internal culture of continuous improvement in the quality controls ensured an active participation and cooperation from their side.

The team then initiated their investigation with the observation of the process at the supplier's end. The process consisted of three steps, i.e., the board making, the coating, and then finally the cutting of the rolls. The mother roll measured around 28,000 m in length, and 4.5 m in width, which was first cut into four rolls, with an approx. length of 7000 each, and then these rolls were further cut into smaller rolls, with the widths of 1.5 m, each. The team kicked off the process by looking at all the available data points which might have been connected together. Their initial research revealed that the variables such as moisture, thickness and grammage of the rolls were being captured by a sensor, and the values were displayed on a monitor. However, the supplier team was neither aware of the data points, nor the storage of the data which could be used to retrieve it for carrying out any further analysis. All they were using was a combined report for the mother roll, which gave the average values which were never found to be out of tolerance. Moreover, the supplier's technical staff had also never considered exploring the process further, since the output met the required customers' specs, and never resulted in any significant customer complaints.

The team tried to go in depth with their exploration of the fact that if the data was being displayed, it must be stored somewhere as well. However surprisingly, even the IT team could not figure out the location of the data storage. They then decided to contact the sensor manufacturer, which happened to be a well know brand, but that particular company did not offer any services in Pakistan. Other than that, they also contacted the machine manufacturer, but could not find much information from their side either. The team then contacted

another international company, which offered the sensors and the allied product of this category. But, the catch was that this particular company offered a solution for Five Hundred Thousand Euros. However, at this stage of the project, with no information of the variables that could be causing defects later, this price was not deemed appropriate and this solution was dropped from the consideration set.

With no input from the sensor manufacturer in sight, the team started to look for improvised solutions. They discussed options that were as simple as stationing a human in front of the screen to capture the data manually. On the other extreme, they also thought of capturing the images, by using a camera, and then using artificial intelligence techniques to capture the data that was being recorded but was lost. Before going any further, the team was also expanded, and an AI researcher was added from a leading university in the city. The amended team with enhanced IT capabilities was now able to extract a text file from the sensor's data that was being captured. The next step was to map the points on the data file. In this regard, the team found that the sensor moved along the width of the machine, while the board moved beneath. As a result of this movement, the sensor captured data in diagonal directions on the paper board. The next step after this was for the team to come up with algorithms that could be used to map the points on the paper board. This entire effort of engaging the supplier, team formation, data exploration, addition of academic researchers, data capturing and algorithm development to map data, took almost a year to materialize.

Equipped with the data from the supplier, the team then moved on to study the product at the focal firm. The next step in this regard was to link the data coming from the supplier, with the machine that was running at the focal firm. One step that could have impacted the properties of the paper board, was the production of crease marks on the board, which facilitated the package formation at the filling machines that were set up at the customer's end. These creases were formed by passing the board between a male plate and a female plate. Thus, the creases formed contained certain properties, in terms of height of the crease, width and the gradient, that were collectively called as the crease profile. The probable impact of the crease profile had never been explored earlier by anyone working in these companies. In addition to this, there was no mechanism available to measure the crease profile.

Keeping these limitations in check, the team started exploring multiple options to come up with a plausible explanation of the damaged paper rolls. One idea was to develop a crease profiler. Therefore, the team, with assistance from their academic network, developed a crease profiler which was equipped with a laser sensor. The sensor moved along on the packaging material, specifically where the creases were present, and measured the crease profile. The sensor also read a crease, and based on that, summarized the other three creases, while moving on to the other patterns that were present (collectively, there were three creases at the right angle that came together to form a corner, on which the bending was being studied). This activity unearthed the fact that significant variations were present in the crease profiles. The measured crease patterns for every roll were then mapped on the roll data.

The problem happened to be the dents in the final product, after filling and packing the product. While, the objective was to find out the cause of the dents, in order to fix the problem in real time at the customer's filling machines, focal firm process or at the process stage at of the board supplier.

Having mapped the data from the supplier and the focal firm, the next stage was to capture the data from the customer's filling machines, and to link it with the data coming from the first to entities in the value chain. At the customer's end, no mechanism existed to monitor the dent formation in the packages, even as they occurred. Also, the machine operated with an output speed of 24,000 packs/per hour, and it was only after a batch had been manufactured, that the dents were identified through visual monitoring.

Once again in a fix, the team sat down to deliberate the available options of capturing the defects first, and then link them with the available data. They decided to install high speed cameras at the filling machine, where the packet was exiting the machine from. In order to capture the dents, they decided to make use of Artificial Intelligence. As a first step however, the different visual profiles of the dents on the packages were captured, and fed into the system. They developed a machine learning module, which would give a positive signal for the dents that were deemed similar to ones fed to the data base.

Moreover, they also installed a camera at the customer machine. Interestingly, this camera caught certain dents, which were not possible to be caught by the human eye. Once a dent was identified, the next step was to work backwards to plot the dents on the data available on the paper board properties, and the crease profile. The idea was to look for any correlation of the crease profile, most specifically, the crease height (they found that the crease height was the most significant), and see whether there were any variations in the crease height around that point. Data analysis revealed that every roll had a unique ID, and before putting the roll on to the filling machine, the roll ID was scanned. In the case of a dent, that particular point was correlated with the existing data of the board mill, as well as the focal firm data.

During the first stage of the implementation, the camera was just capturing the top of the packet. The next stage planned was to install a camera under the filling machine to capture the dents at the bottom. This required more collaboration with the customers, as putting a camera beneath the required modification of machine at the customer end was a risky initiative to take. As a subsequent task, the team also planned on connecting the system with a mobile application, which would be activated with the dent identification, while linking together, the data collected from three areas; the sensors at the supplier and the focal company, plus the camera installed at the customer's end.

5. Discussion

Recent advances in the technology have led to the development of smart factories, or at least have initiated a journey towards that direction. The smart factories/industry 4.0 consist of a networked and interconnected system, where the information flow is optimized between the physical infrastructure and the cyber space. With the help of the advanced data management and analytics tools, the entire system is expected to perform optimally. However, until and unless the smart factory concept is not translated across the supply chain i.e. smart supply chains, the benefits of industry 4.0 concept would not materialize in its true essence. Numerous big businesses, as well as the small businesses, are shifting towards smart manufacturing. These include businesses such as the automotive, electrical, pharmaceutical, and the defense organizations (Müller, 2019).

This study has explored the start to end journey, using the industry 4.0 concepts, to link multiple tiers across the supply chain. The interplay between the multiple entities was initiated by a need or a problem that appeared at the downstream end of the value chain. The lead was taken by the firm, which was in the middle of the three entities, and played the role of the dominant partner. The dominance was not only because of being a major firm in the category, but also because of the knowledge and implementation of the advanced management tools that were used to find the solutions (WCM implementation).

The case data depicts the presence of multiple stages in the journey of the industry 4.0 adaptation, across the value chain. These stages have been broken down into the visualization phase, first level linkage phase, connected supply chain phase, and finally the smart supply chain phase.

Phase 1: The Visualization level

The visualization level may also be termed as the trigger phase, which would underpin the entire idea of the connected supply chains. Here, the term 'connected' supply chain, however, does not refer to the term usually used in the supply chain collaboration literature. In the supply chain collaboration literature, mutual trust leads to the joint

activities, such as information sharing, planning and product development, which leads to a higher level collaboration, in order to enhance the efficiencies across the entire value chain (Chopra and Meindl 2016). The term 'connected' being used here is considered to be more so in literal terms, but it builds on the earlier concept, that is, that the 'connection' in the traditional terms is a pre requisite to the 'connection' in literal terms. This means that it is based along the same lines of POS data sharing, but at a much advanced and transparent level. The objective in the POS is the visibility for joint planning (Simchi-Levi et al., 2003), but here, in terms of the industry 4.0 concept, this connection forms the basis of automatic decision making by a smart system. Furthermore, the supply chain efficiency is enhanced by the automation of physical planning, information sharing processes, control, tasks (Pereira and Romero, 2017) and the end to end visibility across the value chain (Miragliotta et al., 2018).

In this case, the three-tier supply chain was orchestrated by the middle entity, termed as the focal firm. This journey rallied around a problem that was identified at the downstream end. Once the problem was identified, the focal firm took the initiative, and assumed the position of the 'champion' of the new journey. This ideally means that the visualization has to be championed by the firm, which has the resources, vision, as well as the capability to lead the initiative (Tangpong et al., 2008). This was legitimized by the major and dominant players in the category, the advanced management practices that were adopted, as well as the key product owner.

The first step started within the walls of the 'champion' firm. A project team was initiated to address, and chalk out a relevant plan. The focal firm had already achieved an advanced level of WCM implementation, and was not a novice to the cross functional kaizen activities. In fact, it championed the cross functional management approach under the pillared structure of the WCM model (Furlan and Vinelli, 2018). In addition to this, the focal firm, in its journey towards higher level implementation of WCM principle, had been internally working on the digitization concept, and had an internal roadmap that was placed in parallel. The human resource was also well equipped with the basic digitization concepts, and the advanced level trainings on the role of the digitization were already in place as well.

Phase 2: Level 1 linkage

When considering the level 1 linkages, it was observed known that once the multi-tier connection roadmap had been visualized, the focal firm connected with it the immediate supplier, in order to work collaboratively to explore and study the problem in depth. However, the supplier initially showed resistance in owning the problem (Handfield et al., 2000) despite the fact that the focal firm had a history of working together (Zhang and Cao 2018) with the supplier, and had remained not only as a major customer, but had also shared management practices, improvement tools and techniques over the years. The relationship element was essential to bring the two firms together on a joint platform (Zhang and Cao 2018), where the problem was known; however, the roadmap was not clear.

A team was then set-up at the supplier's end as well to coordinate and work with the focal firm's team. There were frequent meetings at the supplier's plant to explore the various aspects of the problem (Handfield et al., 2000). The supplier also had an existing culture of carrying out problem solving and continuous improvement activities through these teams, so the two teams were soon merged into a single team that was headed by the focal firm personnel. The physical proximity and cultural similarity between the two organizations also helped in the coordination and the sharing of ideas for an extended period of time (Cannon et al., 2010).

The team carried on to explore the answers to their questions, looking at different solutions while engaging different stakeholders during the course of the time. Moreover, at some point in time, the team was also expanded by adding academic researchers in the area of data sciences and IT (Gulati et al., 2012). It was after almost a year of effort that the team was able to align the data being captured at the supplier's

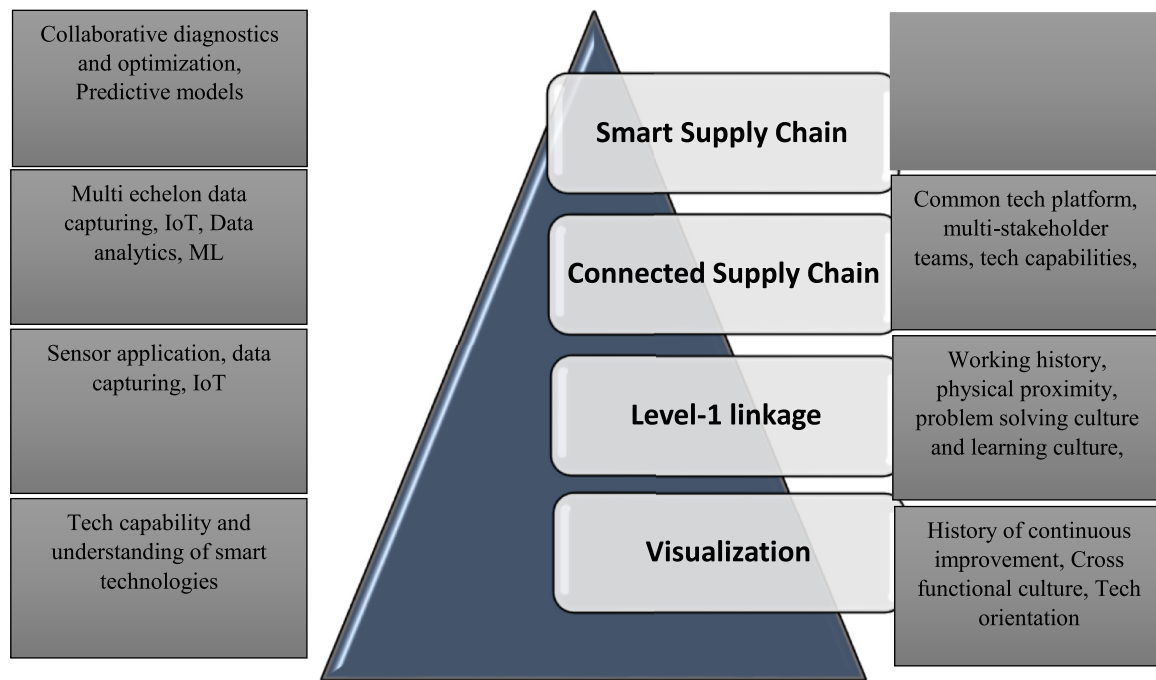


Fig. 2. Stages of Industry 4.0 implementation across supply chain.

end, with the data already existing at the focal firm level. Luckily, the data existed, but the challenge was only to extract the data, otherwise the solution would have required going to the next step, and installing sensors to capture the required data as well, which would have been a very tedious process. In addition to this, the cloud environment was used to link the data with the existing data.

The phase 2 required the initial elements of collaboration in which the past history, continuous improvement culture at both organizations, physical proximity, and the earlier projects, all helped the two organizations to move forward towards a solution (Handfield et al., 2000). This was augmented in the later stage, with the addition to the focal team, as per the project requirements, the use of smart manufacturing technologies, such as data capturing, and the IoT to connect the required components of the two organizations, and also meet the objectives of this phase.

Phase 3: Connected Supply Chain

Equipped with the data from the supplier's end, the team moved on to gather the data on the required specs at their facility. The first step was to capture data, in order to build on to the data that was captured at the supplier's end. The joint team had to set-up the equipment, using the sensors to capture the data on the crease profiles. This activity unearthed the process issues at the focal firm's level as well. The next step was to link that data with the data that was being captured at the supplier's end (Barratt and Barratt 2011). With the help from the data science experts, the team was then able to map the data, on to the data that was coming from the supplier (Gulati et al., 2012).

The next step within this phase was to connect with the third partner in the value chain. The issue at this stage was, that they needed to code the physical appearance of the product, i.e. the dents appearing in the final product. However, there wasn't any parameter or measuring instrument that could have been used for gaging this attribute. In addition to this dilemma, the speed of the out, i.e. 24,000 packs per hour, made it humanly impossible to count the defectives in real time. The human inspection could only have been instituted post the production process, with the attached costs and delays going side by side. Therefore, the team had to explore alternative options which could automatically detect the occurrence of dents, and then integrate that knowledge further. With input from the data experts, the team installed a camera that could make use of the Artificial Intelligence, in order to

detect the dents (da Costa, Figueroa, and Fracarolli 2020; Pang et al., 2020). The camera was fed the data, so as to decipher which dent would be counted, and which would be ignored. Once the team was able to capture the data on the dents, the next step was to link that data with the paper board data that was coming from the earlier echelons of the supply chain. During this stage, the multi-tier collaboration, common objective (Handfield et al., 2000), and the use of advanced tools, such as the advanced sensing tools, AI, and data mapping, enabled the supply chain partners to link the relevant data to a central networked system (Novais et al., 2019).

Stage 4: Smart Supply Chain

The final stage was to link the data together, and based on the defect, the identification made the system self-adaptive by taking corrective measures at the relevant stage. However, this would ideally require continued investment into the technology aspect of this issue, and the relationship part as well. Moreover, this would also require investment in the IoT devices, for the real time information exchange, throughout the supply chain members (Haddud et al., 2017), RFID sensors for real time automobile tracing (Barreto et al., 2017) and the centralized manufacturing execution systems through cloud computing (Almada-Lobo, 2015). It is essential to understand that this must not be seen as the end of the journey to adapt to the smart technology that industry 4.0 aims to introduce in the supply chain processes. Rather, this was the start of a journey that would hopefully highlight a considerable amount of interconnected areas of improvement, but would also require repeated commitment in terms of the time and money for the continued experimentation to take place. Also, this might require further broadening of the team's profile, as they would have to continuously move to explore the use of advanced technologies even further (Ghadimi et al., 2019).

Fig. 2 captures these stages of collaboration, while listing the technological aspects of the stages, along with the organizational enablers that are needed to move to advanced stages of collaboration.

6. Conclusion

With the advent of the industry 4.0 concept, the increasing adoption of innovative technologies such as the IoT, cloud computing, big data analytics, use of smart sensors, robotic, etc. is being observed across

various industries. The organizations have started to reap the benefits of deploying advanced technologies in their manufacturing systems, in order to improve the process efficiencies. However, it is imperative to adopt this concept from the supply chain perspective for two reasons. The first reason is that, as organizations embark to adopt the concept of smart factories in isolation, this might bring issues of compatibility later on, when the concept would be rolled out in broader supply chains. Secondly, it is a universal fact that is most commonly featured in the supply chain literature that, in order to improve the processes and gain efficiencies, an end to end approach must be adopted. However, up till now, only a limited number of researches have empirically explored the concept of industry 4.0, with regards to the supply chains. Moreover, studies that have also looked at the supply chain view, predominantly fall in the conceptual category. Very little research exists with regards to the actual implementation of the industry 4.0 concept, across the supply chains.

The exploratory study of the journey of the industry 4.0 application across the supply chains has been used to propose a phased framework for supply chain wide implementation of industry 4.0. The framework consists of four distinct stages of interaction among the supply chain actors. These stages, while identifying the adoption of advanced technologies, also highlight the organizational enablers that are essential to the industry 4.0 rollout, across the supply chain. Moreover, the previous studies have presented conceptual models, while this framework is based on the actual implementation study. The first stage deals relatively more with the implementation of the ground work that is based on the visualization of the project, team building, and the cross functional elements, etc. it is noteworthy that, organizations with a history of cross functional continuous improvement initiatives are better suited to proceed to the next stage, with lesser efforts. The next two stages, where the advanced tools such as the IoT, AI, ML are adopted, the existing collaboration between the supply chain partners, acts as an enabler. Finally, the implementation of industry 4.0 concepts, across the supply chains, must not be seen as an end of a project. Rather, it must be approached with the spirit of initiation of a new journey of exploration and implementation of the ever advancing technologies.

The proposed framework will provide insights to the companies that are looking to take advantage of the industry 4.0 concept, across the supply chains. The framework also highlights the importance of the relationship elements across the supply chain members, in successful the adoption of the supply chain wide, smart initiatives. This study also highlights the significance of expanding the scope of the team, by including data experts who can tap into the knowledge that is residing outside the organizations. This framework also provides a base model to the researchers, so as to test and expand the framework, by capturing different industries and geographic regions.

As with other exploratory studies, this study has certain limitations. The study has relied on one implementation incident of the industry 4.0 concept, across the supply chain. Researchers relying on other methods of research often question the generalizability of the qualitative or case based research. However, the objective of the exploratory studies, along with this study, is to capture a certain phenomenon, in a certain setting, and to generate a set of hypothesis which can later be tested for generalizability (Eisenhardt 1989).

This study explored the implementation of only a few tools of the industry 4.0 (sensor technology, IoT, AI), whereas it did not provide the opportunity to study the implementation of other technologies, such as the additive manufacturing, augmented reality, autonomous robots, etc. Therefore, the future studies could explore broader applications of these tools across different levels of the supply chains. Industry 4.0 is an emerging phenomena that requires cross organization coordination and linkages, which provide the opportunities to explore the relationship dynamics within the broader phenomena. In addition this, the technology expertise of partnering firms, along with their history of collaboration, also requires to be further explored.

Authorship contribution statement

Xue-Feng Shao: Conceptualization, Resources, Data curation, Writing - original draft, Visualization; **Wei Liu:** Supervision, Validation, Writing - original draft, Writing-review & editing; **Yi Li:** Project administration, Supervision, Writing-review & editing; **Hassan Rauf Chaudhry:** Conceptualization, Methodology, Formal analysis, Investigation, Writing-review & editing; **Xiao-Guang Yue:** Conceptualization, Writing - original draft, Writing-review & editing

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David Xuefeng Shao is a lecturer at University of Sydney. His-research interests focus on international risk management and management capability. He was awarded the first prize in the ANZAM pitch competition during his PhD candidature and also won the best paper award in Strategic Management Stream in ANZAM conference. His-research has appeared in international journals including *Enterprise Information Systems*, *Journal of Global Information Management*, and *International Journal of Environmental Research and Public Health*. Dr. Shao can be reached at xuefeng.shao@sydney.edu.au.

Wei Liu is a PhD candidate in the Discipline of International Business, at the University of Sydney Business School. His-research interests include corporate strategy in the Chinese context, international business, technology and innovation. His-research has appeared in *Emerging Markets Review*, *Renewable and Sustainable Energy Reviews*, *Enterprise Information Systems* and others. He also served as guest editor in *International Journal of*

Technology Management, International Journal of Environment and Pollution and others. He has won two finalists of the AIB and AOM conference best paper.

Yi Li is Senior Lecturer in Discipline of International Business, at the University of Sydney Business School, Australia. His-research interests include internationalization of firms in emerging economy, institutional approaches of business strategy, and dynamic evolution of control in international joint ventures. His-work has been published or forthcoming in journals such as Organization Studies, Regional Studies, Global Strategy Journal, International Business Review, Management International Review, Journal of Business Research, Technovation and others. He has won national competitive research grants such as National Natural Science Foundation of China Grant. He currently serves as communication editor of Journal of International Management, and an associate editor of Chinese Management Studies.

Dr. Hassan Chaudhry is an Assistant Professor at Suleman Dawood School of Business, Lahore University of Management Sciences. He holds a doctorate in Operations and Supply Chain Management from North Carolina State University. His-research interests lie in the areas of Manufacturing Excellence, Sustainable Supply Chains, Supply Chain Strategies and manufacturing management. Dr. Chaudhry has published in journals like 'Journal of Cleaner Production', 'Journal of Fashion Marketing & Management' and 'Asian Journal of Management Cases'. Besides his academic and research activities, Dr. Chaudhry actively engages in consulting assignments.

Xiao-Guang Yue is the Adjunct Professor of Department of Computer Science and Engineering, School of Sciences, European University Cyprus, Cyprus. He is the IETI Foundation Fellow (FFIETI) and Fellow of Pakistan Academy of Engineering (FPAE). His-research interests include Artificial Intelligence, Intelligence Information Processing. Email: x.yue@external.euc.ac.cy Url: <https://euc.ac.cy/en/faculty-profiles/xiao-guang-yue/>