

# An empirical investigation on Big data in Supply chain management: Case from the Smart Connected Products

Xu J.\*, Ciccullo F.\*, Sianesi A.\*

\* Dipartimento di Ingegneria Gestionale, Politecnico di Milano, Via Lambruschini, 4b 20158 - Milano – Italy  
([jinou.xu@polimi.it](mailto:jinou.xu@polimi.it); [federica.ciccullo@polimi.it](mailto:federica.ciccullo@polimi.it); [andrea.sianesi@polimi.it](mailto:andrea.sianesi@polimi.it))

**Abstract:** Data has always been at the centre of planning activities, while recent advancement in computing capacity presents further opportunities to the supply chain context. Despite the research community holds high expectations on the potential of big data and advanced analytics, little empirical evidences is brought to support the conceptual development in this field. In this regard, building on the context of “smart connected products”, our paper aims at shedding light on how big data will reshape supply chains and supply chain management in the manufacturing industry. This paper is based on a single-embedded case study, where multiple sources of evidence are granted by collecting data from semi-structured interviews and secondary materials. Result shows that manufacturing companies can benefit from the use of big data from smart connected products mainly leveraging on *data timeliness* (i.e. velocity) and *data richness* (i.e. variety and volume), that, in turn, affect supply chain planning, as well as supply chain configuration and relationship. We further highlight that, such influence is dependent on *data quality* (i.e. veracity, value) and *data ownership* determined by the type of product (i.e. component or final product). Our manuscript enriches empirical evidence to literature on how the characteristics and management of big data from smart connected product will affect supply chain management. The resulted conceptual framework can be used as the basis for future studies towards theory testing.

**Keywords:** Big data, smart connected products, supply chain planning, supply chain configuration, supply chain relationship

## 1. Introduction

The US Library of Congress reported to have possession of 235 terabytes of data by April 2011, which is actually smaller than the data storage in companies from 15 sectors (Manyika et al., 2011). At a glance, the issue is no more about when *big data* will arrive, but rather how management could reap the potential from the data at hand, and to be able to interpret its implication to management. Over the past years, the industry has pushed the frontier on how to make use of data to inform business and management. Amazon realized “anticipatory shipping” based on the huge number of historical transactions to ship goods close to the customer location before they actually make the order (OnMarketing, 2014). IBM has joint-force with the Weather Company to use weather and location data in improving supply chain resilience (Banker, 2016), while various opportunities are hidden also in social media data in monitoring supply chain events (Sinha, 2019).

A handy of reviews on big data in supply chain management have clarified several issues related to the field. Some of them identified the relevant supply chain areas where big data will potentially contribute (e.g. (Guha and Kumar, 2018; Nguyen et al., 2018; Tiwari et al., 2018), while others developed conceptual models in analysing the maturity of supply chain big data analytics (e.g. (Wang et al., 2016), highlighting the capabilities related the use of big data analytics within supply chains (Arunachalam et al., 2018). Despite these literature reviews has elucidated the general picture on big data in the supply chain context, the research field suffers from a lack of clarity in

contextualizing the benefit and implications. In other words, while synthesis of literature can contribute to the conceptual development by consolidating implications from different contexts, empirical evidence is relatively scarce to fuel the conceptual development (Arunachalam et al., 2018; Fosso Wamba et al., 2015; Yu et al., 2018).

Therefore, this paper is set to addresses the paucity of empirical research, aiming to develop theoretical implications on how the characteristics and management of big data will reshape supply chains and supply chain management. In particular, we aimed to answer the questions on *how does big data impact supply chain management on the dimension of supply chain planning, supply chain configuration and supply chain relationship*.

We employed the empirical setting on a case of *smart connected products*, that are products simultaneously exhibit two fundamental properties: *smartness* – the ability to record and interact with operating conditions enabled by sensors, data storage and controls, and *connectivity* – the establishment of wired or wireless connections with external systems via ports and protocols (Porter and Heppelmann, 2015). These two intrinsic properties of *smart connected products* guarantee the presence of big data in our research setting.

## 2. Research background

### 2.1 Big data analytics and supply chain management

Literature has not reached a perfect consensus on the definition of *big data* due to the continuous evolvement of

the term (Manyika et al., 2011), however, the three key features of big data are generally acknowledged as *volume* – the considerable size of big data due to the elevated number of records, *velocity* – the frequency in big data in generation and delivery, and *variety* – the diversity in big data sources, data format and dimensions (Fosso Wamba et al., 2015; Richey et al., 2016; Russom, 2011). As a result, big data challenges the traditional systems in capturing, storage, management and analysis due to its width (multiplicity of information within a record) and depth (high number of records) (Manyika et al., 2011; Wang et al., 2016).

Research on big data in the supply chain domain has quickly flourished following several early works. To name a few, Waller and Fawcett (2013) pointed out the need of developing both analytical skills and business understanding to empower supply chain transformation. Christopher and Ryals (2014) coined “demand chain management” as a result of the drastically shortened time-to-market and high responsiveness introduced by big data and other digital technologies. Focusing on the customer side, Huang and Van Mieghem (2014) and See-To and Ngai (2018) addressed the potential of using retail big data from e-commerce, together with customer reviews and record on clickstream data, to improve sales forecast and inventory management. Shifting to the internal operations, other researchers investigated the use of data on sensor-generated machine-state monitoring and failure to support shopfloor flow optimization, machine scheduling and predictive maintenance (Bumblauskas et al., 2017; Wu et al., 2018; Zhong et al., 2017).

In short, extant studies have explored a wide range of topics on using diverse supply chain-related big data, however, to the best of our knowledge, limited research has taken reference to a single source of big data (e.g. data from smart connected product) while investigating its supply chain-wide implication. Without challenging the value of multiple data sources, we believe a comprehensive understanding on a single data source would lead to further theoretical advancement that can eventually bring actionable insight to practitioners.

## 2.2 Smart connected products

As the name suggests, smart connected products can be interpreted literally as the collection of “smart” and “connected” product. Three fundamental pillars stand at the centre of these products: *i*) provision of core functionality ensured by the *physical* components which comprise a combination of mechanical and electrical units; *ii*) amplified capability introduced by *smart* components which are composed by sensors and control units hosting operating system and enhancing user interface; and *iii*) ability of establishing *connections* with other products and/or systems bridging information exchange and functional extension (Porter and Heppelmann, 2014). As the level of smartness increase, the ability of these products moves from merely supporting human decisions, taking decisions in a structured context, gaining awareness and learn for self-improvement to achieving self-awareness (Davenport and Kirby, 2016).

Smart connected products offer four fundamental capabilities: monitoring, control, optimization and autonomy (Porter and Heppelmann, 2014). Smart components can execute *monitoring* on production performance, external environment and operating condition thanks to the embedded sensors, microprocessors and storage unit, and therefore, enable interactions with the external conditions. Once integrated to connectivity, they can perform *control* on the production functions and user experience personalization. Result of these two functions leads to *optimization* of the product performance and diagnostics, while *autonomy* is built on top of all the above capabilities that allows self-coordination, self-diagnosis and autonomous improvement of the products and systems.

According to Porter and Heppelmann (2014), the presence of smart connected products would further dim the boundary between industries, and competition will shift from the performance of a discrete product to the entire system composed by multiple actors. In the transformation of transactional selling to the provision of product-as-a-service (Porter and Heppelmann, 2015), an increased number of supply chain actors will join in the process of creating new offering equipped with more integrated and comprehensive sets of functionalities. Such transformation could shed light on the management of supply chains and the relationship between supply chain actors. At the same time, as the entire process is growing in complexity, data management is deemed to be of higher strategic value and could imply the need of inter-organizational collaborations (Porter and Heppelmann, 2015). Processes in the supply chain that highly rely on the use of data, such as supply chain planning activities, should reflect upon issues apart from marketing initiatives, including disintermediation in distribution channels, data ownership, and monetization of product data.

## 3. Research design

### 3.1 Research questions

Extant literature on big data impact on supply chain management provides a sound basis to develop empirical research on understanding how big data from smart connected product will impact on the various aspects of supply chain management. In particular, we address the following two research questions by looking into the relationship of big data from smart connected product and supply chain management issues.

RQ1: How does big data from smart connected products impact supply chain planning process?

Supply chain planning refers to the activities “*associated with developing plans to operate the supply chain...*” including “*the gathering of requirements, ... information on available resources, balancing requirements and resources to determine planned capabilities and gaps in demand or resources and identify actions to correct these gaps*” (APICS, 2017). The planning activities can be considered in phases of input (i.e. the information feeding into the planning process), process (i.e. the planning process itself) and output (i.e. the planning outcome and its performance). Big data from smart connected products is

expected to have implications on all the three phases in planning, by offering more abundant data as input, joining advanced analytics to the planning process, with a more efficient and accurate planning outcome.

RQ2: How does big data from smart connected products impact supply chain configuration and relationship?

Supply chain configuration refers the “*set of supply chain units and links among these units defining the underlying supply chain structure and the key attributes of the supply chain network*” (Chandra and Grabis, 2016). The primary problem within supply chain configuration involves decisions on the tiered structure in the supply chains. Big data from smart connected products is likely influence these decisions, as the number and roles within the tiered structure could be revised when firms are gaining better visibility on their customers. As big data, from smart connected products, offers much richer information in comparison to the traditional products, the sharing of these data between supply chain actors and their collaboration could potentially become of greater concern.

### 3.2 Methodology

Single case study is particularly suitable to collect richer and in-depth information. We consider the single case of a company which represents a *typical or representative* case of a manufacturing company (Yin, 2009) and as an interesting context for the application of smart connected products impacting on different supply chain planning processes. Single case study, is a method adopted also in studies which has an intent similar to ours, e.g. (Andersson and Jonsson, 2018; Salleh and Janczewski, 2019). We employed the case study embedding two units of analysis (Yin, 2009), which are represented by the distinct supply chains of two channels of the case company (i.e. the *OE channel* and the *Replacement channel*).

Data have been collected through semi-structured face-to-face interviews directed to the managers in the equivalent functions of: i) integrated supply chain planning (ISCP), ii) demand planning (DemP), iii) procurement planning (PrcP), iv) production planning (PrdP), and v) distribution planning (DisP). The interviews last from 1 to 1.5 hour, addressing respectively the two units of analysis. For each unit of analysis, the case study protocol is designed with two sections with the first one aims at understanding the status quo, and the second addresses a hypothetical scenario where smart connected products is introduced.

### 4. The case context, products and as-is processes

The focal case of this study refers to a manufacturer and retailer of tyres operating in the automotive industry with a global production and distribution network. Indeed, the automotive industry has been moving fast in pursuing digital technologies, and has shown extensive commitment in R&D. Following this trend, automotive suppliers, such as system integrators and tyre manufacturers, are pushed to secure significant investment in advancing technologies and connectivity in their own product to keep pace with the automotive producers. Therefore, the smart connected products are brought into discussion as the next frontier.

In the case company, it is expected that the introduction of smart connected products (i.e. tyres) will also generate momentum in the planning and management of their proprietary supply chains. These smart connected products will be distributed through the same channels of extant products that are: *i) the OE channel* – direct sales of the product to original equipment manufacturers (OEM) primarily based on production forecast and specifications directed provided by the OEM, and *ii) the replacement channel* – delivery of final products (i.e. tyres) through internal distribution network, in combination with wholesaler, retailers and tyre specialists as contact points with the final consumers.

The two channels entail many intrinsic differences, especially in the supply chain planning logic and processes, which is currently managed in functional silos involving the equivalent function of DemP, PrcP, PrdP, and DisP, as well as ISCP that act as a cross-functional coordination of all planning processes. In particular, DemP distinguishes between the two channels. In the OE channel, demand planning is performed with the pull logic, and the input to the process is explicitly communicated by the OEMs in collaboration, granted contractual terms at the strategic level. In the replacement channel, demand planning is performed with the push logic, considering the historical sales of tyres, and the historical sales of the related car models. The processes of PrdP and PrcP are fed with the output from DemP that are responsible in working out production plans at the regional level, and purchasing plans that integrate the internal ERP data. Similarly, the current process of DisP also relies primarily on the use of internal data of sales and production. In short, the extant planning process relies primarily on the use of internal data, having limited access to data generated from final customers.

## 5. Results

### 5.1 Relevant big data features

Our study shows that big data from smart connected products demonstrates various intrinsic features simultaneously, namely data *richness* and data *timeliness*. These intrinsic features condition potential impact on different supply chain planning, configuration and relationships. Moreover, data *quality* and data *ownership* are two relevant issues related to the management of big data in supply chains. Further details are reported in the following paragraphs.

Firstly, all big data features (i.e. data richness, data timeliness) and big data management issues (i.e. data quality and data ownership) are discovered relevant for all the supply chain planning processes under investigation, even if with different relative importance. In particular, result shows that, data richness is the most relevant big data feature stemming from smart connected products, which primarily exhibits the potential to reinforce DemP, PrcP and DisP with information connected to the external factors (e.g. weather conditions, tyre replacement rate) affecting the customers’ decision towards tyre use. It also presents the opportunity to access product-in-use data directly emerged from the final customer.

Data quality, referring to the reliability and usability of the data collected, appears to be the major big data management issue, whose implication potential outweighs the ones of the intrinsic big data features (e.g. in ISCP). In particular, data ownership emerged relevant especially in the case of end-to-end ISCP, DemP and DisP. It is not surprising as these three processes have a direct interface with customers and are, therefore, more sensitive to the issue connected to the ownership of the data collected from smart connected product, especially for the OE channel. *“We will be able to achieve a better supply chain planning only if we agree with carmakers to share the data and the information collected through the smart connected products (...)”*, in the words of the DemP.

Regarding individual supply chain planning process, DemP, PrdP and DisP are expected to benefit from the increased granularity of big data from smart connected product, namely the current and target stock level at the warehouse of the customers, in combination with high reliability (i.e. data quality). In particular, for DemP, the assumption holds true especially for the replacement channel, in which the ownership of the information from smart connected product is not subject to the mediation of the OEMs. As for PrcP, the main area of improvement, introduced by big data from smart connected product, lies in the potential of obtaining more stabilised plans, leveraging on the increased amount of data (i.e. data richness) in combination with their real-time nature (i.e. data timeliness). In the case of ISCP, acting as the coordinating function across all supply chain planning activities, the quality of big data is highly evaluated in the interviews compared to other functions.

Table 1 exhibits the evidences supporting the previous discussion on the different big data features (in row) for each supply chain planning process investigated (in column). For each column, the values in percentage indicate the occurrence of each big data features stemming from the interviews. These values are considered as proxy of the perceived extensive of changes, reflecting the relevance of the big data features for each supply chain planning function. It is reasonable to highlight that, for PrcP and PrdP, data ownership of big data from smart connected product is not particularly relevant, as data feeding to these processes are primarily internal ones.

**Table 1 Occurrence of big data features in interviews**

	ISCP	DemP	PrcP	PrdP	DisP	Arg
Data Richness	25%	<b>47%</b>	<b>45%</b>	<b>38%</b>	<b>44%</b>	<b>40%</b>
Data Timeliness	17%	13%	28%	25%	11%	19%
Data Quality	<b>33%</b>	20%	27%	37%	34%	30%
Data Ownership	25%	20%	0%	0%	11%	11%

## 5.2 Impact on supply chain planning

Big data from smart connected products can impact different supply chain planning processes on input, planning process and output (performance).

For ISCP and DemP, data timeliness and data richness (i.e. data on tyre usage and its annual replacement rate) could potentially lead to a change in the overall supply chain planning logic. *“Adopting smart connected tyres (in the replacement channel), would allow us to have real-time information about the wear level of the tyres and the replacement frequency. This leads to a substantial impact on the company’s demand forecasting accuracy, shifting our production approach from a Make-to-Stock to a Make-to-Order”* explained the integrated planning manager. Performance improvement is estimated both in the area of efficiency and effectiveness. Referring to the replacement channel, the DemP manager puts *“If we could gather information from final consumers, this will result in a drastic decrease in the amount of stock for the wholesaler, which will need less stocks to cope with uncertainty”*. Referring to the OE channel, the impact on the planning process is considered less disruptive, allowing to have more and precise information on the performance of the product-in-use, relying on valuable data during the lifecycle, favouring the adoption of additional input to correct product design or production failures.

Consequently, PrdP and PrcP of both channels would benefit from a higher stability thanks to increased data timeliness and richness. *“The substantial improvement in the demand forecast would bring the purchasing process to receive much more accurate input data from the production planning phase (...)”*, explained the purchasing manager. *“More stable and predictable demand would entail, higher efficiency for example producing larger lots with less scraps and lower stock-out costs”*.

Finally, from the perspective of the distribution manager data timeliness is fundamental to achieve another performance improvement connected to inventory management in the replacement channel. *“Real-time visibility on degradation of the tyres, consumers geo-localization could optimize the stock level and localization throughout our network”*.

The main impacts on each supply chain planning matrix is summarized in Table 2<sup>1</sup>.

## 5.3 Impact on SC configuration and relationship

Big data from smart connected product will potentially change the downstream supply chain in terms of *replacement channel disintermediation*. Traditionally, wholesalers and retailers in the replacement channel intermediate the physical and information flow between the manufacturer and its customers, where an additional tier could be introduced as the tyre specialists. These intermediaries in the supply chain add up inefficiency in the process by introducing information asymmetry. The introduction of smart connected products is expected to eliminate these inefficiencies by directly bringing the timely and granular data from individual end-users to the tier manufacturer. Thanks to the connectivity provided by the smart connected products, the tyre manufacturer will be able to bypass the multiple layers in the downstream supply chain, having direct contact with end consumers through interactive application. By using of these product-in-use data, e.g. tyre wear and whether condition, the tyre producer will be able to generate more precise demand and

<sup>1</sup> Available at: <https://bit.ly/3dvvVIT>

production plans, and the traditional intermediaries in the downstream (i.e. wholesalers and retailers) will lose the relevant informational power that they used to possess with traditional products. However, the manager of ISCP clarified that the role of intermediaries is still relevant in distant geographical areas and as physical contact points with the customers in terms of service provision.

Concerning the OE channel, smart connected products are expected to facilitate *tighter and more strategic collaboration with OEMs, especially during the development process*. The demand of automotive components in the OE channel, including tyres, is strictly coupled with the sales of car models. As it entails high costs to set up strategic collaboration with an OEM and to engineer a tyre that specifically meets all the needs, it is generally not feasible for automotive suppliers to set up relationships with all potential OEMs. Therefore, identifying the correct partners and, thereby, establishing strategic relationships becomes a priority. *“Carmakers are our technology partners, and if one of their car models will be successful, it is very likely that the demand for tyres of those models will grow”*, explained by the DemP manager. However, customers generally make purchasing decisions based on the reputation and performance of car models rather than what systems it equips. This provides a higher probability that the information from smart connected production will be intermediated by the OEM between the tyre manufacturer and the end-users. Therefore, qualified data would be fed to the manufacturer only if the OEMs are willing to share this information. As a consequence, a higher level of power asymmetry is directed towards the OEM, and consequently, advantages from the smart connected products will arrive at the tyre manufacturer only if a strong collaborative relationship with OEM is in place.

Regarding the upstream supply chain configuration and relationship, it is expected to achieve *slight improvement of power against material and component suppliers*. The effect is mainly achieved through two reasons. On the one hand, as the introduction of the smart connected tyres would offer higher precision in the planning of demand and production, it can transmit this benefit further towards the upstream suppliers. In turn, the sharing of benefit will potentially bring better contract conditions when dealing with material and component suppliers. As the procurement planning manager put, *“the smart connected products will stabilize our demand towards suppliers, thus, it gives us more confidence in cost savings tactics towards speculative purchases and power in negotiation with our suppliers.”* On the other hand, the introduction of smart connected products will trigger the “service” side of the product alongside its basic functionality. This will lead to a further level of commoditization in the upstream of the function-centric supply chain.

However, introducing smart connected products could potentially infer the need for *establishing new relationships with technological suppliers*, e.g. suppliers of software, where these suppliers do not belong to the traditional automotive supply chains. Automotive suppliers have limited experience in collaborating with these suppliers that offer IT service, platforms and software development support, who are generally multi-national organizations specialized in technical offerings, and could be of larger size. As raised

by the ISCP manager, *“the service- and software-related part of the supply chain is expected to experience the toughest competition with high margins”*. Therefore, the establishment of these new relationships with technological suppliers could be potentially create power asymmetry towards these technology giants, for which automotive suppliers need to be aware on the potential implications to relationship management.

## 6. Discussion

Interestingly, our findings presented in Table 1, shed lights on how extensively could span the impact of big data analytics on supply chain planning processes. Put differently, supply chain planning processes are likely to change thanks to big data analytics from smart connected products, leveraging on different big data features. Data richness is a feature that is likely to have an extensive impact in all supply chain planning processes. Notably, *data richness* focuses on the amount and the type of data and it is the feature that most likely will lead to an extensive change in any planning processes. Big data analytics collected through smart products can lead to improvements which touch different aspects of the planning process, not necessarily in terms of marking radical changes, but also small process improvements in different process elements. In downstream processes (e.g., DisP and DemP) these changes are more likely to be radical, possibly including organizational changes (Patrucco et al., 2020), whereas in upstream processes changes induced by big data analytics might allow to take more timely decisions to transmit accurate and rich information regarding downstream processes as decisional inputs for upstream process planning (e.g., how much to produce/purchase and when).

Moreover, the previous analysis highlighted obvious distinction in the two distribution channels, namely, the replacement channel and the OE channel. These results led us in drafting three propositions respectively for the two channels.

For what concerns the replacement channel, the presence of more granular data from smart connected product in real-time provides better input to the supply chain planning process. It provides the possibility to turn product-in-use data from individual end-user into useful information when planning demand in the replacement channel. Thereby, the performance of supply chain planning is expected to be improved in terms of accuracy and reliability (Andersson and Jonsson, 2018).

*P1: Better data timeliness and data richness lead to better supply chain planning performance.*

The introduction of the smart connected products guarantees better performance in planning. Benefit from a more accurate and stabilized planning can be transmitted upstream to the material suppliers, as well downstream in the replacement channel. The sharing of benefit can bring higher informational power to the focal tyre manufacturer, which could potentially lead to downstream supply chain restructuring, such as disintermediation of the wholesalers.

P2: Better data timeliness and data richness lead to a more advantageous position in supply chain relationship through benefit sharing.

Smart connected tyres have the potential to provide input data with higher precision and reliability (i.e. veracity) alongside data timeliness and data richness. As smart connected products can collect product-in-use information directly from the embedded sensors, manipulation and human intervention can be avoided before data reaches the manufacturer. Therefore, as shown in Figure 1, the dimension of data quality further strengthen the relationship between big data features and supply chain planning and supply chain relationship.

P3: Data quality exemplifies the impact of data timeliness, data richness on supply chain planning and supply chain configuration and relationship.

Finally, data ownership here is not an issue, in which the network of tyre specialists are independent from OEMs centres.

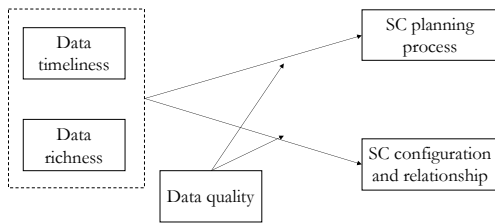


Figure 1 Conceptual framework in Replacement channel

As outlined in in Figure 2, different patterns are observed in the OE channel, emphasizing the concept of data ownership. We use this concept to underline the possession of big data by the focal company as well as the right to grant access (Corbett, 2018).

The possession of big data in the OE channel is typically a strategic decision. OEMs are generally the initiators, coordinating the effort from various system integrators and software providers. Therefore, it demonstrates the tendency that OEMs in these projects are declaring the ownership of data generated from the multiple smart connected products and systems, likely through an integrated platform. The possession of such large-scale comprehensive data generates absolute informational power towards the OEMs. Therefore, the structure of data ownership will strongly affect the supply chain configuration and the relationships (i.e. power distribution and collaborative structure).

P4: Data ownership presents a decisive impact on supply chain configuration and relationship.

To continue with the previous discussion, the decision on sharing of such big data with individual system integrator would decisively impact on the possibility to integrate them in the supply chain planning of each player. When data ownership is in the hand of the OEM while in absent of data sharing, the supply chain planning will not be able to grant improvement from the introduction of the smart connected product.

P5: Data ownership presents a decisive impact on the improvement of supply chain planning performance.

However, as smart connected products enable significant improvement in data timeliness and data richness, it will further enhance the relationship between data ownership and supply chain planning and supply chain relationship.

P6: Better data timeliness and data richness exemplify the impact of data ownership on supply chain planning and supply chain configuration and relationship.

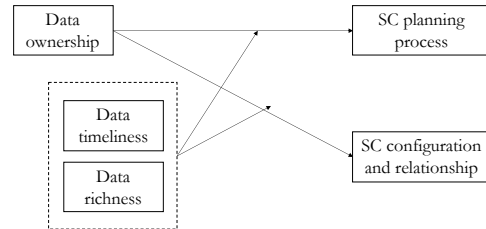


Figure 2 Conceptual framework in OE channel

## 7. Conclusions

Based on a single embedded case study, this research reveals several implications on how big data will impact supply chain management on the dimension of supply chain planning, supply chain configuration and supply chain relationship. The study highlights that manufacturing company can benefit from the use of big data from smart connected products by leveraging on the dimensions of data timeliness and data richness. Meanwhile, pertaining to the type of product (i.e. component or final product), data quality and data ownership also exert significant impact.

Despite the richness of the embedded single case study, results in this study are limited to a single reality, thus exposing the study to the problem of generalizability of the results to other contexts. Nevertheless, the implication from this research can seek for generalization with future research. The result and discussion presented respectively for the distribution channels (i.e. replacement channel and OE channel) can be extended to other types of products. The features of the replacement channel resemble the “final product” in other industry which could potentially have or develop direct interaction with end-users. Examples of this type could be various type of consumer goods and consumer electronics (e.g. smart-home appliances). While the OE channel represents features of materials or components in the industrial setting, where components of the smart factory could be considered.

This research also provides theoretical contributions. The six propositions elaborated in this study can guide future studies towards theory testing, to validate the relationship between big data and the supply chain-related issues, as well as assessing the strength of these relationships.

## References

Andersson, J. and Jonsson, P. (2018), Big data in spare parts supply chains: The potential of using product-in-use data in aftermarket demand planning, *International Journal of*

- Physical Distribution and Logistics Management*, Vol. 48 No. 5, pp. 524–544.
- APICS. (2017), *Supply Chain Operations Reference Model, V12.0, Supply Chain Operations Management*.
- Arunachalam, D., Kumar, N. and Kawalek, J.P. (2018), Understanding big data analytics capabilities in supply chain management: Unravelling the issues, challenges and implications for practice, *Transportation Research Part E: Logistics and Transportation Review*, Elsevier Ltd, Vol. 114, pp. 416–436.
- Banker, S. (2016), Using Weather Data to Improve Supply Chain Resiliency, *Forbes*.
- Bumblauskas, D., Gemmill, D., Igou, A. and Anzengruber, J. (2017), Smart Maintenance Decision Support Systems (SMDSS) based on corporate big data analytics, *Expert Systems with Applications*, Elsevier Ltd, Vol. 90, pp. 303–317.
- Chandra, C. and Grabis, J. (2016), *Supply Chain Configuration, 2nd Edition, Springer*.
- Christopher, M. and Ryals, L.J. (2014), The supply chain becomes the demand chain, *Journal of Business Logistics*, Vol. 35 No. 1, pp. 29–35.
- Corbett, C.J. (2018), How Sustainable Is Big Data?, *Production and Operations Management*, Vol. 27 No. 9, pp. 1685–1695.
- Davenport, T.H. and Kirby, J. (2016), Just how smart are smart machines?, *MIT Sloan Management Review*, Vol. 57 No. 3, 16856.
- Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G. and Gnanzou, D. (2015), How “big data” can make big impact: Findings from a systematic review and a longitudinal case study, *International Journal of Production Economics*, Elsevier, Vol. 165, pp. 234–246.
- Guha, S. and Kumar, S. (2018), Emergence of Big Data Research in Operations Management, Information Systems, and Healthcare: Past Contributions and Future Roadmap, *Production and Operations Management*, Vol. 27 No. 9, pp. 1724–1735.
- Huang, T. and Van Mieghem, J.A. (2014), Clickstream data and inventory management: Model and empirical analysis, *Production and Operations Management*, Vol. 23 No. 3, pp. 333–347.
- Ilie-Zudor, E., Ekárt, A., Kemeny, Z., Buckingham, C., Welch, P. and Monostori, L. (2015), Advanced predictive-analysis-based decision support for collaborative logistics networks, *Supply Chain Management: An International Journal*, Vol. 20 No. 4, pp. 369–388.
- Ivanov, D. (2017), Simulation-based single vs. dual sourcing analysis in the supply chain with consideration of capacity disruptions, big data and demand patterns, *International Journal of Integrated Supply Management*, Vol. 11 No. 1, p. 24.
- Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C. and Byers, A.H. (2011), *Big Data: The next Frontier for Innovation, Competition and Productivity*, McKinsey Global Institute.
- McAfee, A. and Brynjolfsson, E. (2012), Big data: The management revolution, *Harvard Business Review*, Vol. 90 No. 10, p. 4.
- Nguyen, T., Zhou, L., Spiegler, V., Ieromonachou, P. and Lin, Y. (2018), Big data analytics in supply chain management: A state-of-the-art literature review, *Computers and Operations Research*, Elsevier Ltd, Vol. 98, pp. 254–264.
- OnMarketing. (2014), Why Amazon’s Anticipatory Shipping Is Pure Genius, *Forbes*.
- Patrucco A, Ciccullo F, Pero M (2020) Industry 4.0 and supply chain process re-engineering: A coproduction study of materials management in construction. *Business Process Management Journal*
- Porter, M.E. and Heppelmann, J.E. (2014), How smart, connected products are transforming competition, *Harvard Business Review*, No. November 2014, pp. 1–49.
- Porter, M.E. and Heppelmann, J.E. (2015), How smart, connected products are transforming companies, *Harvard Business Review*, No. October, pp. 1–38.
- Richey, R.G.J., Morgan, T.R., Lindsey-Hall, K. and Adams, F.G. (2016), A global exploration of Big Data in the supply chain, *International Journal of Physical Distribution & Logistics Management*, Vol. 46 No. 8, pp. 710–739.
- Russom, P. (2011), *Big Data Analytics, TDWI Best Practices Report, Fourth Quarter*.
- Salleh, K.A. and Janczewski, L. (2019), Security Considerations in Big Data Solutions Adoption: Lessons from a Case Study on a Banking Institution, *Procedia Computer Science*, Elsevier B.V., Vol. 164, pp. 168–176.
- See-To, E.W.K. and Ngai, E.W.T. (2018), Customer reviews for demand distribution and sales nowcasting: a big data approach, *Annals of Operations Research*, Springer US, Vol. 270 No. 1–2, pp. 415–431.
- Sinha, R. (2019), Role of Social Media in Supply Chain Management, *Board Infinity*.
- Tiwari, S., Wee, H.M. and Daryanto, Y. (2018), Big data analytics in supply chain management between 2010 and 2016: Insights to industries, *Computers and Industrial Engineering*, Elsevier, Vol. 115 No. October 2017, pp. 319–330.
- Waller, M.A. and Fawcett, S.E. (2013), Click here for a data scientist: Big data, predictive analytics, and theory development in the era of a maker movement supply chain, *Journal of Business Logistics*, Vol. 34 No. 4, pp. 249–252.
- Wang, G., Gunasekaran, A., Ngai, E.W.T. and Papadopoulos, T. (2016), Big data analytics in logistics and supply chain management: Certain investigations for research and applications, *International Journal of Production Economics*, Elsevier, Vol. 176, pp. 98–110.
- Wu, X., Zhao, J. and Tong, Y. (2018), Big Data Analysis and Scheduling Optimization System Oriented Assembly Process for Complex Equipment, *IEEE Access*, IEEE, Vol. 6, pp. 36479–36486.
- Yin, R.K. (2009), *Case Study Research: Design and Methods (4th Edition)*, SAGE Publications, 4th ed., SAGE publications.
- Yu, W., Chavez, R., Jacobs, M.A. and Feng, M. (2018), Data-driven supply chain capabilities and performance: A resource-based view, *Transportation Research Part E: Logistics and Transportation Review*, Elsevier Ltd, Vol. 114, pp. 371–385.
- Zhong, R.Y., Xu, C., Chen, C., Huang, G.Q., Zhong, R.Y., Xu, C., Chen, C., et al. (2017), Big Data Analytics for Physical Internet-based intelligent manufacturing shop floors, *International Journal of Production Research*, Taylor & Francis, Vol. 55 No. 9, pp. 2610–2621.