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Barriers of Embedding Big Data Solutions in Smart Factories: Insights from SAP Consultants

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Abstract

Purpose: Big data is a key component to realize the vision of smart factories, but the implementation and usage of big data analytical tools in the smart factory context can be fraught with challenges and difficulties. The study reported in this paper aimed to identify potential barriers that hinder organisations from applying big data solutions in their smart factory initiatives, as well as to explore causal relationships between these barriers.

Design/Methodology: The study followed an inductive and exploratory nature. Ten in-depth semi-structured interviews were conducted with a group of highly experienced SAP Consultants and Projects Managers. The qualitative data collected was then systematically analysed by using a thematic analysis approach.

Findings: A comprehensive set of barriers affecting the implementation of big data solutions in smart factories had been identified and divided into individual, organisational and technological categories. An empirical framework was also developed to highlight the emerged inter-relationships between these barriers.

Originality /value: This study built on and extended existing knowledge and theories on smart factory, big data and information systems research. Its findings can also raise awareness of business managers regarding the complexity and difficulties for embedding big data tools in smart factories, and so assist them in strategic planning and decision-making.

Keywords: Smart Factory, Big Data, Barriers, Information Systems

1. Introduction

Remarkable improvements in autonomous technologies and significant changes in market requirement are shifting the industrial evolutionary journey towards the 4th generation, or so called Industry 4.0 (Shrouf et al., 2014; Peng et al., 2017). This has become an important concept promoted by both developed (e.g. US, UK, Germany and Japan) and developing (e.g. China and India) countries, with the aims of profoundly enhancing efficiency and maximising sustainability in manufacturing environment through new technologies (Almada-Lobo, 2015). Smart factory is a key concept emerged together with the vision of Industry 4.0. It utilises a set of advanced technologies (including Internet of Things or IoT, cyber physical systems or CPS, cloud computing, big data and artificial intelligence) to enable peer-to-peer communication and negotiation between machines, systems and products, as well as to respond to constantly growing amount of data generated in manufacturing processes (Davis et al., 2015). As a result, smart factory addresses vertical integration of different components and facilitates the factory to reconfigure itself for flexible production of different types of products (Lopez Research, 2014).

Ever since the emergence of the concept, smart factory has been heatedly investigated by researchers and practitioners in fields of engineering and computer sciences. One of the most critical and influential problems, widely recognised by researchers (e.g. Lee et al.,2014), is how to utilise advanced tools to process and analyse the huge amount of data generated in smart factories to support production automation and decision making. In this context, big data solutions are perceived as a crucial component to ensure the success of smart factory development, by providing the needed mechanisms in analysing, coordinating and making full use of the generated data (Wang et al., 2016). In organisational practice, pioneers and practitioners pursuing leading-edge smart factory initiatives are actively leveraging big data solutions (e.g. SAP Hana) for optimising operations and automation on a real-time basis (Zhong et al., 2016).

Despite the strong need, however, there seems to be a scarcity of research and studies to explore the phenomenon of embedding big data solutions in smart factories. In particular, our review of the literature showed that most studies in the field explored the issue of smart factory or big data separately. There are few empirical studies assessing the combination and potential of big data solutions in the context of smart factories (Riggins & Fosso, 2015). More importantly, current studies on smart factory or big data are focusing on technical and engineering aspects such as security aspects (Sadeghi, Wachsmann & Waidner, 2015), smart operators and enhanced supply chains (Kolberg & Zühlke, 2015) and application of CPS in Industry 4.0 environments (Jazdi, 2014). In fact, although smart factory and big data analytics are driven by advanced technologies, their success is highly dependent on the application environment and organisational settings (Peng et al., 2017). In other words, challenges and problems occurred when implementing big data solutions in smart factory cannot be addressed by merely focusing on technology or engineering innovation, but also rely on how to effectively adopt and manage such technology in organisation contexts. In light of this discussion, an important omission identified in the current literature was the lack of study to investigate challenges and barriers for embedding big data solutions in smart factories from a socio-technical angle, especially from an information system (IS) perspective that takes into account the intersections of technology, data, management and people.

The study reported in this paper aims to fill these knowledge gaps, by investigating and exploring socio-technical barriers affecting the implementation and usage of big data solutions in the context of smart factory. Considering that most user companies may still be in infant stage toward embedding big data solutions in their new smart factory initiatives, they may not be able to offer sufficient insights for the phenomenon under investigation. As such, this study was specifically conducted from an IS consultancy perspective. A group of experienced SAP consultants were interviewed, and the results of data analysis led to the establishment of a framework that contains 12 critical barriers divided into three main categories. This study contributes to the body of knowledge by extending current theory in big data and smart factory, and producing a practical framework with guidance and emphasis on its organisational implementation.

The rest of this paper is structured as follows. The next section provides a systematic review of literature on smart factory and big data, followed by an explanation of the research methodology. Subsequently, the findings derived from the interviews were presented and discussed. The last section provides the overall conclusion, implications and limitation of this study.

2. Related research on smart factory and big data

2.1 Overview of literature on smart factory

Smart factory is a term used to describe industrial operation improvements through integration and automation of production systems, linking physical and cyber capabilities, and maximising data power including the leverage of big data evolution (Moyne & Iskandar, 2017). Companies initiating smart factory innovation seek to obtain competitive advantages through adopting and applying cutting-edge information technologies (Kang et al., 2016). By applying IoT technologies (e.g. wireless sensors, RFID tags, cyber-physical systems etc.), smart factory can monitor real-time machine processes in the production line, create a virtual copy of its physical world, and finally leads to a shift from centralised control system to new forms of decentralised, distributed and autonomous control and operations (Zhong et al., 2017). This brings in many benefits including flexibility (Veza, Mladineo & Gjeldum, 2015), productivity and resource efficiency (Furthermore, Kolberg & Zuhlke, 2015).

Aligned with its importance in the industry, smart factory has remained to be one of the most popular areas in engineering and computer science related research in recent years. Specifically, our review of the literature showed that current studies on smart factory could be categorized into three streams. The first stream concentrated on proposing general system architectures and engineering solutions by analysing the requirements of smart factory, in order to bring smart factory from a concept into technical practice (e.g. Lee et al., 2015; Lin, Lee, Lau & Yang, 2018). Another set of research showcased pilot applications and technical prototypes of smart factory in particular industries, such as automobile and aircraft manufacturing industry (e.g. Zhong et al., 2016), petrochemical industry (e.g. Li, 2016; Yuan et al., 2017) and green energy industry (e.g. Shrouf et al., 2014). The third group of studies attempted to explore potential challenges and risks associated with smart factory but from a very specific (and in fact rather limited) perspective, e.g. information security issues (Lasi et al., 2014) and information access and process issues (Dhungana et al., 2015).

In contrast to this rich amount of technical literature, there is relatively a lack of focus from socio-technical perspectives to investigate social, organisational, management and people issues in smart factories. For example, Zhou and Zhou (2015) suggest that smart factory is still at a low level of development and that it is confronted with challenges including political, economic, technological and social aspects. This indicates the importance of socio-technical challenges in the development of smart factory. In fact, many past studies on information systems demonstrated that, technology is important but not the only determinant of success of IS projects in organisations (e.g. Peng et al., 2017). The intersection and interrelation of technology, organization and users will have significant influences on deployment and usage of information systems in general and smart manufacturing technologies in particular. This thus reinforces the argument made earlier in this paper and indicates that there is a need to investigate smart factory related issues from a "softer" and IS perspective, in order to realise the vision of Industry 4.0.

2.2 Overview of literature on big data

Big data refers to the data set that cannot be processed or used via traditional data processing methods because of its complex structure, wide range and size (Kang et al., 2016). Big data symbolises a revolutionary step forward in its application by means of its three main characteristics, namely variety, velocity and volume. In particular, variety represents the different forms of structured, semi structured and unstructured data that can be processed; velocity symbolises the capacity of processing large volumes of data in (near) real time; and volume denotes the amount of data generated tremendously every second (Sagiroglu & Sinanc, 2013).

Whilst big data is commonly recognised to have the potential of generating enormous benefits to organisations, the analytics of big data is still an ongoing issue that has yet been fully explored (Comuzzi & Patel, 2016). People's diverse information needs, misfit in organisational culture, resistance to change, and rapid development in technology and industrial facilities can create challenges in both analysis and usage of big data (Santos et al., 2017). Our review of literature showed that current research of big data and their application in the organisation context has three main focusses. The first type of studies tends to explore and discuss, from a conceptual level, the definition, characteristics and nature of big data (e.g. Wamba et al., 2015). The second stream of research tends to explore the interactions and interconnections among big data, technology, methods and impacts with aims of finding technical solutions to extract meanings and value from the data and to enable better analysis (e.g. Kaisler et al., 2013; Provost & Fawcett, 2013; Ren et al., 2017). More recently, studies focusing on the socio and organisational perspectives start to appear, for example, to propose model for organisations to realise the value of big data (Comuzzi & Patel, 2016) and to investigate big data usage in human resources management (Angrave et al., 2016). However, the issues of how to consider organisational and human factors in big data analytics and the associated barriers in applying big data solutions in organisations are less explored in the literature, especially through empirical studies (Arunachalam, Kumar & Kawalek, 2018).

2.3 Overview of literature on applying big data in smart factories

Big data is a fundamental driving factor in achieving the vision of smart factory. Big data of a smart factory can be gathered from three main sources, i.e. networked sensors embedded in machines and facilities where real-time data is collected; information systems used in organisations such as enterprise resource planning and customer relation management systems; and external data including social media records, market statistics, industrial regulations and competitor annual reports as retrieved from the Internet (Katal, Wazid & Goudar, 2013). A lot of research suggests big data analytics being a solution for different smart factory problems (Kang et al., 2016). In particular, sensors and IoT infrastructure can help to collect a large volume of production and machine data in real-time (Shah, 2016). Big data solutions can then be used to realise production automatic control and predictive machine maintenance, as well as to detect and prevent potential problems, by analysing actual conditions disclosed from real-time data and comparing them with historic data (Riggins & Fosso, 2015). Further to production, big data solutions can be used to support operations and decision making of other business divisions (including R&D, sales, logistics, purchasing and after-sales services) throughout the whole product lifecycle of a smart factory (Provost & Fawcett, 2013).

Nonetheless, the application of big data solution in smart factory will not be a straightforward task and can in fact be fraught with challenges. The most frequently mentioned challenge is related with technical ability to process huge amount of real-time data, derive findings from it and change machine behaviours accordingly (Bagozi et al., 2017). In addition, information security and trust had been highlighted as other key problems occurred when applying big data in smart factories (Sadeghi et al., 2015). Furthermore, this new wave of factory transformation could also result in changes of job roles, reduction in manpower, and innovations in organizational structure, management and operations (Lin et al., 2018). But employees may be reluctant to accept these emerging manufacturing and operational changes (Kusiak, 2018). Previous research showed that these are important but only some of the key challenges affecting the success of innovation triggered by advanced information technologies (Peng & Nunes, 2009). A further review of the literature indicated that there are currently very limited studies exploring the range of socio-technical difficulties and problems associated with the application of big data analytics in smart factories. It is therefore difficult to draw meaningful theories and guidance from current literature to support this data-driven smart innovation in manufacturing firms. To address this knowledge gap, this paper empirically investigates different types of barriers that organisations are confronted with in their application of big data analytics in smart factory context. Particularly, through an empirical approach, the paper contributes to the literature by proposing a framework of barriers in this context.

3. Research methodology

In order to achieve the research aims presented above, this study followed an inductive qualitative approach with the use of semi-structured interview as the data collection method. This section provides detailed justification of the adopted research methodology together with explanation about how it was implemented.

3.1 Data collection

Due to the lack of existing theory and literature to conduct a deductive study, this research followed an inductive approach. It is widely acknowledged that inductive research approach aims to build theory based on collected data, and is so suitable for studies focusing on new topics which do not have many existing theory and literature (Saunders et al., 1997). Moreover, considering the complexity of big data challenges in a smart factory, this study required the collection of in-depth human opinions, insights and perceptions (rather than just numerical data) in order to explore related phenomena in details. Consequently, this inductive study also adopted a qualitative data collection method, namely semi-structured interview .

As most user companies are still in infant stage toward embedding big data solutions in their new smart factory initiatives, their managers and staff may not have sufficient insights for the phenomenon under investigation. As such, this study was specifically done from an IS consultancy perspective, with the hope that experienced consultants can offer more in-depth insights on both big data and smart factory development and so lead to more meaningful findings. Consequently, 10 SAP Project Managers and Consultants with 5+ years of experience in world-class IT implementation (including big data, smart factory, CPS and/or IoT) projects were interviewed. Interviewing professionals holding different roles served the purpose of receiving various perspectives of the challenges in big data implementation in a smart factory context. Table 1 shows the pseudonyms given to the participants and their experience in different fields of interest.

Role	Pseudonym	Years of experience in IT	Years of exp. in SAP	Experience in Big Data	Industry 4.0 awareness
SAP Project Manager	SAP PM A	18	18	2 years	Yes
	SAP PM B	19	8	No	CPS, IoT
SAP Consultant	SAP Consultant A	6	6	No	No
	SAP Consultant B	15	15	No	IoT
	SAP Consultant C	11	7	No	No
	SAP Consultant D	8	8	2 years	CPS
	SAP Consultant E	5	5	3 months	CPS
	SAP Consultant F	5	4	1 year	No
	SAP Consultant G	15	15	1 year	CPS, IoT
	SAP Consultant H	20	8	3 months	IoT

Table 1. Profile of participants

The interview questions were elaborated with the objective of obtaining the previous experience and knowledge from the consultants regarding to big data implementation in general and in the context of smart factory in particular. Therefore, the interview was structured into three parts, all of which consisting on initiating, follow-up, trigger and closed questions. The first part assisted in understanding current role, background and related experience of the interviewee. The following second part of the interview was focused on requirements for client/manufacturing companies in implementing big data solutions and/or undergoing smart factory transformation. Interviewees were also asked to recall and explain the challenges and changes for companies implementing these solutions. The last part of the interview was to obtain demographic information about the interviewees. Each interview was conducted in the participant's office with pre-booked appointment, and lasted for 50 minutes to 1.5 hours.

3.2 Data analysis

The research data was analysed in five stages following the thematic analysis approach, as explained in Table 2. The analysis started by transcribing and obtaining familiarity with the data, in order to gain more in-depth understanding of the data collected and identify possible patterns. In the subsequent coding stage, a wide range of codes was generated in a coding scheme together with relevant quotations. The third phase of analysis was concerned with forming themes and sub-themes of big data implementation challenges through merging and combining different codes. As a result, all the identified codes were distributed into three themes and twelve sub-themes.

Stage	Description of the process
1. Getting familiar with the data	Getting known the data through the process of transcription, reading and re-reading the data.
2. Coding the data	Developing coding scheme - all codes emerged from the data, coding textual data in a systematic fashion across the entire data set.
3. Connecting codes and identifying themes	Collating codes into potential themes, gathering all data relevant to each potential theme.

4. Reviewing themes and developing concept maps	Checking if the themes work in relation to the coded quotes and the entire data set, generating concept maps of the analysis.
5. Reporting findings	Final analysis of selected quotes, relating back of the analysis to the research question, questionnaire findings & literature, producing a chapter of findings.

Table 2. Five Stages of thematic analysis (Peng & Nunes, 2010)

In the fourth stage, all the codes and quotations that assigned to each theme and sub-theme were reviewed for coherent pattern checking. A concepts map was also developed in this stage as a tool to represent the identified themes, as shown in Figure 1. The findings were reported in the final stage of analysis with assistance of the concept map as the infrastructure and selected quotations as evidence and supports.

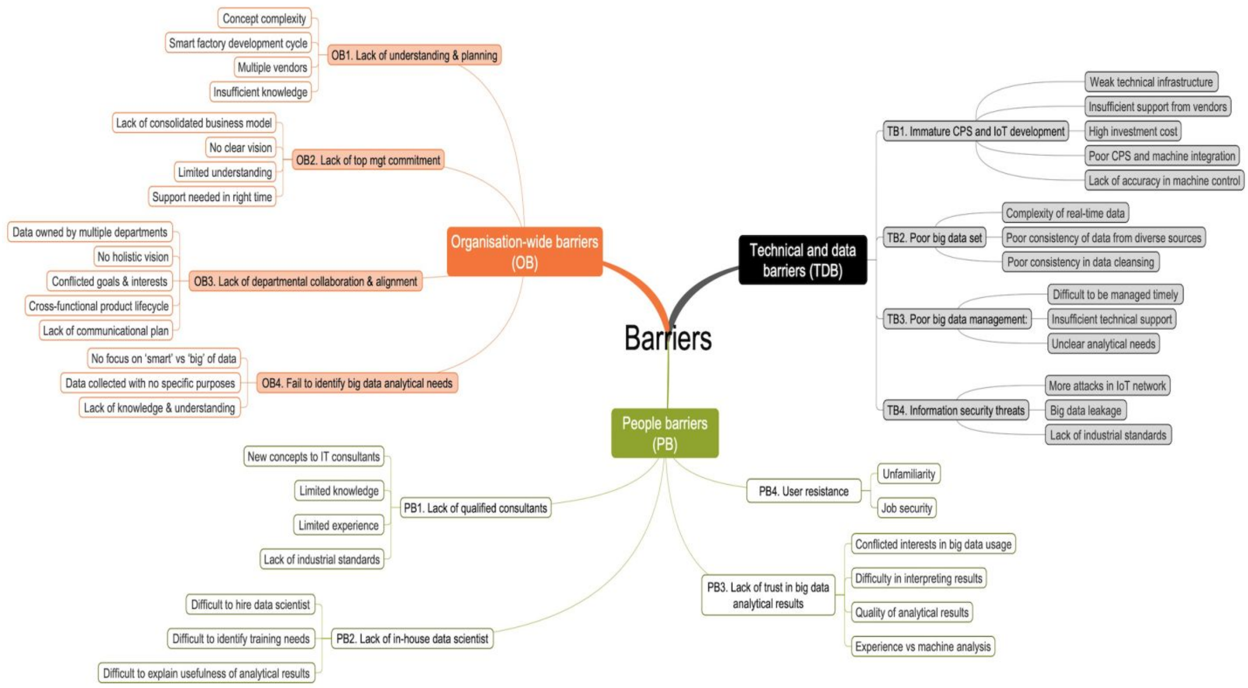


Figure 1. Concept map of codes, sub-themes and themes

4. Barriers for implementing big data solutions in smart factory

It is not easy to develop and achieve smart factory for organisations. Currently, implementing big data solutions in smart factory is more of a vision for the future as it is still at a low level of development and faces many types of challenges and barriers. In a study investigating the organisational and management practices of big data, result suggests that many organisations are far away from ready to embrace big data analytics for organisational and industrial development (Alharthim Krotov & Bowman, 2017). This requires overcoming different barriers that are associated within the organisational practice. In this paper, we discuss the socio related barriers from the aspects of project managers as practitioners, including organisational wide barriers, people barriers, and technical barriers.

4.1 Organisation-wide barriers

4.1.1 Lack of understanding and strategic planning

Lack of understanding and strategic planning is a common barrier faced by user companies when adopting new information technologies and systems. In this study, this barrier specifically refers to a lack of knowledge and understanding on smart factory in general and big data tools in particular. As such, our interviewees highlighted that managers and practitioners often may neither envision related technical and business development strategically nor plan the whole implementation project properly. Similar problem was also observed by Riggins and Wamba (2015), who stated that managers and users in the industry often experienced difficulties in understanding IoT and big data solutions and so could not make proper strategic plans for these innovation projects.

Further analysis of the interview data identified that this barrier is caused by a number of reasons. Firstly, smart factory is a new and very complicated concept, covering a variety of technical components that fall into the areas of electronic engineering, automatic control, telecommunication and software engineering. Business managers and even in-house IT/software experts "often do not have the multidisciplinary knowledge needed to develop a holistic smart factory development plan" (SAP PM B). Moreover, unlike a normal IS implementation project that often has a single vendor providing the system as a package, building a smart factory always involves multiple vendors, who respectively supply the needed CPS systems, manufacturing execution systems, and big data analytics applications. This raises further challenges for "strategic planning, coordination and inter-organisational collaboration in smart factory initiatives" (SAP PM A). Furthermore, it can take "5-10 years for a sizeable manufacturing company to be transformed into a truly smart manufacturing unit" (SAP Consultant G). And this will need to be done at stages, from basic digitalisation at shopfloor level, to full automation and optimization of the entire manufacturing firm through big data solutions (Lee et al., 2015; Leyh et al., 2016). In other words, big data analytics is an important component but will only be practically adopted in later stages of the smart factory development cycle. This makes it even more difficult for manufacturing companies to develop a clear and suitable big data implementation plan when they are mostly at early stage of the smart factory journey. Consequently, a SAP consultant interviewed cogently concluded that:

> *"Manufacturing companies realise the importance of smart factory, but what a smart factory really is, how to build a smart factory from their current situation, and how to embed big data tools to a future smart factory…they always do not have a clear vision."* (SAP Consultant F)

This lack of understanding and strategic planning in turn triggers the appearance of other organisation-wide barriers (including lack of top management commitment and fail to identify big data analytical needs in smart factory), people related barriers (e.g. lack of trust in big data analytical results and user resistance), and also technical and data barriers (e.g. poor big data management and increasing information security threats), as further discussed below.

4.1.2 Lack of top management commitment

Top management commitment and support has been widely recognised and well reported as a key factor affecting the success of IS implementation. Undoubtedly, in the context of smart factory, top management commitment will still be crucial to "enable sufficient resources to be allocated to related technical innovations as well as to resolve potential user resistance and internal conflicts" (SAP PM A). Previous research reinforced that top management support and commitment will also be important to ensure big data sets, which are often distributed across different geographical areas and 'owned' by multiple units both internally and externally, to be properly accessed, collected, analysed and managed (Kaisler et al., 2013; Higgins & Wamba, 2015).

However, due to a lack of understanding about the concepts of big data and smart factory as discussed above, top managers may not be able to envision the full benefits and usage of big data across the product lifecycle in an Industry 4.0 environment. As a consequence, they may "only be willing to adopt some basic analytical functions related to production automation, but could be less inclined to make substantial investment in embedding a full big data solution in their developing smart factory" (SAP Consultant G). Also due to a lack of strategic planning, top managers may often "fail to provide appropriate support at the right stage and right time to facilitate the implementation and usage of specific big data functions across the entire product lifecycle in a smart factory" (SAP PM B).

4.1.3 Lack of collaboration and alignment among organisational departments

As discussed in section 2.3, in the context of Industry 4.0, big data exists in not just the production department but also all other units in the whole product lifecycle including sales, logistics, product research, purchasing, and after-sales service. A holistic big data solution embedded in a smart factory will thus "affect all functional areas of the product lifecycle and will also require cross-departmental collaboration of all units concerned" (SAP PM A).

However, problems like competition for resources, contradicted goals, conflicted interests, and disagreements can always exist between departments in organisations (Peng & Nunes, 2009). As a result, lack of departmental collaboration and alignment has been frequently reported as a crucial barrier leading to failure in enterprise-wide IS implementation (Peng & Nunes, 2009). The SAP experts interviewed confirmed that similar issues would also occur when implementing big data solutions in smart factories:

> *"Departmental leaders representing different areas always raise different data analytic indicators to improve performance of their unit only… These emerge as isolated and in fact conflicted initiatives without holistic and consistent vision… It is not beneficial for the company as a whole."* (SAP Consultant C)

It is apparent that lack of top management commitment will be a direct reason leading to conflicts and misalignment across functional departments when implementing big data solutions in smart factories. This can in turn trigger other problems, e.g. failure in identifying big data analytical needs homogeneously across the full product lifecycle in the smart factory context.

4.1.4 Fail to identify big data analytical needs in smart factory

Regarding the application of big data, there is an emergent discussion among both practitioners and researchers that 'bigness' is no longer the defining parameter; instead, the focus is on how 'smart' it is, i.e. the insights that the large-volume data can reasonably provide (George, Haas & Pentland, 2014). In light of this discussion, a crucial barrier identified from our study was related to the phenomenon that companies often fail to identify specific big data analytical needs across different units of the product lifecycle and thus cannot maximize the usage of their big datasets to generate meaningful insights to support decision making in a smart factory environment:

> *"Client companies often have massive amount of data, but since they often don't know what to achieve with it and don't know their precise analytical needs, it's worthless."* (SAP Consultant A)

Further analysis of the interview data showed that the two barriers discussed above (i.e. lack of understanding about big data and smart factory, and lack of collaboration and alignment among departments) can cause severe difficulties to prevent companies from identifying clear and precise big data analytical needs. The situation will become even more challenging to handle when considering the existence of our identified people-related barriers, specifically, lack of qualified and experienced consultants and lack of in-house data scientists, as further discussed below.

4.2 People barriers

4.2.1 Lack of qualified and experienced consultants

External IS consultants play a crucial role to ensure the success of IS development and implementation projects (Peng & Nunes, 2009). These high-level IS professionals will generally possess multiple skills, including functional, technical and interpersonal skills (Bingi, Sharma & Godla, 1999). Given the technical and business complexity of smart factory and big data, consultants needed in these implementation projects will be required to have even more insights and skills than usual:

> *"To meet the requirements of applying big data solutions in the development of smart factory, consultants need to have not just technical knowledge of the solution, but also deep insights about how this big data tool can be applied to deal with specific user needs, in a particular business and production context."* (SAP PM A)

Usually, high-skilled IS consultants are very valuable asset in the IT industry and thus can be difficult to recruit and retain (Peng & Nunes, 2009). Considering the level of project complexity and the fact that big data and Industry 4.0 are relatively new concepts, "finding and keeping suitable consultants with the needed experience and skills to implement big data solutions in smart factories is currently very challenging for IT companies" (SAP PM B). Due to a shortage of qualified and experienced consultants, manufacturing companies can face many challenges when trying to apply big data analytics in their Industry 4.0 initiatives:

> *"Without sufficient support from external consultants, organisations cannot easily link big data analytics with their actual business needs… it is also difficult for them to realise the full potential of the solution and receive proper user training."* (SAP Consultant F)

4.2.2 Lack of in-house data scientist

With the development and implementation of big data solutions, there has been an increasing demand of data scientists in organisations (Kaisler et al., 2013). A highly qualified and experienced data scientist can serve as the "bridge" to link users and their requirements seamlessly with big data tools, and so help to transform the collected data into meaningful insights as well as reliable business predictions to support decision making (Waller & Fawcett, 2013). However, as illustrated by the interviewees, "manufacturing companies often found it difficult to recruit qualified in-house data scientists from the current job market, and could be even more difficult to retain them due to both an industrial shortage and high demand of this type of professional" (SAP Consultant D).

Historically, external IS consultants and internal experts need to work collaboratively to provide trainings to key users and so make sure the right people have the right skills and knowledge to operate the new system properly (Peng & Nunes, 2009). However, in the context of implementing big data solutions in smart factories, a lack of both external consultants and internal data scientists will often make it "difficult to deliver the necessary training to targeted user groups with suitable methods and contents" (SAP PM B). This lack of user training can in turn lead to other people-related problems within smart factories, e.g. lack of trust in the results of big data analytics as well as user resistance towards changes initiated by big data analytics and smart automation, as further discussed below.

4.2.3 Lack of trust in big data analytical results

When big data is receiving increasing attention from business managers, it is important to consider whether the analytical results generated by big data solutions can be trusted. In fact, some academics (e.g. Zhou et al., 2014) argue that big data may compromise too many "interests" in a company and can even lead to the situation that different individuals can find supporting evidence for any argument they are in favour of. In light of this discussion, practitioners may have doubts about "whether big data analytical results can make decision-making process more efficient or in fact lead to more confusion and potential conflicts" (SAP PM A).

On the other hand, it is inevitable that the value and accuracy of big data analytical results is dependent on the quality of original datasets. However, lack of integrated and consistent dataset was found to be a problem commonly existing in manufacturing companies (as further discussed later). Consequently, business managers may "tend to make decisions based on their experience and intuition, rather than on unreliable or inaccurate results suggested and predicted by new analytical tools" (SAP Consultant G).

Further analysis of the interview data showed that, also owing to a lack of understanding, planning and training (as discussed above), some users in manufacturing companies may be "less inclined to trust, accept and use big data tools, even if the related analytical results can in essence be useful to support their decision making" (SAP PM B). In this case, the full power of big data analytics will be greatly underutilised.

4.2.4 User resistance caused by changes in job roles and skills

User resistance is a typical and in fact inevitable phenomenon during the implementation of enterprise-wide information systems, which will substantially change the company's *status quo* and take people out of their comfort zone (Aladwani, 2001). In the context of smart factory, production automation enabled by smart IoT technologies will lead to substantial reduction of manpower: "companies no longer need to dedicate people to oversee the operation of machines, as cyber-physical systems can achieve self-operation, self-monitoring and even self-maintenance" (SAP Consultant F). The adoption of big data solutions in smart factories will extend such degree of automation and changes from the production unit to other business divisions (e.g. sales, logistics, purchasing and after-sales services) across the product lifecycle (Stock & Seliger, 2016). These changes and potential fear of job loss can lead to strong user resistance towards big data and smart factory development as cogently highlighted by the interviewees:

> *"There will always be a reluctance to change, which is natural, because you get people out of their comfort zone by engaging them in a totally different operational environment and requiring them to have a whole new set of skills"* (SAP Consultant D)

Further analysis of the interview data indicated that, lack of understanding as well as lack of top management commitment and user training will increase the level of user reluctance and resistance. Suggested by interviewees, in order to reduce resistance, efficient communication and user training will be of extreme importance. Other researchers (e.g. Kagermann, 2015, p. 36) reinforced that despite the reduction of job roles, people who remain in the organisation after smart factory transformation would expect an enhancement on their roles, and this represents a great learning and promotion opportunity which should be clearly communicated with staff.

4.3 Technical and data barriers

4.3.1 Immature CPS and IoT development

A highly efficient IoT infrastructure, which is composed of sensors and cyber-physical systems, provide the foundation of smart automation (Davis et al., 2015). Companies thus generally consider CPS and IoT sensing infrastructure as the first important milestone to be achieved in the development of smart factory. However, given the cost and technical complexity of transforming existing manufacturing equipment and production lines into fully automated cyber-physical systems, this milestone cannot be achieved easily, as confirmed by the interviewees:

> *"CPS and IoT infrastructure currently had been very immature and underdeveloped in many manufacturing companies…this is not a short-term endeavor and can take years to come true consuming a huge amount of resources"* (SAP PM B)

In light of this discussion, it emerged from our data analysis that lack of strategic planning and top management commitment would substantially slow down the progress of IoT development and equipment upgrades in smart factories. It is also evident that, since production equipment and devices are normally provided by different external suppliers, it can be difficult for manufacturing firms to carry out further development, customization, extension and integration of these devices during smart factory upgrades:

> *"Manufacturing firms will need to negotiate with different external suppliers to open up interface in their devices to enable system integration and new sensor installation. Such negotiation is never easy, especially with large equipment providers, who always want to have absolute control on their products and provide less flexibility for self-customization in the user side"* (SAP Consultant D).

The problem of immature CPS and IoT development will not just lead to data fragmentation and inconsistency, but can also raise potential information security threats, which will in turn affect the implementation and usage of big data solutions in smart factories (as further discussed in the following sections).

4.3.2 Lack of integrated and consistent big data set

As discussed earlier, big data of a smart factory can be collected from various internal and external sources, including machine sensors, management information systems, social media platforms and the Internet. Such data is not just "big" in volumes but also contains very different forms and formats, e.g. signals, texts, graphs, photos, videos, and audios. It is crucial that these big datasets are properly collected, processed and cleaned to ensure that they have high accuracy, integrity and consistency prior to data analysis (Chen & Zhang, 2014; Herschel & Jones, 2005). Otherwise, big data solutions will not be able to produce accurate and meaningful analytical results and predictions to support automated production and business decision-making. The importance of data quality was also stressed by the SAP consultants interviewed:

> *"Data quality is a key determinant of the success of any big data initiative in smart factories […] we need to generate datasets that are consistent and complete before trying to exploit them [...] the rule is 'garbage in, garbage out'. [...] Only top quality data can ensure top quality data analytical outputs."* (SAP Consultant D)

However, due to the volume, complexity and diversity of big datasets, it can often be challenging for smart factories to maintain high data integrity and consistency. Historically, inaccurate, inconsistent and redundant data may exist in management information systems due to inappropriate system usage and maintenance (Peng & Nunes, 2009). The situation of a smart factory is even more complicated, as data quality problems can be caused by not just human errors but also immature CPS and IoT development, as highlighted by the interviewees:

> *"Many manufacturing firms have not yet deployed CPS and IoT devices across the whole production line, and so result in weak communication between back-office analytical systems and shop-floor machines. Without collecting all needed production and machine data accurately and constantly, it is difficult for factories to perform real-time data analysis to realize full automation and predictive maintenance."* (SAP PM B)

4.3.3 Poor big data management

Big data, with its size and complexity, raises new challenges for data management and storage (Chen, Preston & Swink, 2015). As a rule of thumb, companies should ideally just collect the right data they need, store these data for the necessary period of time, and discard any unneeded data according to operational requirements. This ideal situation however may not always occur in practice, as highlighted by the interviewees:

> *"Many manufacturing firms have no clear idea about what data are needed, what are not needed, how to filter unneeded data, what standards can be used in data filtering, what and for how long historical data should be kept"* (SAP PM A)

Further analysis of the interview data indicated that, poor big data management could often be a direct result of a lack of understanding and strategic planning. Moreover, when companies fail to identify their analytical needs clearly, it will be difficult for them to choose and use the right standards, approaches and tools to filter and manage their big data. Overall, without efficient and appropriate big data management, "the volume of big datasets can grow extremely fast in smart factories, with a large chunk of unneeded and useless data to be kept in the data warehouse, and eventually affecting system efficiency" (SAP PM A).

4.3.4 Increasing information security threats

With a significant increase in the number of devices connected to the industrial IoT network, information security has become one of the most important aspects to consider in the smart factory context. More specifically, the use of sensors and IoT devices, on one hand facilitate production automation, but on the other hand open more doors for potential cyber attacks (Sadeghi et al., 2015). As the whole smart production line is automatically monitored, controlled and operated by systems with minimum human involvement, system breakdowns caused by cyber attacks can cease production and lead to significant financial loss (Sadeghi et al., 2015). In addition, when companies collect more big datasets from diverse internal and external sources and are able to generate more valuable data analytical reports and predictions, they may face greater information security and data leakage risks:

> *"We can allow a computer virus, but certainly cannot let a control plant system to be attacked and make production stop […] when you have greater analytical power and possess valuable business insights and predictions that other people don't have, you may be in a more vulnerable position that your factory system is attacked or your data is stolen by hackers and competitors."* (SAP PM B)

Faced with these increasing information security threats, smart factories need to be equipped with appropriate data encryption and protection tools. Further to technical solutions, other researchers highlighted that smart factories should also better support employees with trainings, establish adequate information protection policies, and clearly determine confidential terms in contracts with both employees and IT service providers (Dhungana, Falkner, Haselböck, & Schreine, 2015). Similar suggestions were also made by the interviewees:

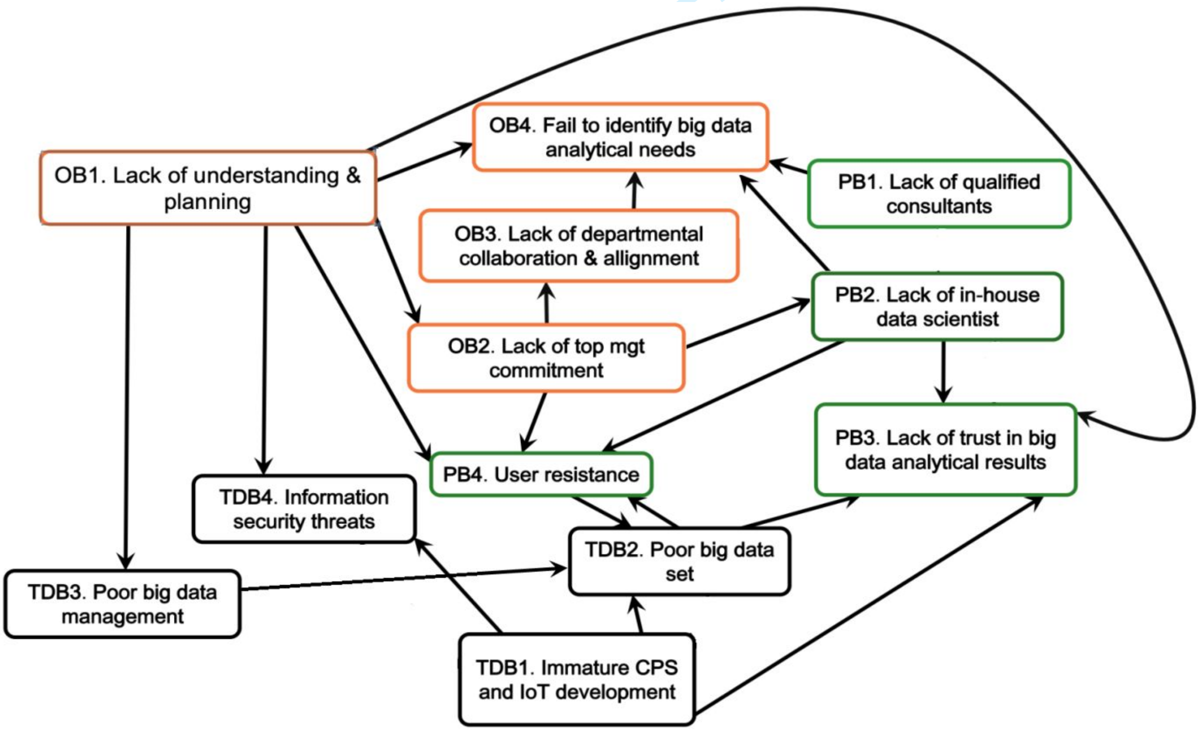
> *"Through security policies, through training to all users, through restrictions of information access to certain people, companies can reduce information threats […] You also need to make sure the right data protection terms are used in* Service Level Agreements with IT suppliers.*"* (SAP Consultant F)

5. Further discussion

Existing studies on barriers in the context of smart factory focused mainly on the layer of IoT infrastructure, with particular emphasis on challenges affecting the development of production automation, sensor networks and cyber-physical systems (e.g. Tu, Lim & Yang, 2018; Lin et al., 2018; Leitao, Colombo & Karnouskos, 2016). This study extends the understanding of smart factory barriers and challenges from the IoT layer (i.e. hardware aspects) to a "softer" side (i.e. big data analytics with an IS view). A comprehensive set of barriers had been identified and categorised according to individual, organisational and technological perspectives, as presented and discussed in the above section.

After a further comparison of our results and the literature, it became apparent that our identified barriers echo and are aligned with the findings and theories derived from previous smart factory and IS research. Specifically, information security issues raised by industrial IoT network as identified in this research are aligned with findings from Leitao et al (2016) in their investigation of challenges for developing cyber-physical systems in smart factories. Our research also revealed that the quality of big datasets could be affected by immature CPS and IoT development in smart factory. This finding is in line with Lin et al's (2018) framework with regard to the relationship between mature level of technology and the adoption and development of smart factory. On the other hand, our identified barriers are also aligned with socio-technical challenges reported in previous IS research, such as top management commitment and business-IT misalignment (e.g. Henderson & Venkatraman, 1992), user training and acceptance issues (e.g. Attaran, 1997), resistance to IS-enabled changes (e.g. Peng & Nunes, 2009), and a shortage of relevant personal skills (e.g. Cannon & Edmondson, 2005). Despite this consistency with the current literature, this study extended existing knowledge respectively reported in previous IS and smart factory studies, and generated new insights toward a phenomenon that is getting increasingly prevalent and important, namely the application of big data analytics in smart factories.

More importantly, it clearly emerged from our above findings that the identified barriers are not isolated but in fact are closely inter-related. An empirical framework is therefore developed in order to further demonstrate the emerged relationships between the identified barriers, as shown in Figure 2. This framework illustrates an inter-related nature of the barriers hindering the implementation and usage of big data applications in the smart factory context. It is apparent from the framework that barriers within a category and across different categories can influence each other. For example, lack of understanding and planning in big data analytics application can lead to many organisational problems, such as lacking top management commitment; it can also result in user resistance at the individual level; and it can also raise more information security threats at the technological level. By further examining the framework presented in Figure 2, it became clearly that the complicated network of barriers seem to be triggered by a lack of understanding and strategic planning in manufacturing companies. This result leads to an important suggestion: before investing blindly in big data and smart factory technologies, and in order to increase the chance of success, there is an imperative need for leaders and managers in manufacturing firms to increase their level of knowledge and so better prepare themselves for this type of exciting but complicated technological innovation.



OB = Organisational Barrier; PB = People Barrier; TDB = Technical and Data Barrier

Figure 2. Empirical framework of barrier relationships

6. Conclusion, implications and future studies

This paper reported on an inductive qualitative study, which aimed to fill the research gap of barriers for embedding big data solutions in smart factories, by exploring in-depth insights from a group of very experienced SAP consultants in the industry. The study has led to several important conclusions. Specifically, the results confirmed that processing, analysing and utilising big data in smart factories is not an easy task and can be fraught with challenges and difficulties related to diverse people, organisational and technological aspects. More importantly, the findings also showed that a big data barrier might often be the cause or consequence of other barriers in the context of smart factory. Because these identified barriers seem to be interwoven and closely related with each other, they may be very difficult to manage and resolve. The results of this study have important implications for both practitioners and researchers.

For practitioners, the list of identified barriers can raise awareness of business managers and in-house experts regarding the complexity and difficulties for embedding big data tools in smart factories. In particular, and from a technical and data perspective, the study confirmed that immature CPS/IoT infrastructure, poor big data sets, poor big data management and potential information security threats could all affect the adoption of big data solutions in smart factories. These findings thus suggest that smart manufacturing practitioners cannot merely consider big data implementation from a software layer, but need to have a more thorough analysis including also IoT infrastructure and data-related aspects. On the other hand, and further to technical issues, the study identified a wide range of organisation-wide (e.g. lack of understanding, failing to identify big data analytical needs) and human barriers (e.g. user resistance, lack of trust in big data results, lack of in-house data scientists) hindering the success of big data adoption in smart factories. More importantly, when these different types of barriers were found to be interwoven and influencing each other, there seemed to be particularly complicated relationships among organisation-wide and people barriers, which were also identified to be the trigger of many technical problems. Business managers and practitioners should therefore be extremely careful with possible organizational and human issues, rather than simply treating big data and smart factory development as a pure technical endeavor. It is also hoped that the established framework of barrier relationships can help practitioners to understand and anticipate potential causes and/or consequences of the identified barriers, and so assist practitioners in the processes of problem identification, strategic planning and decision making.

For researchers, this study built on and extended existing knowledge and theories on smart factory, big data and IS research. In fact, it was well studied and demonstrated in the IS literature (e.g. Cannon & Edmondson, 2005; Peng & Nunes, 2009) that the implementation and usage of information systems could be fraught with organisational, human and technical issues. This study confirmed that the same categories of issues would occur in the adoption of big data tools in smart factories. In other words, previous findings reported in the IS literature can be highly valuable and useful for the context of big data and smart factory development. Nevertheless, it is clearly demonstrated in this study that although the identified categories of barriers and even certain barrier items (e.g. lack of top management commitment, lack of understanding, lack of departmental collaboration) are frequently reported in the IS literature (e.g. Henderson & Venkatraman, 1992; Attaran, 1997; Cannon & Edmondson, 2005; Peng & Nunes, 2009), the actual phenomena (i.e. the problem itself and its causes and consequences) are considerably different in the big data and smart factory context. As such, there is a clear need for more studies to explore and understand these new phenomena in a more in-depth level. And we hope that the findings of our study can provide a good foundation for fellow IS researchers to carry out further studies in this increasingly important research area.

A noticeable limitation of the study is related to the fact that the interviews were done with a relatively small (although highly experienced) group of SAP consultants. We thus suggest that, a questionnaire survey may be used in future studies to validate the list of identified barriers, as well as to test the causal relationships between them. Further qualitative studies can also be carried out to explore the identified barriers and any other potential big data and smart factory challenges in the contexts of specific manufacturing sectors and countries, as well as to provide possible recommendations.

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