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Critical Obstacles Affecting Adoption of Industrial Big Data Solutions in Smart Factories:
An Empirical Study in China

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ABSTRACT

Industrial big data is the key to realize the vision of smart factories. This research aims to identify and explore potential barriers that prevent organizations from deploying industrial big data solutions in the development of smart factories through a socio-technical perspective. The research follows an inductive qualitative approach. Twenty-seven semi-structured interviews were conducted with the CEO, smart factory manager, IT managers, departmental heads, and IS consultants in the selected case company. The interview data were analyzed using a thematic analysis method. Derived from a thematic analysis, six sets of barriers including technical, data, technical support, organization, individual, and social issues were identified, as well as the relationships between them. An empirical framework was developed to highlight the relationship between these barriers. This study contributes to the knowledge of industrial big data in general and provides constructive insight into industrial big data implementation in smart factory development particularly.

KEYWORDS

Barriers, Industrial Big Data, Information System, Smart Factory, Socio-Technical

INTRODUCTION

Since the 2010s, many innovative and advanced information and communication technologies (ICTs) have emerged in our society, such as cyber-physical systems (CPS), advanced sensor technology, and big data. These technologies are increasingly integrated into the manufacturing industry, shifting the traditional mode of production toward smart manufacturing, called Industry 4.0 (Culot et al., 2020; Hwang et al., 2017). Industry 4.0 is an important concept for both developed and developing countries to enhance the core competitiveness and maintain manufacturing enterprise's sustainable development. The smart factory is a key concept concerned with the vision of Industry 4.0. Based on a set of advanced technologies, a smart factory integrates personnel, products, and machines to

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enable real-time management, coordination, and control among multiple systems, as well as dealing with constantly growing amounts of data generated in production processes (Kovacova & Lewis, 2021). Furthermore, a smart factory addresses the vertical integration of different components for the flexible production of different products to realize a more refined and dynamic production pattern (Shi et al., 2020; Strozzi et al., 2017).

Since the concept of smart factories was developed, academic researchers and industrial practitioners have investigated it. One of the most urgent problems in smart factory development is how to use advanced tools and algorithm models to process huge amounts of industrial data generated in product research and design, manufacturing, marketing, supply chain, and the after-sales service that aims to support intelligent production and decision-making (Jwo et al., 2021; Wang et al., 2018). In this situation, 'industrial big data' solutions become the key component to ensuring the success of smart factory development by providing the mechanism of data planning, data governance, and data application (Sultana et al., 2021). If we regard CPS and smart devices as the 'trunk' of smart factory initiatives, technology applications based on industrial big data are the 'brain,' which directly affects the successful construction of smart factories (Xing et al., 2019). In a real application, several industrial big data solutions, such as MindSphere developed by Siemens and Predix developed by GE, are leveraged by smart factory pioneers for improving the flexibility of manufacturing product lines and the utilization efficiency of the resources (Pauli et al., 2021).

Despite the strong demand and enormous opportunities that industrial big data solutions bring, there seems to be a scarcity of research to study the phenomenon of embedding industrial big data solutions in smart factories. Particularly, current literature and studies showed that most studies in this field focus on the issues of industrial big data solutions or smart factories separately (Kovacova & Lewis, 2021; Won & Park, 2020). There is little empirical research studying the combination of industrial big data solutions in a smart factory context. Meanwhile, technical perspectives, such as smart sensors and operators, primarily drive current studies in the industrial big data solutions and smart factory field (Zolotová et al., 2020), data security (Javaid et al., 2021), data model and matching algorithm (Yan et al., 2018), application of CPS in Industry 4.0 from an engineering perspective (Tucker, 2021). Indeed, the development of industrial big data analytics and smart factories highly depends on advanced technologies. However, its success still relies on how to use and manage the industrial big data solutions in smart factories more efficiently and effectively from an information system's (IS) point of view. In other words, barriers and problems cannot be addressed by simply focusing on the technical perspective. Considering this discussion, studies on utilizing industrial big data in the smart factory context are important and currently neglected, especially from an IS perspective. Therefore, there is a lack of studies that explore the barriers to industrial big data implementation in smart factories from a socio-technical view.

Based on the above literature gap, this research aims to empirically investigate the socio-technical barriers that affect the usage of industrial big data solutions in the smart factory context, not only by experienced IS project managers and consultants but also from the angle of users in the company. Therefore, the following research questions guide this study:

RQ1: What are the barriers from not only IS consultants but also a user perspective that affect the implementation and usage of industrial big data solutions in the smart factory context?
RQ2: What are the relationships between the identified barriers?

In-depth interviews were conducted with 27 participants from a selected manufacturing company in China to achieve this aim. This study focuses on the Chinese context because China is the world's largest manufacturer in terms of output and has earned a reputation as the 'world factory' (Ancarani et al., 2021). However, low-added value has become a severe issue affecting China's manufacturing companies' long-term survival and development. Therefore, the Chinese government launched the 'Made in China 2025' initiative in 2015 to upgrade China's manufacturing power nationwide (Li, 2018). Many Chinese firms have striven to carry out digital transformation and upgrading in response to this national initiative. Consequently, China presents itself as an important and timely context for carrying out this study. We interviewed key stakeholders within the selected case company, including the CEO, smart factory manager, IT managers, and IS consultants. The outcomes of the qualitative data analysis resulted in establishing a framework that includes forty-eight barriers divided into six major categories.

The rest of the paper is structured as follows. First, we present a systematic review of literature on smart factories and industrial big data before we present the research methods used in the study. Subsequently, the findings derived from the interviews were presented and discussed. We then provide this study's overall conclusions, implications, and limitations.

LITERATURE REVIEW

Related Studies on Smart Factories

A smart factory is defined as a factory where physical devices, machinery, and production processes are combined with digital technologies to create a more opportunistic system (Deng, 2021). Manufacturing companies initiating smart factory innovation seek to gain competitive advantages through implementing advanced information technologies. By adopting cutting-edge IoT technologies, a smart factory can democratize industrial data and empower plant personnel with advanced analytics to process the industrial data and enable them to get real-time production process insights, and result in a shift from the physical world to a virtual copy (Chen et al., 2022). As a result, smart factories' development can bring significant business benefits, including productivity and resource efficiency, sustainability and safety, and better product quality (Deng, 2021).

As the significance of smart factories has risen it attracted the attention of researchers and practitioners. Specifically, the current literature review showed that we divide the studies of smart factories into three directions. The first stream mainly focuses on the engineering requirements of smart factories, particularly in the entire system's architecture (Ralph et al., 2021); its purpose is to bring smart factories from a conceptual idea into technical practice. The second group of studies concentrates on smart factories' use cases and technical prototypes. For example, the chemical, aerospace, and smelting industries are involved in current research (Chehri et al., 2020; Hwang et al.,2017). Additionally, the third set of research primarily focuses on exploring the potential economic benefits, challenges, and risks associated with developing smart factories (Won & Park, 2020). However, the studies mentioned above are mainly conceptual research and lack empirical evidence.

Compared with numerous papers from a technical perspective, relatively few studies concentrate on the socio-technical point of view to explore the issues in fields of organization, society, management, and people. For example, Rauch et al. (2020) showed that the maturity level of smart factory development is still low, and it is confronted with difficulties and challenges (such as in economics, technology, politics, and culture), which asserts the importance of the socio-technical angle in smart factory development.

Industrial Big Data

Industrial big data refers to all kinds of data and related applications generated in the industrial production process, including customer requirements, research and development, product design, procurement, manufacturing, logistics, sales and service, and maintenance (Tucker, 2021). Industrial big data differs greatly from traditional big data because of the diversity of its data sources, the integrity of data samples, and data timeliness (Yan et al., 2018). According to the data source, industrial big data is divided into three categories: enterprise system data, IoT data, and external data. Enterprise system data represents the data generated from various enterprise information systems such as enterprise resource planning (ERP), supply chain management (SCM), and customer relationship management

(CRM) (Yan et al., 2017). Internet of Things (IoT) data symbolizes the data captured by embedded sensors (e.g., radio frequency identification (RFID) or barcode readers), which is transmitted in real-time through the MES (Xu & Hua, 2017). Currently, the amount of IoT data is growing fast as the intelligent equipment is widely used in smart factories (Wang et al., 2018). Finally, external data includes data on the use and operation of industrial products after they are sold and many external internet data (Yan et al., 2017).

However, issues of industrial big data analytics have not been studied completely. Several organizational problems, such as enterprise users' diverse needs, conflict in organizational culture, and resistance to change, can create difficulties in using industrial big data (Baig et al., 2019). Prior studies on industrial big data had three principal focuses. The first focus of industrial big data studies is to discuss its definition, characteristics, and potential benefits from a conceptual view (Zhang et al., 2020). The second type of study explores the advanced algorithms and models to find technical solutions to exploit the potential value of industrial big data analysis (Zhou et al., 2020). Recently, research concentrating on the organizational perspective has appeared, the third stream of industrial big data studies. For example, researchers (Xing et al., 2019) have proposed a change management model of industrial big data application in organizations; others have studied the use of industrial big data in finance, marketing, and supply (Belaud et al., 2019). However, current studies mainly discuss the application of industrial big data from a single scenario; there is a lack of exploration into the issues of considering human and organizational factors that affect industrial big data application in organizations, particularly in discussing its barriers.

Deploying Industrial Big Data Solutions in Smart Factories

Industrial big data is the fundamental component of realizing the vision of smart factories. Many studies have shown that industrial big data analysis can solve distinct problems in smart factories. For example, smart sensors can collect a large production volume and machine (Krishnamurthi et al., 2020). In the past, these data would be discarded because of high storage costs. In a smart factory, industrial big data solutions can achieve information transparency in the production process (Peng et al., 2021). Meanwhile, production machine fault diagnosis and prediction can be achieved by processing the machine data, including temperature, vibration, energy, and consumption (Xu et al., 2017). Apart from the production field, industrial big data solutions can be deployed to support the optimal configuration of the supply chain and decision-making of enterprise business divisions (Wang & Luo, 2021).

Despite its benefits, deploying industrial big data solutions in a smart factory is not smooth sailing and can be difficult. The most frequent challenge is the technical issues related to real-time data acquisition and data analysis (Srivastava & Eachempati, 2021). To be specific, one of the technical challenges is how to manage industrial big data and identify their role in (1) the horizontal integration of data value across manufacturing processes, (2) their vertical integration among the different data components within specific manufacturing processes (Xu et al., 2017). Moreover, data security issues have been emphasized as an important challenge (Almomani et al., 2021). In addition, during the transformation of factories, the job roles and positions have changed, resulting in a reduction in personnel and innovation in organizational structure and management (Tucker, 2021). Previous studies have shown that these are important, but only some key challenges are triggered by applying advanced information technologies. A further review of the literature shows that industrial big data solutions are more complex; there are currently very limited studies exploring the socio-technical challenges linked with industrial big data analytics in the smart factories context (Bednar & Welch, 2020; Mikalef et al., 2021). As a result, it will be difficult for researchers and practitioners to propose an effective framework to support this data-driven innovation in the manufacturing industry. Hence, this paper aims to empirically investigate the barriers that manufacturing organizations may face in their industrial big data application.

RESEARCH METHODS

Data Collection

Given the qualitative nature of the research questions, this study followed an inductive approach and used a case study design. It is widely acknowledged that a case study is an in-depth inquiry into the study of a social phenomenon in its real-life setting. Therefore, it is suitable for studies to understand the dynamics of the issue being investigated within its particular context (Tellis, 1997). Therefore, a case study is an ideal approach to explore the barriers to industrial big data application in smart factories.

Xuzhou Zhonglian Co., Ltd. (in short, Zhonglian) was selected as the case company for this research. Zhonglian is a local market leader in cement production and smart factory development solutions in Jiangsu province, eastern China. Over years of effort, Zhonglian has gained substantial success, particularly in CPS transformation and industrial big data transformation. Most notably, Zhonglian is deploying a smart manufacturing system based on high informatization and automation to meet the needs of collaborative development, customization service, flexible production. Therefore, the Ministry of Industry and Information Technology recognized Zhonglian as the demonstration base of smart cement production in 2019. Their CEO, managers, staff, and IS consultants have sufficient insights and experience for the phenomenon under industrial big data application. Consequently, 27 employees were interviewed, including the CEO, smart factory manager, staff, and consultants with over five years' experience. The selected interviewees take on different roles and can provide various perspectives on industrial big data application challenges. We show the profiles of the 27 participants in Table 1.

Table 1. Profile of interview participants in the case company

ID	Professional Position	Area of Expertise	Years of Experience
Participant-1	CEO	Business and project management	25
Participant-2	CTO	IoT and ICT technologies	25
Participant-3	IT manager	IS development and application	20
Participant-4	Operations manager	Factory and operation management	18
Participant-5	Supply chain manager	Supply chain management	12
Participant-6	R&D manager	Research and development	14
Participant-7	Sales manager	Sales and service management	13
Participant-8	IoT engineer A	IoT design and development	14
Participant-9	IoT engineer B	IoT design and development	9
Participant-10	IoT engineer C	IoT coding and testing	8
Participant-11	IoT engineer D	IoT coding and testing	10
Participant-12	IS consultant A	Smart factory design	11
Participant-13	IS consultant B	Industrial big data roadmap design	7
Participant-14	IS consultant C	Industrial big data implementation	12
Participant-15	Technical director	Industrial big data management	8
Participant-16	Cloud engineer	Data warehouse and security	6
Participant-17	System engineer	Industrial big data system design	7
Participant-18	Algorithm engineer A	Data analytics and algorithm design	9

Table 1 continued on next page

Table 1 continued

ID	Professional Position	Area of Expertise	Years of Experience
Participant-19	Algorithm engineer B	Data analytics and algorithm design	5
Participant-20	R&D engineer A	Research and development	9
Participant-21	R&D engineer B	Research and development	8
Participant-22	Supply chain staff A	Supply chain management	6
Participant-23	Supply chain staff B	Supply chain management	7
Participant-24	Facility engineer A	Equipment management	12
Participant-25	Facility engineer B	Equipment management	9
Participant-26	Sales staff A	Sales and service management	7
Participant-27	Sales staff B	Sales and service management	5

Furthermore, semi-structured interviews obtained in-depth insights from users involved in Zhonglian's industrial big data application project. Thus, the interview questions were elaborated with research questions and structured into three parts. The first part introduces current job roles and their experience in smart factories or industrial big data fields, which helps open the conversation. After gaining some general information regarding the interviewees' experience, the second part of the interview focused on asking specific questions about the requirements of implementing industrial big data solutions in a smart factory context, explaining the challenges for companies implementing these solutions. Finally, the third part of the interview concentrated on gathering demographic information about the interviewees.

The first round of data collection took place with the management layer of Zhonglian, including the CEO, CTO, IT manager, operation manager, and sales manager, which provides a broad 'picture' of the research phenomenon. Then, the second round of data collection was done with the technical engineers, IS consultants, and enterprise users, focusing on technological development and users' views. We arranged each interview in advance and undertook them in the participant's office, lasting for 60–90 minutes. Finally, a Sogou recording AI application transcribed the interview data into text.

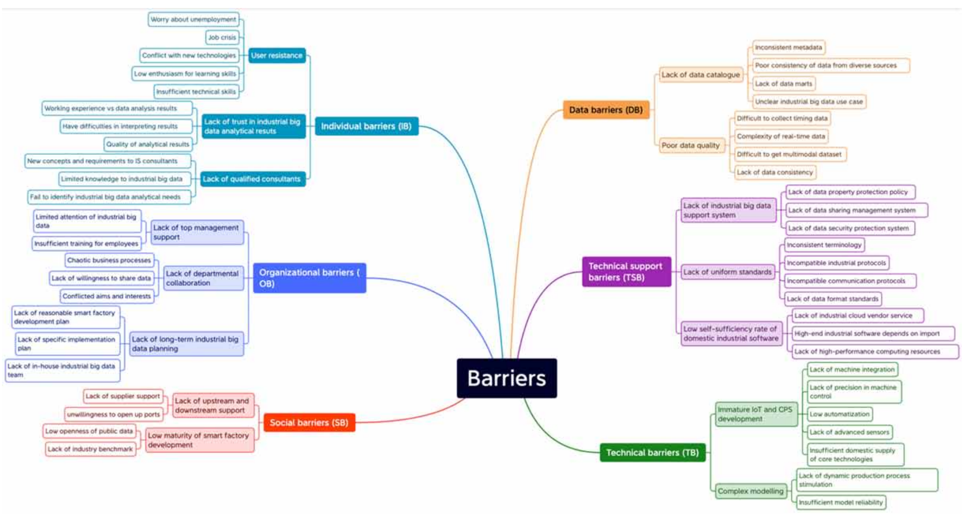
Data Analysis

We analyzed the data through a thematic analysis approach, which typically contains five stages, as demonstrated in Table 2. The interview data was transcribed into text so that researchers could become familiar with the data. In the second coding stage, they generated a wide range of codes with relevant quotations. The third phase focused on developing and forming themes of industrial big data application challenges by identifying and comparing the interrelationships between the different codes (Clarke et al., 2015). Following these steps, we distributed all identified codes into fifteen sub-themes and regrouped into six major themes. We reviewed all the codes and quotations for coherent pattern checking in the final stage. We developed a concept map representing the identified themes, as shown in Figure 1. The theme, codes, and selected quotations were discussed in the next section on the concept map.

Table 2. Five Steps for the Thematic Analysis

Stage	Description of the process
1. Familiar with the data	Getting to know the data through transcription, reading, and re-reading.
2. Coding the data	Developing a coding scheme: all codes emerged from data, coding textual data systematically across the entire data set.
3. Connecting codes and identifying themes	Collating codes into potential themes, gathering all data relevant to each theme.
4. Reviewing themes	Checking if the themes work concerning the coded quotes and the entire data set.
5. Developing concept maps and writing the report	Final analysis of selected quotes, relating back to the research question, producing the chapter of findings.

Figure 1. Concept Map for the Data Analysis



Barriers to Industrial Big Data Solutions Implementation in Smart Factories

Smart factory development would be herculean and encounter many challenges and barriers. This section presents the findings from this study and shows how different barriers hinder the implementation of industrial big data solutions in smart factory development. Overall, the barriers fall into six principal dimensions, namely technical barriers, technical support barriers, data barriers, individual barriers, organizational barriers, and social barriers.

Technical Barriers

Immature IoT and CPS Development

A highly efficient and mature IoT infrastructure, including smart sensors, cyber-physical systems, and machine integration, is a prerequisite for developing smart factories (Yao et al., 2019). Therefore, manufacturing companies consider IoT and CPS development a priority in their smart manufacturing agenda. Furthermore, according to Xu and Hua (2017), the automation of production device and production lines are the basis of industrial big data applications. However, it will be an enormous challenge for most manufacturing companies to transform immature manufacturing equipment and production lines into a highly automated cyber-physical system given the technical complexity and cost, as confirmed by the interviewees:

Interconnection of industrial equipment is the primary condition for smart factory. Currently, many domestic manufacturing firms are still in the state of semi-automation, particularly in small and medium-sized enterprises…it is not an easy job to achieve automation fully. (Operations Manager)

Moreover, results of data analysis indicated a lack of long-term industrial big data plan and top management support would slow the progress of IoT development and upgrade of smart devices. Meanwhile, since different external suppliers provide the manufacturing equipment, different brand suppliers always adopt different protocols and ports; therefore, it can be difficult for manufacturing firms to carry out further development, integration, and extension, as one interviewee suggested:

System vendors often are not inclined to open up their application for user companies as they don't want to lose control and want to charge a higher system maintenance fee in the later stage. (IoT Engineer B)

Complex Data Modeling

Modeling is creating a simplified diagram of a software system and its data elements, using text and symbols to represent the data (Hwang et al., 2017). Thus, modeling can help an organization use its data effectively to meet its business information needs. Furthermore, well-designed data models can help an organization develop and implement a data strategy that takes full advantage of its data (Ganguly & Euchner, 2018); however, data modeling is a complicated process that can be difficult to complete in industrial big data initiatives, as highlighted by the interviewees:

On one hand, in-house IT experts in many enterprises are not familiar with operational requirements and needs. On the other hand, our operational staff have limited knowhow about big data analytics. Consequently, this created a dilemma and made it difficult for us to develop effective data analytic models in practical terms. (CTO)

Because most employees' have insufficient technical skills, such a situation is common (Ganguly & Euchner, 2018). It is also clear that, considering the division of working tasks and benefits distribution between different departments of a firm, it may be hard for different departments to cooperate well and share data effectively:

There is a lack of cooperation within enterprises, which hinders the implementation of industrial big data. Industrial big data comes from a wide range of sources, and all departments need to provide their own business data to make sure data integrity. But once the business data was shared, they will think that these data will be unified into the information center, which means the decline of power. (IT Manager)

Technical Support Barriers

Lack of Industrial Big Data Support Systems

As discussed earlier, industrial big data analytics of a smart factory is a complicated process that comprises a data collection system, data storage system, and data protection system. Currently, manufacturing enterprise product and operation data is the most important part of data assets. According to the research conducted by KPMG, nearly half of data leakage (48%) comes from the lack of a data support system (Pauli et al., 2021). Once an enterprise's data is leaked, the share price of the enterprise falls by an average of 7.5%, with an average loss of market value of 5.4 billion dollars (Pauli et al., 2021). Thus, it is likely to be attacked by competitors in the same industry because of the lack of a data security protection system, which can cause data leakage and damage commercial interests (Ganguly & Euchner, 2018). As confirmed by one employee:

Data is the engine to realize the vision of Industry 4.0. We always pay more attention to new technologies and new algorithms. However, how to make sure the security of data in a smart factory? How to share internal data? What kinds of data can employees at different levels have access to? These problems need to be solved in advance. (IS consultant A)

Lack of Uniform Standards

Standard is especially important to an enterprise, which means ensuring all facilities use the same quality management. Furthermore, as manufacturing is becoming smart with self-awareness, autonomous decision-making, and adaptive collaboration capabilities, the standard is a crucial enabler for achieving the required intelligence of a smart factory (Mittal et al., 2018). There are many standardized areas in the manufacturing industry, such as production processes, interfaces, and terminology. However, given inconsistent industrial protocols, and communication interfaces, the acquisition of industrial big data is directly affected by the lack of uniform standards, increasing the difficulties of storing and analyzing industrial big data sets (Li et al., 2018).

To be specific, industrial communication protocol mainly refers to the rules and agreements that all entities should follow in manufacturing. However, a smart factory integrates devices from different manufacturer suppliers, and they are likely to adopt different communication protocols (Kovacova & Lewis, 2021). In such a context, it will cause difficulties in equipment interconnection and industrial data collection, as confirmed by one interviewee:

HTTP is commonly adopted to collect internet data, however, data collection in industrial production environment will be much more complicated. Many different types of industrial protocols like Modbus, OPC, CAN, Profibus, and ControlNet, etc. are used by different equipment suppliers. Some non-standard equipment suppliers even refuse to open their ports, which greatly increases the difficulties of device interconnection in smart factories. (System engineer)

Different smart factory components can only work together if cross-manufacturer standards are established and unified. Consequently, there is a consensus that a lack of uniform standards for smart manufacturing is one of the top challenges in industrial big data deployment in smart factories.

Low Self-Sufficiency of Domestic Industrial Software

The development of smart factories has deepened the dependence on industrial software since industrial big data is generated at high speed (Hwang et al., 2017). Industrial software (such as computer-aided design (CAD), manufacturing execution systems (MES), or product lifecycle management (PLM)) is widely used to harness the data and aims to control different engineering processes of manufacturing enterprises precisely. However, the analysis of our interview data showed that the low self-sufficiency rate of domestic industrial software is one barrier to smart factory development. The self-sufficiency rate of domestic industrial software calculates the percentage of industrial software applications developed and used in a smart factory. Therefore, it defines whether developing industrial software for smart manufacturing satisfies domestic needs (Xie et al., 2015). As confirmed by the interviewees,

Most high-end industrial software is outsourced. For example, procurement and upgrading of CAD has cost more than 2 billion dollars. There are two major reasons for this, one is the low self-sufficiency *rate of domestic industrial software, another reason is that there are few leading enterprises of industrial software design in China. (IS consultant B)*

Therefore, manufacturing firms in China must pay high fees to purchase foreign industrial software to support their smart factory development. Because of this, the low self-sufficiency rate of domestic industrial software may affect the integrity of industrial big data collection and high investment in industrial big data solutions, as the interviewees stated:

Enterprise informatization data is a major source of industrial big data, and this kind of data are collected from industrial software. However, the majority of industrial software is developed by foreign countries. Once the software suppliers do not open their permissions, data related R&D, production cannot be obtained. (IoT engineer C)

Data Barriers

Lack of Data Catalogs

A data catalog is a detailed inventory of all data assets in an organization, designed to help data professionals quickly find the most appropriate data for any analytics or business purpose (Yan et al., 2018). As discussed earlier, we can collect industrial big data from various internal and external sources, including machine sensors, management information systems (e.g., ERP and MES), and social media platforms. Such industrial big data is not just big in volume but also contains very different forms, such as signals, texts, images, web pages, and videos (Yan et al., 2017). Tao et al. (2018) considered that with more data in smart factories than ever, finding the right data has become harder. Therefore, real-time and efficient industrial big data analytics cannot be achieved without a good data catalog. The cloud engineer also stressed the importance of a good data catalog,

Many companies began to collect all types of data (about products, manufacturing processes, logistics and transportation) due to its solid IoT foundation. Data is stored in cloud servers, which indicates that their smart factory development is successful. However, the essential thing is how these collected data can generate value for the enterprise. In order to handle the data catalog work effectively, we adopt the concepts of data warehouse and data mart, which is helpful to classify data according to analysis requirements. (Cloud engineer)

Further analysis of the interview data showed that a poor data catalog could often directly result from a lack of qualified consultants and strategic planning. Moreover, when companies fail to specify their analytic requirement, it will be difficult to organize a good data catalog.

Poor Data Quality

Data has quickly become one of the most valuable resources that a business can have. For smart factory development, it is especially true once the manufacturers have adopted smart technology; real-time and high-quality data can help manufacturers optimize factory processes and extend the life spans of factory equipment (Kovacova & Lewis, 2021). Data quality, therefore, becomes critical for manufacturing companies at both operational and strategic levels. However, analysis of interview data showed that real-time, low-latency data collection is complex. There are many machines and devices from which we need to collect data. They do not speak the same language and have different business owners. The interviewee also stressed the significance of data quality:

Data quality is a key determinant of the success of any industrial big data solutions in smart factory imitative. The purpose of data quality management in enterprise is to provide clean and clear data *for enterprise, which is also a prerequisite for enterprise data asset management. High-quality data is usually very helpful for us to do modeling. (Algorithm engineer A)*

However, because of the volume, complexity, and diversity of industrial big data assets, it can often be difficult for smart factories to maintain data quality and consistency. Studies conducted by IS researchers indicated that inaccurate, inconsistent, and redundant data might exist in ERP, MES because of some defect in technical implementation (e.g., immature IoT) and human errors (e.g., lack of audit process during data entry) (Sony & Naik, 2020). As highlighted by IoT engineers:

Many manufacturing firms have not yet deployed cyber-physical systems and IoT across the whole product lifecycle. As a result, the communication between back-office and shop-floor machines is week, it will be difficult to collect production data accurately, resulting in the difficulties of predictive maintenance of manufacturing device. (IoT Engineer B)

Individual Barriers

User Resistance

User resistance in this study refers to covert individual behaviors that oppose changes toward the avoidance of industrial big data manifested as reactance, distrust, scrutiny, or inertia. According to IS research results, user resistance is a typical and inevitable phenomenon during the process of new information systems or information technology implementation in the enterprise, which changes the company's status quo and takes employees out of their comfort zone (Ali et al., 2016). In a smart factory context, smart manufacturing enabled by IoT, CPS, AI will reduce personnel. As the interviewee highlighted,

Companies no longer need to arrange a lot of manpower in production and product quality control because of the adoption of smart equipment. In addition, with the help of artificial intelligence algorithm, cyber physical system can achieve self-operation, self-monitoring, and self-maintenance, which greatly reduces the maintenance cost. (Facility Engineer A)

Moreover, adopting industrial big data solutions in smart factories will extend such automation and changes from production to other enterprise units across the product lifecycle (Kovacova & Lewis, 2021). However, these changes might lead to strong user resistance to developing smart factories.

Refusing to change is a natural phenomenon, because it will take people out of their comfort zone. In general, people fear the unknown and not having the required skillset for upcoming tasks. Some employees worried about whether they will lose their jobs when the smart factory is developed. (Facility Engineer A)

Further analysis of interview data showed that lack of insufficient technical skills and top management support would increase resistance. In order to reduce resistance, Bednar and Welch (2020) considered efficient communication and user training to be important in the application of industrial big data solutions. In addition, one of the main reasons for refusing to change is not seeing any personal or overall benefits of utilizing the new technology (Hwang et al., 2017).

Lack of Trust in Industrial Big Data Analytics

Despite major investments in industrial data analytics (e.g., smart sensors and IoT), research suggested that most decision-makers do not trust the insights they reveal (Peng et al., 2021). According to the KPMG and Forrester Consulting survey across ten countries, only 38% of respondents have high confidence and trust in the analytics results they generate from their business operations (Pauli et al., 2021). Therefore, IS consultant C argued that "many industrial practitioners may have doubts about whether industrial big data analytical results can make a high-quality and efficient decision."

The industrial big data analytical results highly depended on the quality of the original industrial data sets. As discussed above, poor data quality and lack of a data catalog have been two fundamental challenges for manufacturing companies. Substantially, managers may decide based on their working experience instead of analytical results, as confirmed by the interviewee:

We have tried to promote our R&D through industrial big data analytics. However, the result of data analysis is completely inconsistent with scientific logic. We suspect there are problems in original data quality, particularly in the stage of data cleaning, and some obviously abnormal data have not been screened out. (R&D Engineer A)

In addition, further analysis showed that due to users' resistance to industrial big data tools, some employees in manufacturing companies might refuse to use industrial big data tools, even though the analytical results are useful to their decision-making. Here, industrial big data analysis investments will become worthless.

Lack of Qualified Consultants

The role of IS consultants is important in assisting manufacturing companies in optimizing IT/IS infrastructures to achieve their business purposes. Usually, a qualified and professional consultant must be equipped with multiple skills, including creative thinking, clear and empathetic communication, time management, and collaboration with all job levels (Peng et al., 2021). Moreover, even more insights and skills than usual are required for qualified consultants because of the technical and business complexity of industrial big data solutions in smart factories:

The role of consultants is like a bridge, connecting enterprise users with technology providers. Consultants need to have not only technical knowledge of industrial big data and smart factories, but also deep insights about how industrial big data can help and meet enterprise users' needs. Experienced and professional consultants can help enterprises avoid detours and improve efficiency. (CTO)

Moreover, highly skilled consultants are scarce in the IT industry, which has been confirmed by IS researchers (Jung & Lim, 2020). Therefore, recruiting a consultant within the company will be a big challenge. At the same time, considering the level of complexity of industrial big data and smart factories, they need a qualified consultant in smart factory development, as suggested by the IT manager:

Insufficient support from consultants will be a big challenge for organizations to link industrial big data with enterprise business needs…Usually, an in-house IBD team will be organized, which directly reported to CTO or CEO. At the same time, IBD team will collaborate with external consultant in identifying business needs of enterprise and formulate the implementation plan jointly. In this way, the professional knowledge of consultants can be learned; secondly, enterprise can better grasp real-time progress of industrial big data solutions. (IT Manager)

Organizational Barriers

Lack of Top Management Support

Top management support refers to the degree to which top management understands the importance of IS function and is involved in related activities. Top management support has been widely recognized as one of the essential factors in different technology adoption contexts (Li et al., 2019; Liu et al., 2021). For example, during the process of smart factory development, diverse technologies have been adopted (such as smart sensor technology, CPS, cloud computing, and artificial intelligence), which required strong top management support to allocate sufficient resources related to technical innovation as well as to solve the potential user resistance, as highlighted by the technical director:

Without the power-centralization top management support in smart factory development, there will be no investment and sufficient resource in deploying diverse technologies. (IT Manager)

However, considering the new concepts of industrial big data and smart factories, some top managers may not envision the potential benefits of industrial big data implementation in an Industry 4.0 context. Top managers may only invest in some basic analytical functions like production automation because of a lack of long-term industrial big data planning. In order to solve this problem, as IS consultant A suggested:

The only way is to let the top managers accept the trend of smart factory development and see the benefits of IBD analytics. In such context, top managers will be more willing to accept it and give support. (IS consultant A)

Lack of Departmental Collaboration

Industrial big data exists in different departments in manufacturing companies. As a result, they will embed industrial big data solutions in all units across the product lifecycle, thus requiring the cross-departmental collaboration of all units concerned.

However, Mikalef et al. (2021) considered that potential problems like resource competition and conflicting goals can always exist in departmental collaboration. Therefore, some cases of information system implementation failure in the enterprise were caused due to a lack of departmental collaboration (Kumar & Lee, 2022). We have confirmed this phenomenon in the selected case company in their smart factory development, as the interviewee mentioned:

First of all, departmental leaders usually represent their own interests and sometimes their goals are conflicted. Secondly, the level of each departmental leader is the same, and no one will give in once there is a goal conflict. Moreover, it will be a big challenge for different departments to share their internal data with others in the context of smart factories. (CEO)

Lack of Long-Term Industrial Big Data Planning

Lack of long-term strategic planning is a common barrier faced by user companies when implementing new IT or IS projects (Li et al., 2019). However, in the smart factory context, this kind of barrier is specific to a lack of long-term industrial big data planning, which refers to a lack of knowledge and specific planning in smart factory development and industrial big data deployment in particular, as highlighted by the interviewee:

Industrial big data solutions are a tough project, including shop floor automation, data collection phase, industrial data analytics, data-driven decision making, etc. An appropriate and long-term plan is the premise of industrial big data implementation in smart factory. Lack of strategic planning will lead to aimless investment, which will eventually lead to the failure of the project. (IT Manager)

Further analysis of the interview data reveals numerous factors cause this barrier. Firstly, industrial big data solutions and smart factories are relatively new and complicated concepts from a practical view, containing many technical elements. As the CEO of the selected case company discussed, "it is quite difficult for IT managers or even CTO to have sufficient multidisciplinary knowledge to build up a holistic view of smart factory development." Secondly, considering the importance of industrial big data solutions in smart factories, it will only be implemented based on mature CPS. Therefore, it is not easy to develop a strategic plan for industrial big data solutions early. As a result, one of the experienced IS consultants pointed out:

Most manufacturers already understand the importance of smart factories, and they have realized it is the trend to transform to smart manufacturing. But, what does a smart factory look like? How to transform from the current situation to a smart factory? How and when the industrial big data solutions can be implemented...those questions still do not have clear vision. (IT Manager)

Social Barriers

Lack of Upstream and Downstream Support

Given industrial big data, its primary sources are IoT data, business data, and external data related to product post-usage. For example, one kind of IoT data is machine data. External suppliers mainly provide production machines. However, machine data cannot be obtained if the machine suppliers refuse to open the port because of an ownership problem. Therefore, without support from the supplier, it could be an enormous challenge that affects the consistency and integrity of industrial big data collection. As the IoT engineer stressed:

'Currently, IoT data accounts for the majority of industrial big data. Self-operation and predictive maintenance can be achieved through the analysis of IoT data. However, some of our high-end devices are imported and the ports of these devices are closed. This will directly cause our data collection failure due to lack of support from device vendors.' (IoT Engineer D)

Low Maturity of Smart Factory Development

In general, the term 'maturity' refers to a 'state of being complete, perfect or ready' and implies some progress in the development of a system (Mittal et al., 2018). In this study, smart factory maturity can tell the enterprise leaders where they can improve in an area to achieve a higher maturity level in the enterprise business area. However, current research related to smart factories indicated we have not developed a true smart factory; most of the so-called smart factories are industrial big data applications in partial fields of enterprise, the most typical of which are product sales, customer service, and supply chain, as confirmed by an IS consultant:

Given the diversity of manufacturing enterprise, a mature smart factory has not been built up in the industry. Therefore, enterprise managers will worry about how to find a successful use case to learn about. (IS consultant B)

Our analysis of interview data revealed that the establishment of different smart factory maturity models causes the low maturity of smart factory development. Over recent years, the number of published smart factory maturity models has increased considerably from an academic point of view. However, "the existing maturity evaluation models cannot be applied in practice, and the maturity of smart factory development is still low, which lacks a typical representative" (IS consultant C).

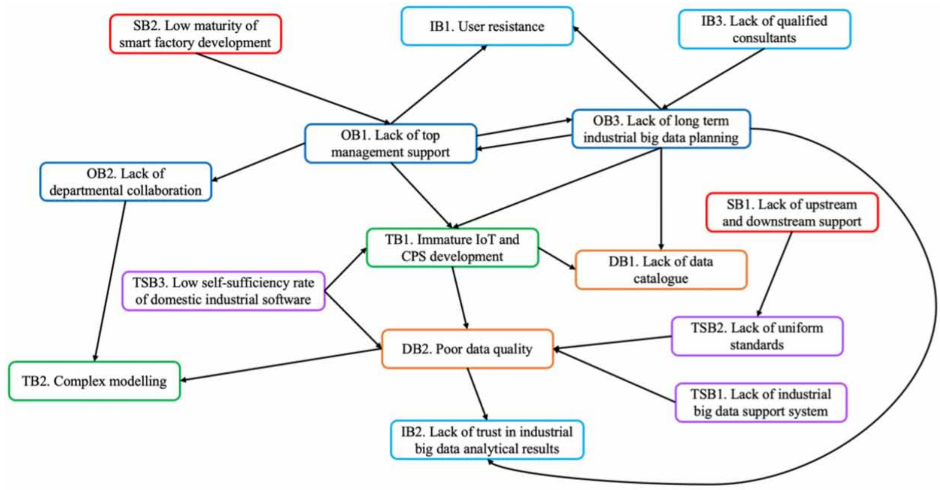
DISCUSSION

The extensive review of existing literature shows that studies on the barriers to smart factory development mainly focus on a 'hardware' perspective (Kovacova & Lewis, 2021; Strozzi et al., 2017). However, a smart factory is a complicated system covering hardware infrastructures, software applications, industrial big data usage, people, and cultural change (Won & Park, 2020). Therefore, this study extends the understanding of exploring barriers to smart factory development from technical aspects to a socio-technical perspective. As a result, a comprehensive set of barriers, including six types of categories, were identified and discussed.

The identified barriers are aligned with the findings of past information system research through comparison. To be specific, poor data quality will inevitably lead to low accuracy of data analysis results, which substantially causes enterprise users' distrust of big data analysis results. Xu and Hua (2017) have also discussed this phenomenon in exploring the difficulties of adopting big data technologies in the enterprise. Our qualitative analysis also showed that the quality of industrial big data sets could be affected by the development of IoT and CPS, particularly their mature level. This finding was confirmed by the industrial AI maturity model in smart manufacturing, in which mature CPS development is emerging as a prerequisite for big data analysis (Peng et al., 2021). On the other hand, partial identified barriers in this paper are also in line with socio-technical challenges reported in previous IS/IT research, such as a lack of top management support, lack of long-term strategic planning (Javaid et al., 2021), user resistance to technology-enabled changes (Peng et al., 2021). Despite this, this study also extended the existing knowledge of IS and smart factory research and generated new insights associated with the barriers to industrial big data implementation in a smart factory context.

More importantly, the identified barriers to industrial big data implementation are not isolated but interact. Consequently, an empirical framework was developed to reveal the interrelationship between these barriers, as shown in Figure 2. Identified barriers within and across different categories can affect each other from the developed framework. Specifically, a lack of top management support can lead to organizational problems such as a lack of departmental collaboration and long-term industrial big data planning. It can also result in problems at the individual level, like user resistance. Moreover, a lack of top management might cause immature IoT and CPS development at the technical level. Obviously, some technical or non-technical problems were triggered by organizational barriers, namely the lack of long-term industrial big data planning. Socio-technical factors, rather than the technology itself, often cause the failure of industrial big data implementation in smart factories. Therefore, an important suggestion was developed: before investing in smart factory development, it is vital to make a long-term plan first with the help of qualified and experienced consultants; leaders of the company need to increase their knowledge of industrial big data, which is helpful to provide sufficient and long-term leadership support. This situation can increase the chance of successful industrial big data implementation and smart factory development.

Figure 2. Framework showing relationships between barriers



CONCLUSION, IMPLICATIONS, AND FUTURE RESEARCH

This study aimed to identify the barriers to embedding industrial big data solutions in smart factories using an inductive qualitative approach. The result has important implications for academic researchers and industrial practitioners.

This study extended existing knowledge of industrial big data, smart factories, and information system research for academic researchers. To be specific, many IS studies have shown that the use of IS could be fraught with organizational, technical, and human issues. The results of this study have confirmed that these same categories of barriers still occur in implementing industrial big data solutions. Moreover, it is clear that several identified barriers (e.g., lack of top management support or user resistance) play an important role in industrial big data usage, which has been frequently reported in the IS literature, but the actual phenomenon is rather different. Therefore, in the future, there is an apparent need to explore this emerging phenomenon in more detail. Nevertheless, the results can provide a good foundation for IS researchers to conduct further studies in smart manufacturing.

Our research findings also provide practical implications for industrial practitioners. First, we found that the identified list of barriers can assist enterprise leaders in preparing industrial big data solutions in advance at the strategic- and macro-levels, and raise the awareness of smart factory managers concerning the difficulties of implementing industrial big data tools in smart factories. In particular, the findings have revealed that immature IoT and CPS development is the fundamental barrier in industrial big data adoption, directly resulting in poor data quality and poor data catalog. Second, the findings also suggest that enterprise leaders cannot merely consider industrial big data implementation from a software layer, but need to plan strategic planning related to IoT infrastructure. However, further to technical issues, a wide range of organization-wide (e.g., lack of departmental collaboration) and individual barriers (e.g., lack of trust in industrial big data analytical results) have been identified that prevent successful usage. More importantly, the findings showed organizational barriers that interact with individual barriers would also trigger technical barriers. For example, a lack of top management support and strategic planning of industrial big data caused immature IoT and CPS. Therefore, enterprise leaders cannot treat industrial big data implementation as a simple technical endeavor. The developed framework of this study can help industrial practitioners to understand the relationship between identified barriers, which helps increase the success of smart factory development.

This study also has several limitations. First, the interviews were conducted with a relatively small group of employees, although the selected interviewees are highly experienced. Therefore, a questionnaire survey may validate the list of identified barriers in the future. Moreover, while we explored relationships between barriers in this qualitative study, a quantitative study may measure relationships and rank the barriers to prioritize improvement initiatives. Meanwhile, a further qualitative study can also be carried out to explore the potential barriers to industrial big data usage of smart factories in the contexts of specific manufacturing sectors and countries.

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