Master Thesis

Developing an adoption process framework for Big Data Analytics by OEM companies

An empirical study in Dutch industrial automation sector

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ABSTRACT

With the rapid growth of large amounts of data in different types from different sources, it is possible for the industrial automation sector to transform raw data from production processes into meaningful and useful information for business purpose. The leverage of Big Data Analytics helps the Original Equipment Manufacturing companies gain more insights from their internal organizational data and to get faster and better fact-based decision-making support. However, many OEM companies are still reluctant to adopt Big Data Analytics in their daily business activities due to different concerns. The investigation of Big Data Analytics adoption by OEM is rarely seen in the literature. Therefore, how to adopt Big Data Analytics by OEM companies in the industrial automation sector is studied. During the execution of this study, TOE theory and DOI theory are utilized to address how the different factors from technological, organizational and environmental contexts affecting different Big Data Analytics adoption phases regarding OEM companies. This framework was developed to provide an overview and guidelines for OEM companies to utilize Big Data Analytics. The influential factors and the adoption process framework for Big Data Analytics by OEM companies were evaluated by face-to-face interviews in a qualitative approach. It is found that OEM companies will experience several phases for Big Data Analytics adoption, including Awareness phase, Strategy phase, Knowledge phase, Trial phase, Implementation phase, and Internalization phase. The competitive pressure and marketing effort from the Big Data Analytics service providers will positively affect the Awareness phase. The relative advantage, top management support and competitive pressure and marketing effort will positively affect the Strategy phase. The top management support and marketing effort are the main drivers for the Knowledge Phase when the Data security is the barrier for this phase. In the Trial phase, the relative advantage, compatibility and financial readiness will be the main drives. The Implementation phase will be mainly affected by Data security and Top management support. In the last Internalization phase, only external environmental factor such as competitive pressure will affect the maturation of Big Data Analytics at the organizational level of OEM companies. The influential factors for Big Data Analytics adoption and adoption process framework can be further evaluated through quantitative approach.

Key words*: Big Data Analytics, OEM, innovation adoption, adoption process framework, industrial automation*

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Chapter 1 Introduction

In order to complete this research project and find a practical approach to guide this research, following steps have been taken. The first section introduced the Big Data trend and its benefits. In section 1.2 the research problem about big data in industrial automation sector will be formulated and explained. After that, the research objective, research questions and research scope will be presented in section 1.3. Section 1.4 illustrates the research societal and scientific relevance respectively. At last, a well-structured research framework with research approach and methods is designed to guide the following study.

1.1 Big Data trend

The human society has already been significantly changed by three industrial revolutions. The first brought steam power, the second introduced electricity and mass production, and the most recent third accelerated automation using electronics and information technologies (Blanchet, Rinn, Thaden, & Thieulloy, 2014). The fourth industrial revolution is also on the way enabled by advanced sensors, further interconnected cyber-physical systems, smart robots and machines, 3D printing, big data and cloud computing, etc. Along with the ongoing development of these technologies, the human society, especially the industrial world is becoming increasingly interconnected and smart. More and more physical and virtual devices are linked via networks that produce enormous amounts of data every second of the day. The total amount of data in every area of the global economy is exploding. According to research by IBM, the whole world generated about 2.72 zettabytes (ZB) digital data in 2012 while the number was 4 ZB in 2013, increased by 60% accordingly (Hagen et al., 2013). A zettabyte, which contains 21 zeros, is a trillion gigabytes (GB), or a billion terabytes (TB). According to Oracle's forecast, the volume of data will keep on growing significantly at an annual rate of 40 percent, reaching approximately 45 ZB by 2020 (Manyika et al., 2011). As companies and organizations operate their business and interact with individuals, massive amounts of data will be generated and need to be acquired, stored, processed and analysed in term of extracting tangible information and knowledge. In contrast to rapid growth of data amount, data is still a kind of hidden resource that offers great potential to enhance corporate business. A lot of companies, especially in the industrial sector, do not use the data in hand at all or have used them not enough to gain more information or knowledge (Hagen et al., 2013).

The application of industrial automation technologies in the manufacturing sector, which results in the operation of machines and systems for industry processes without significant human intervention, achieves performance and efficiency superior to manual operation(Mukkawar & Sawant, 2015). Traditional market leaders in the industrial automation sector and manufacturing companies are facing intensive competition from emerging economics. Asian industrial automation companies are catching up with traditional market leaders like Rockwell, Siemens, Honeywell, etc. from Europe and the United States, and even overtaking them by investing in research and technology (Smart Industry, 2014). As hardware like drives, gears, motion control, sensors, robotics, Programmable logic controller (PLC), human-machine interfaces, etc., are dramatically becoming commodities, customers not only require products with high quality, but also increasingly pay for the knowledge, experience or services (Smart Industry, 2014). The industrial automation company business is no longer limited to sell the industrial products themselves. Software and related industrial services have become a decisive and differentiating factor in the industrial automation sector. In this regard, industrial automation companies, especially the leading market players should try their best to provide excellent industry services.

Traditional services in the industrial automation sector include installed-base management, repair, maintenance and spare parts management, training, modernization and migration from one supplier's products to another, etc. Besides these traditional industrial services, an in-depth knowledge of complex processes like the operation of a manufacturing plant, a hospital, or traffic control centre is an important part which will keep companies ahead of their competitors. And the basis of this knowledge is data. There is a great growth in machine-generated data driven by steadily-diminishing costs and steadily-increasing power of computing and sensing. The technical advances made in miniaturization, wireless communication, data storage and decentralized intelligence further reinforce those developments. Along with big data from machines, industrial automation companies are actively exploring the possibilities of analysing big data to develop new services which can differentiate them from competitors.

In this big data trend, the Original Equipment Manufacturer (OEM), in other word machine builder, represents a very special user group that deserves to be studied. As the product flow illustrated in Figure 1, OEM companies use industrial automation solutions provided by industrial automation companies to build their machine and sell them to business customers or to consumers directly, and then business customers use machines from OEM companies to produce certain products or to provide various services for consumers. OEM companies generally focus on a particular industry, products and technologies (Diehl, 2015). In order to maintain close long-term relationships with clients and provide high-quality services, industrial automation companies must understand not only OEM companies, but also the requirements of OEMs' end customers. The OEM companies leveraging Big Data Analytics offered by industrial automation companies to mine actionable information makes OEM's business increasingly successful. If this type of customer can gain great benefits from the wide use of Big Data Analytics, the fourth industrial revolution will absolutely boost (McCandless, 2015). On the basis of this motivation, OEM customer in the industrial automation sector is considered as a very attractive user group for adopting Big Data Analytics in this research.

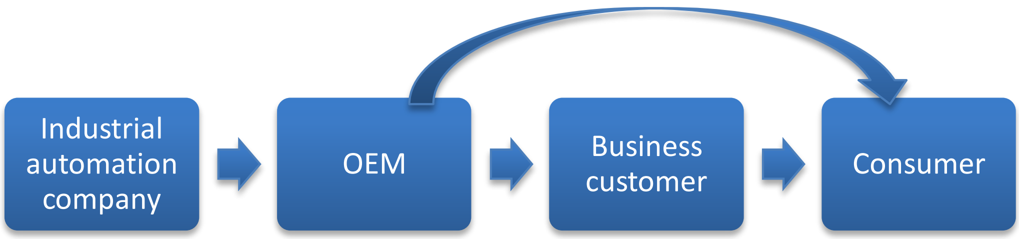

Figure 1 Product flow along with OEM companies' main business

1.2 Problem Definition

1.2.1 Problem exploration

Transformation of raw data into meaningful and useful information for business purpose often refers to business intelligence. The traditional solution in business intelligence normally uses descriptive statistics with structured data from relational database systems to measure things and to detect trends (Nuremberg Chamber of Commerce and Industry, 2014) while big data uses "inductive statistics and concepts from nonlinear system identification"(Billings, 2013) to analyse big volume of unstructured data from various sources and types. From a technical perspective, traditional solutions for business intelligence were built for on-premise use and require large investments in IT infrastructure and specialized analytics software (Nedyalkov, 2013). Specifically, the adjustment for such an IT system is quite inflexible if business requirement changes. Gartner states in its Business Analytics Framework research report on page 2: "The continued growth of business intelligence, analytics and performance management – with an increasing large portfolio of available solutions with divergent functional capabilities, scale and scope […] – has increased the need for a renewed focus from IT to avoid platform parochialism at best and analytic anarchy at worst. If unaddressed […] organizations will fail to achieve optimum business benefits from their investments." (Chandler, Hostmann, Rayner, & Herschel, 2011)

The emergence of cloud computing brings opportunities to solve this challenge. According to the NIST[1] definition, Cloud Computing contains five essential characteristics (on-demand self-service, broad network access, resource pooling, rapid elasticity, measured service), three service models (Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), Software-as-a-Service (SaaS)) and four deployment models (Private cloud, Community cloud, Public cloud, Hybrid cloud) (Mell & Grance, 2011). In order to gain more insights from big data for better decision-making, data storage, process and analytics can be moved from customer on premise solution to a certain type of cloud by choosing services from before-mentioned three cloud service models. Customers do not need to build their proprietary IT infrastructure for business intelligence anymore and pricing schemes can be based on periodic subscriptions. Consequently, cloud computing saves costs of IT infrastructure ownership and enables flexibility in adjusting the customers' service subscriptions.

Although the SaaS model provides a good approach for enterprise application, according to research by the Aberdeen Group, dominant SaaS applications include customer relationship management and email services. However, business intelligence application only accounts for 22% of all deployed SaaS applications (Aberdeen, 2013). OEM customers' application of Big Data Analytics via SaaS in the industrial automation sector has not been widely adopted. Only 13 percent of manufacturing companies are using Big Data Analytics in their business processes, and most industrial manufacturing companies have deployed on average less than one or no SaaS application (Carsten, Timm, & Nikolai, 2015). The fact illustrates that there are still other issues that need to be addressed in order to enable big data analytics adoption via SaaS in such a complex industrial automation sector:

OEM perspective

In many cases, OEM customers in industrial automation sector want to gain business insights from Big Data Analytics while some factors hinder them from harvesting information through big data analytics. For instance, customers have limited IT infrastructure, human resources, technical know-how or financial resources for implementing Big Data Analytics. Customers do not have necessary competencies to recognize which data needs to be analysed and which business performance can be improved by means of Big Data Analytics. Hiring business consultants is not feasible because the consulting fee is high and the external business consultants usually lack of in-depth know-how about the automation products compared with industrial automation vendors that supply the industrial

[1] NIST refers to National Institute of Standards and Technology which is part of the U.S. Department of Commerce.

automation products. In some cases, the big concern of sensitive data privacy and security issues also impede the customers' access to big data analytics from external sources.

Commercial perspective

Empirical analysis shows that besides using powerful technology, the innovation of business models and ecosystems is crucial to capture the full business potential enabled by smart data technologies (Bulger, Taylor, & Schroeder, 2014; Leimeister, Böhm, Riedl, & Krcmar, 2010; Weiller & Neely, 2013). Especially in the big data area, the classical business environment will change and new forms of strategic partnerships will be formed to generate business and holistically serve customers. It becomes increasingly important to clearly define and stabilize a company's role in the new emerging and dynamic business ecosystems in order to maintain its position and manage competition by establishing new strategic partnerships. Dealing with multiple partners is rather the norm than the exception in the area of big data, e.g. to tap new data sources or to leverage new sales channels. Therefore while developing new business ideas, it is vital to consider the overall market ecosystem. Understanding the role of a company's business in its ecosystem is essential for anticipating market challenges and succeeding during change.

Technical perspective

The technical view focuses on the technical aspects such as data, technologies and tools. It describes how to create knowledge based on advanced data analytics. The complexity of data presentation, data modelling, data management and data integration requires new technologies and complex software to deal with. In the industrial automation sector, the leverage of big data is an emerging area while there are few mature technologies and user cases. Nowadays, no provider can offer all the needed technologies, applications and services in an integrated manner. It is quite important for vendors and customers to cooperate with other parties on adopting big data technologies.

1.2.2 Problem statement

In today's service-oriented industrial automation landscape, more and more machine data becomes available to OEM companies from their manufacturing machines. A number of Big Data Analytics solutions from Industrial automation companies are available. OEM companies need to come up with innovation strategies to successfully adopt Big Data Analytics through SaaS platform in their organizations.

Based on our previous analysis, the problem statement is summed up as followed:

> ***There are a lot of uncertainties and concerns around OEM companies in the industrial automation sector who fall short in adopting Big Data Analytics via SaaS platform in terms of gaining business insight for better decision making.***

Based on the aforementioned problem exploration, we formulates some knowledge gaps:

(1) The added value of Big Data Analytics and the barriers to OEM companies for using Big Data Analytics are not systematically explored yet; and

(2) There is no adoption framework guiding the OEM company to use Big Data Analytics via SaaS in the industrial automation sector.

We aim to address these knowledge gaps by developing a research project, which we will present in the following sections.

1.3 Research objective and research questions

1.3.1 Research objective

To address the research problem, our research objective is identified as followed:

> ***To develop an adoption framework by investigating the adoption process of OEM customers in the industrial automation sector leveraging Big Data Analytics via Software as a Service.***

This research objective is achieved through following sub goals:

(1) Examine the involved stakeholders in the adoption of Big Data Analytics by OEM.

(2) Explore the benefits of adopting Big Data Analytics and investigate the drivers and barriers to OEM of adopting Big Data Analytics.

(3) Develop an adoption process framework to guide the adoption of Big Data Analytics of OEM companies in the industrial automation sector.

1.3.2 Research question

On the basis of problem statement and main research objective in the previous section, the main research question is presented as followed:

> ***Which technology adoption framework can support OEM companies in the industrial automation sector to adopt Big Data Analytics by means of the Software as a Service concept?***

In order to give a clear design goal for this research, some integrated concepts will be described as followed:

A **SaaS platform** in this research is a combination of hardware, software and network technologies (Nedyalkov, 2013), which is the foundation of different services. The services in this platform are provided by different companies to subscribers. Subscribers in this platform do not need to manage or control any infrastructure including servers, operation system, database or application, etc. (Mell & Grance, 2011).

Big Data Analytics in this research includes accessing, acquisition, storage and analysis of large amount structured and unstructured data in different types and from various sources in the industrial automation products and processes.

To clearly state the major research question and guide my further research, five sub-questions are proposed. These sub-questions will also guide the outline of the final research report.

1) ***How does the potential value network look like in the industrial automation sector towards Big Data Analytics for OEM customers?***

    1.1 Who are the key stakeholders in Big Data Analytics provision in the industrial automation sector?

    1.2 What are different stakeholders' interrelationships and value exchanges in this value network?

2) ***How do Big Data Analytics connect the requirements of OEM?***

    2.1 What can Big Data Analytics offer to OEM?

    2.2 What are the requirements of OEM on Big Data Analytics provision?

3) What are the key factors that influence the adoption of Big Data Analytics from an OEM's perspective?

3.1 What are the drivers for OEM to adopt Big Data Analytics?

3.2 What are the barriers for OEM to adopt Big Data Analytics?

4) How does an adoption process framework look like when OEM customers want to utilize Big Data Analytics in the industrial automation sector?

4.1 What are adoption phases in terms of facilitating big data analytics adoption?

4.2 How do the influential factors affect the adoption process?

4.3 Which key activities are related to different adoption phases?

1.3.3 Research scope

The scope of this research is limited to the exploration of Big Data Analytics adoption at the organizational level by OEM customers in the industrial automation sector.

What is OEM?

According to Siemens, in the industrial automation sector, an OEM is defined as a company whose primary business is of building machines or equipment for resale, or in short machine builder. The industrial automation supplier offers OEM customer with a comprehensive portfolio of instrumentations, systems and services to meet not only the requirements of manufacturing processes but also requirements of OEM's end customers.

1.4 Research relevance

The possible outcome of this research will lie in two areas. The societal relevance and scientific relevance are respectively demonstrated in the following two subsections.

1.4.1 Societal relevance

The possible outcome of this research will lie in two areas. On the social level, due to the fact that the manufacturing industry is a major supporting sector for world and national economics (Nuremberg Chamber of Commerce and Industry, 2014), any step forward in the industrial automation sector will contributes to the international competiveness of the manufacturing industry. The focus on the OEMs in the research help in understanding the value exchanges in the industrial automation sector towards Big Data innovation. This research addresses the influential factors for OEM to adopt Big Data Analytics, from which guidance can be derived for the industrial automation sector to deliver new add-value services based on Big Data Analytics and create new business value and opportunities.

1.4.2 Scientific relevance

On the scientific level, this research project investigates the influential factors for adopting Big Data innovation and develops an adoption process framework to guide the utilization of Big Data Analytics for the manufacturing industry. To my knowledge, this is the first empirical study on the adoption of Big Data Analytics in the industrial automation sector. Most of the existing studies in the literature examined in IT innovation adoption are "adoption versus non-adoption"(Jeyaraj, Rottman, & Lacity, 2006; Nam, Kang, & Kim, 2015), this study will integrate the processes of innovation adoption with differential effects of TOE and DOI factors. The findings of this research allow us to clearly understand the influence of different factors in organizational innovation adoption process. The final adoption process framework will contribute to the development of innovation adoption theory. In addition, this study will apply value network analysis approach to understand the various market roles involved for adopting Big Data Analytics as a service by OEM companies. This will assess the applicability of value network theory.

1.5 Research Approach and Structure

In order to answer the research questions proposed in the previous chapter, the following research framework in Figure 2 describes the logical flow of knowledge generation in this thesis.

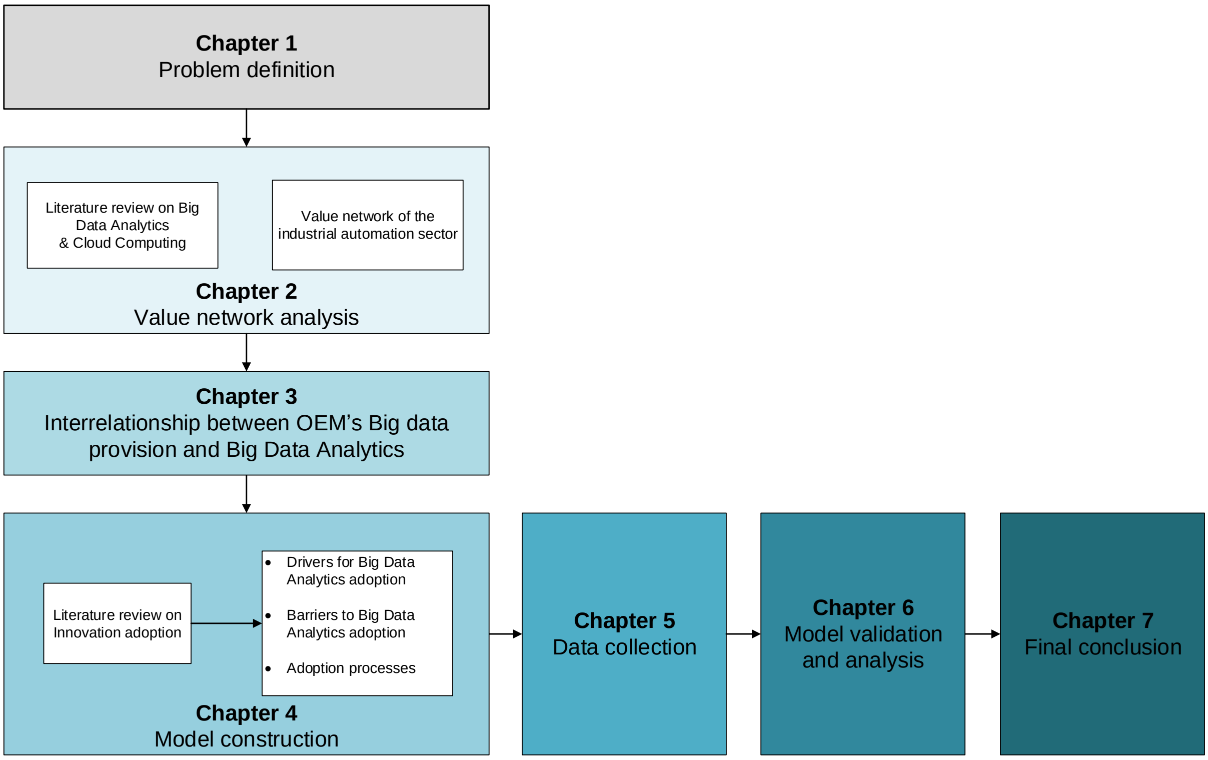

Figure 2 Research approach

The first chapter introduces the rationale behind this research project. It comprises the motivation for the research, the definition of research problem, the research objectives and the research questions. The research relevance at both social and scientific level was presented, after which a systematic research framework is designed.

The background information of this research regarding the industrial automation domain, Big Data Analytics, and cloud computing is described in the second chapter on the basis of relevant literature. The introduction of the products, services and business activities of industrial companies gives the readers an overview of the industrial automation sector. Next, Big Data Analytics, cloud computing as well as the big data trend in the industrial automation sector are explained. At the end of chapter 2, the value network of offering Big Data Analytics as a service is analysed in term of better understanding involved stakeholders.

In the third chapter, the benefits of using Big Data Analytics in the industrial automation sector from the OEM as user's perspective is presented. Then, the characteristics of OEM are analysed to explore their requirements of using Big Data Analytics.

In the fourth chapter, a literature review of innovation adoption is performed to understand the factors affecting the Big Data Analytics adoption at the organizational level. After that, the adoption process framework regarding Big Data Analytics is constructed for further evaluation.

In the fifth chapter, the data collection methodology is discussed in order to evaluate the adoption process framework. Accordingly, the research design and interview protocol are described. Once all data are collected, the analysis of data and results are discussed in the sixth chapter and followed by the evaluation of adoption process model.

The last chapter first presents the main research findings to answer the initial research questions formulated in the first chapter and makes the final conclusions. Then, last chapter analyses the scientific contribution and societal contribution with several recommendations for OEM companies regarding adopting Big Data Analytics, the research limitations and the future work.

CHAPTER 2 VALUE NETWORK OF THE INDUSTRIAL AUTOMATION SECTOR

The chapter 2 is to answer the first sub research question: "*How does the potential value network look like in the industrial automation sector towards Big Data Analytics for OEM customers?*" Before understanding the adoption of Big Data Analytics by OEM companies, it is very important to understand the involved actors and their interrelationships for the adoption. Therefore, we conduct a stakeholder analysis regarding the adoption of Big Data Analytics by OEMs in the industrial automation sector. This chapter starts with the delimitation of the industrial automation in section 2.1. Subsequently, the definition of big data and cloud computing and their relationship are conveyed in section 2.2. From the technical perspective, the application of big data and cloud computing are conjoined concepts (Hashem et al., 2015). Although the main focus of this research is adopting Big Data Analytics, it is necessary to briefly elaborate on the related concepts in order to have a comprehensive and better understanding of this condition. Then the main application of Big Data Analytics in the industrial automation sector is illustrated in section 2.3. Finally, the value network of the industrial automation sector for adopting the big data via SaaS is clarified in section 2.4.

2.1 Introduction of industrial automation

2.1.1 Industrial automation sector

The word of automation originated from irregular formation of "automatic" and "action". Oxford dictionary defines automation as "the use or introduction of automatic equipment in a manufacturing or other process or facility". The automation industry is an interdisciplinary sector that links mechanical engineering, electrical engineering and information technology, involving a mass of activities and interrelationships between suppliers and customer sectors. The extremely complex condition makes it difficult to make a commonly acceptable definition (Nuremberg Chamber of Commerce and Industry, 2014). The International Society of Automation defines automation as "the creation and application of technology to monitor and control the production and delivery of products and services" (The International Society of Automation, 2014). According to the definition of Deutsches Institut für Normung (German Institute for Standardization, DIN) in DIN V 19233, automation is "equipping a device so that it operates as intended, either entirely or in part, without human intervention". According to the International Organization for Standardization (ISO), industrial automation technologies includes "automated manufacturing equipment, control systems and supporting information systems, communications and physical interfaces" (Mason, 2007). In an automation market study of Nuremberg Chamber of Commerce and Industry, this organization used a layer model to represent the automation sector (Nuremberg Chamber of Commerce and Industry, 2014). In Figure 3, first layer represents sectors and branches of economic activity that can be uniquely (but usually not completely) assigned to automation sector. The second layer represents sectors that serve automation sector while the third layer represents sectors whose products indirectly assigned to automation sector. The multi-layered Services, which cannot be assigned to an individual layer, are usually provided as value-added services supplemented to automation products. This picture also shows the wide range of offerings in the industrial automation sector. Credit Suisse define industrial automation as “ the use of control systems and software to independently operate and monitor a mechanized system of industrial processes ” (Credit Suisse, 2012). As we can see, different organizations define industrial automation from their own perspective.

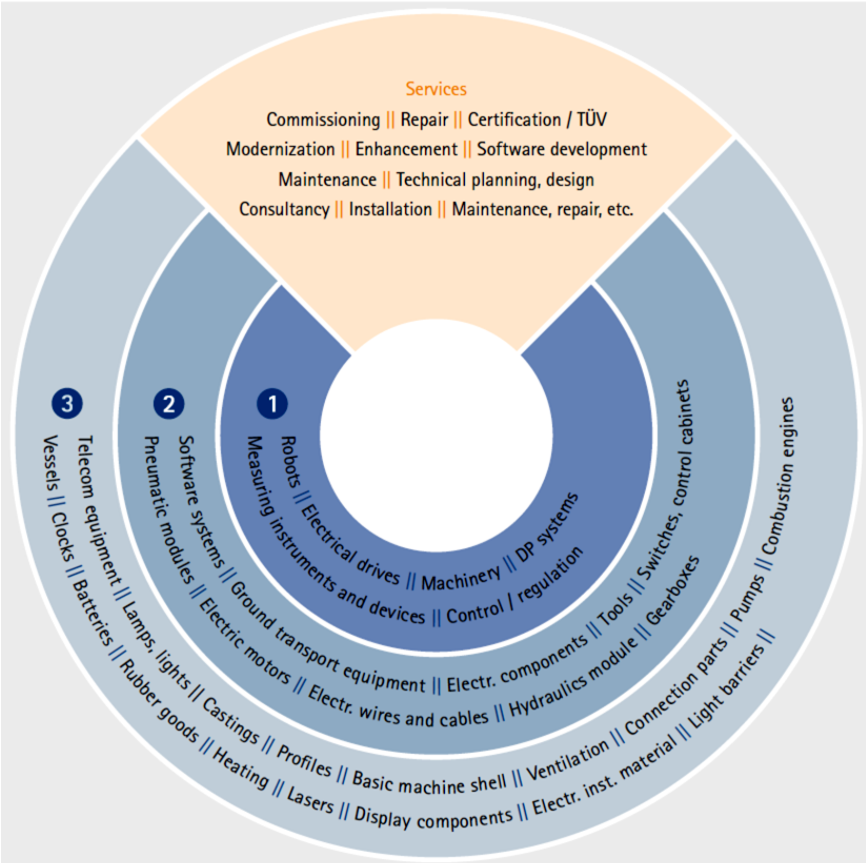

Figure 3 Product and service segmentation of Industrial Automation by Nuremberg Chamber of Commerce and Industry (Nuremberg Chamber of Commerce and Industry, 2014)

According to a market research by Credit Suisse, the products offerings in the industrial automation market can be categorized into 3 different levels, Enterprise level, Plant level and Instrumentation level. In the enterprise level, industrial products mainly include enterprise management software such as PLM, ERP and MES, etc. In the plant level, automation products contain both software and hardware for process and production control, such as SCADA system, DCS, PLC, CNC, HMI, etc. Instrumentation products include different sensors, robots, drives and motion control products. Figure 4 shows the typical products from different levels.

However, the different products are not equal to real industrial automation solutions. In order to implement the industrial automation solutions and ensure stable operation of industrial automation, these products are usually intelligently integrated to form customized industrial automation solution for customers. Meanwhile, services are also usually delivered as supplements to automation products. Figure 5 shows the various industrial service offerings from major automation companies in the industrial automation market, such as repair, training, technical support, consultancy, migration etc. According to a market research by MarketsandMarkets (a company dedicated to premium worldwide market research), the global industrial automation market is expected to “reach $301.9 billion by 2020, from $ 172.2 billion in 2013”, with an annual growth of 8.53% approximately, and “services play a crucial role in terms of overall value creation in the industrial automation sector ", and a main driver for the growth of the industrial automation sector (MarketsandMarkets, 2014) (Nuremberg Chamber of Commerce and Industry, 2014).

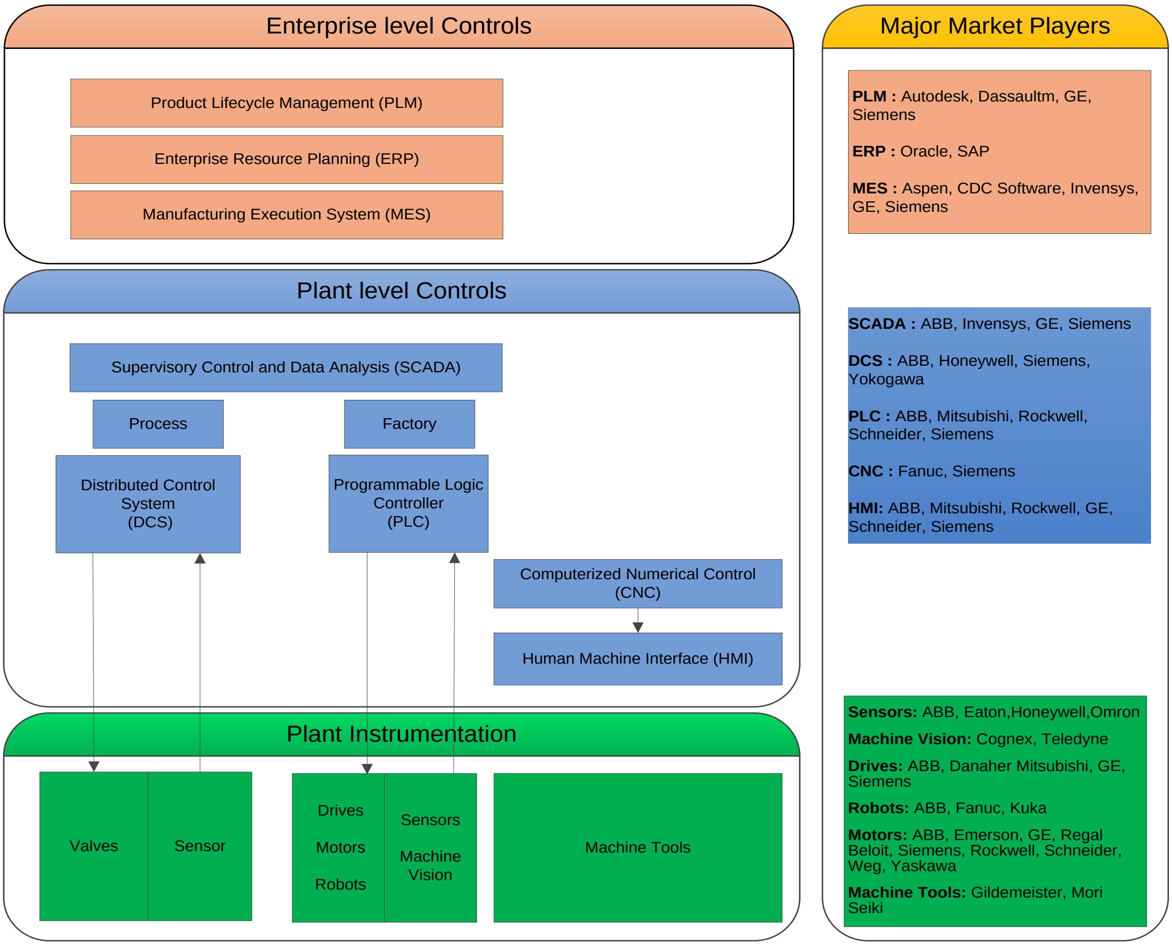

Figure 4 Products range in the industrial automation sector, adapted from (Credit Suisse, 2013)

	SIEMENS	ABB	Rockwell Automation	GE	Schneider Electric	ROVISYS
Preventive Service	√	√	√	√ Third-party services	√	√
On-site Expert Assistance	√	√	√	√	√	√
Extended Warranty	√	√	√	√	√	√
Remote technical support	√ •Mobile app •Remote Control	√ Remote Control	√ •Mobile app •Remote Control	√	√ •Mobile app	
Inventory Management	√	√	√	√	√	√
Exchange & Repair	√	√ End of life service	√	√	√	√ End of life service
Software update support	√	√	√	√	√	
Training	√	√	√	√	√	
Maintenance & Modernisation Consultancy	√	√ Parts Root Cause Analysis	√	√	√	
Industrial Performance Consultancy	√	√	√	√	√	√
Security Services	√ Industrial security	Cyber security monitoring service	√			
Modernisation & Migration services	√	√ Migration to ABB	√ Migrate to Rockwell	√	√ Migrate to Schneider	

Figure 5 Services offering in the industrial automation sector.

2.1.2 Use case of the industrial automation products

Automotive industry

An automotive company, whose main businesses are vehicle design and manufacturing, is a typical OEM customer in the industrial automation sector. The production of a car includes several core processes as followed: pressing (press shop), body manufacturing (body shop), Painting (Shop), Power train (engine & transmission) construction, final assembly (e.g. doors equipped, electric wiring, windows, wheels and lights assembly). During the whole production process, the industrial automation products and systems are used to realize design-to-production, operate and monitor the production processes. For example, industrial robots carry out the following activities in body manufacturing process: gas-shielded welding, gluing, handing, stud welding. Drives and motors are used in painting process. In the final assembly process, the car body hangs from an electric monorail system, and then the carriage controller determines the exact position of different parts. The skid stops or moves on accordingly. Robotic arms assemble all different parts into the car body. All these processes are monitored and operated by automation control system.

Baking equipment manufacturer

In the food industry, baking equipment manufacturer is the supplier of equipment used to produce bread, biscuits and pet treats. Its equipment is built and used for very high-volume baking production in different companies in the food industry. Each baking system needs to be customized to some extent. This type of manufacturer uses PLM software to design large assemblies and other equipment in a fast and accurate way. Industrial automation are integrated with temperature and pressure sensors and motors in baking equipment to control the food production process for the end customers of baking equipment manufacturer.

2.2 Big Data Analytics in cloud computing

2.2.1 Big Data Analytics

Big data usually refers to datasets whose size are beyond the ability of conventional information communication technologies to capture, store, manage and analyse (Manyika et al., 2011). The first use of big data concept appeared in a paper published by NASA in 1997, when computer systems faced the problems in visualizing large datasets (Cox & Ellsworth, 1997). In 2001, Doug Laney from Gartner introduced the 3Vs concept: volume (amount of data), velocity (speed of data in and out), and variety (range of data types and sources), to define big data (Laney, 2001). In a later update, big data is defined by Gartner, "high volume, high velocity, and/or high variety information assets that require new forms of processing to enable enhanced decision making, insight discovery and process optimization". This is the most cited definition. Some researchers added other V-based descriptors to this definition, such as variability and visibility, and IBM added the veracity characteristic recently in response to the data quality and source issues (Laney, 2001; Paul Zikopoulos, Parasuraman, Deutsch, Giles, & Corrigan, 2012). Big data is mainly associated with two underlying ideas: data storage and data analysis (Ward & Barker, 2013). Despite the definition only focuses on the acquisition and storage of massive amount of data, which did not notably differentiate from conventional data processing techniques, the application of big data concept transits towards analysing data from various sources to gain a competitive edge. So data analytics is the most important part in the application of big data concept. As companies and organizations operate their business and interact with individuals, massive amount of data are generated and regarded as important asset. It is very important to mention that data is not information. In contrast to rapid growth of data amount, data is still a hidden resource for companies that offers great potential to enhance their business. A lot of companies don't use the data in hand at all or haven't used them enough to gain more information and knowledge (Hagen et al., 2013).

In Oxford Dictionary, Analytics is defined the systematic computational analysis of data or statistics. In a book written by Davenport and Harris, Analytics is defined as " the extensive use of data, statistical and quantitative analysis, exploratory and predictive models, and fact-based management to drive decisions and actions" (Davenport & Harris, 2007). In simple term, Analytics means the process of using various techniques to transform the data into actionable knowledge for better decision-making. As the amount of data is exploding and information communication technologies are developed, more opportunities are emerging for analytics. According to a literature review regarding Big Data Analytics, the terms of "big data" and "Big Data Analytics" are used interchangeably. This phenomenon reflects that "big data" refers to the problem of oversize of datasets as well as the extraction of actionable information from available data. Hence, Russom emphasized that Big Data Analytics includes two thing-Big Data and Analytics, wherein he defined Big Data Analytics as " advanced analytic techniques operate on big datasets" (Russom, 2011). The most widely used definition of Big Data Analytics is " the process of analysing and examining large volumes of data of a variety of types to uncover hidden patterns, unknown correlations and other useful information "(Shang et al., 2013).

Although there are different definitions regarding Big Data Analytics based on different perspectives, the analysis of big data can be categorized into three types by Lustig et al: Descriptive Analytics, Predictive Analytics and Prescriptive Analytics (Lustig, Dietrich, Johnson, & Dzekian, 2010). Figure 6 represents three different Analytics. These three types of analytics answer following key questions.

1) What did happen or is happening in certain business activities? And why do these happen?
2) What will happen in certain business activities?
3) What actions or decisions can business take regarding the current or predicted condition?

Descriptive Analytics: Use data to represent and analyse the past and real-time business performance. The typical descriptive analytics include standard reporting and dashboards, ad-hoc reporting, analysis/query/Drill-down.

Predictive Analytics: Use data and mathematical techniques to build explanatory and predictive models of business performance. The mainly used techniques include data mining, *pattern recognition and alerts, Monte-Carlo simulation, forecasting, root cause analysis, predictive modelling*, etc.

Prescriptive Analytics: Use mathematical techniques to form set of actions and decisions for business performance improvement with limited enterprise resources. This is advance analytics based on the concept of optimization.

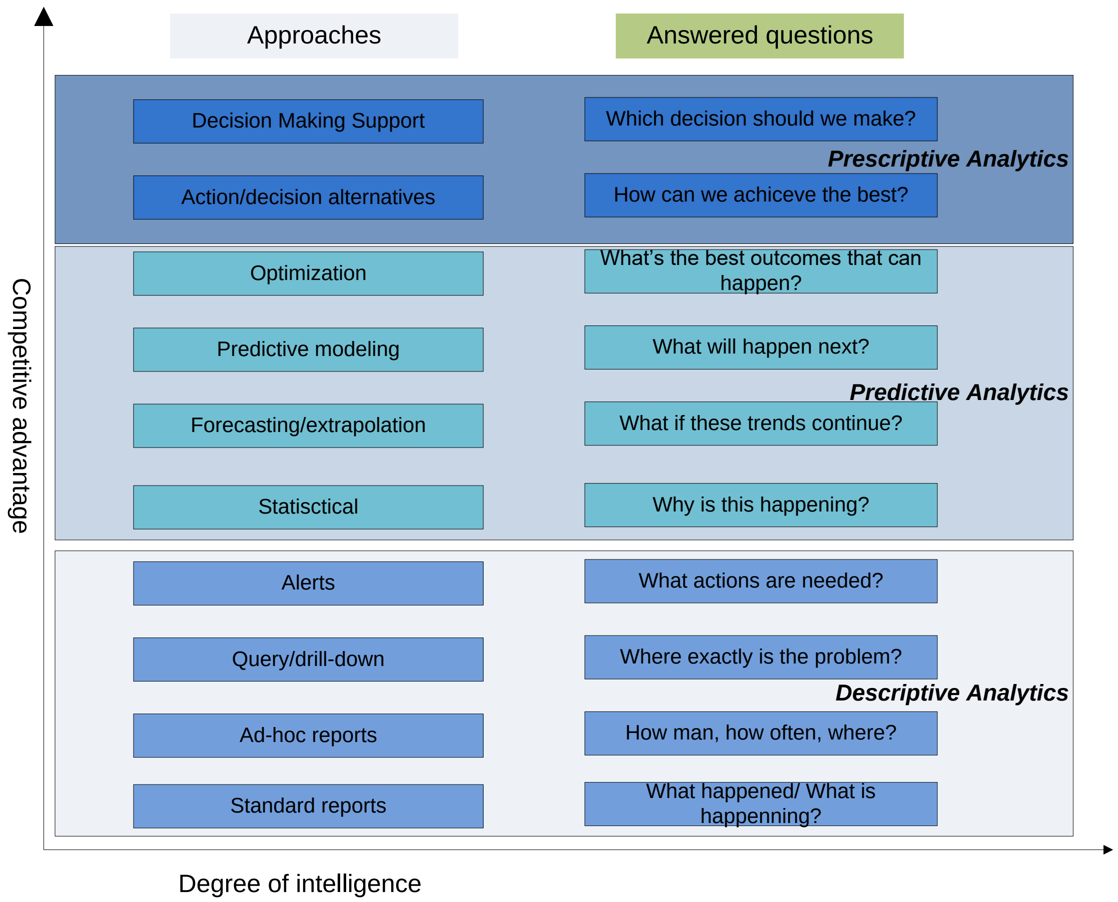

Figure 6 Analytics types modified from Davenport & Harris 's model (Davenport & Harris, 2007).

2.2.2 Cloud computing

Cloud computing is a widely used concept with a lot of definitions in the literature. The National Institute of Standards and Technology (NIST) defined that "Cloud computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction" (Mell & Grance, 2011). NIST also proposed three service models and four deployment models of cloud computing, which is widely accepted by many scholars (Marston, Li, Bandyopadhyay, Zhang, & Ghalsasi, 2011; Subashini & Kavitha, 2011; Youseff, Butrico, & Da Silva, 2008). Cloud computing service model includes Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software –as-a-Service (SaaS). In traditional IT domain, users need to manage entire technology stack that is called an on-premise solution (in the user's workplace). In contrast to traditional IT domain, the "as a service " provisioning showed in Figure 7 represents that end users don't need to manage the entire technology stack. Although this research will focus on the adoption of Big Data Analytics via SaaS, a brief description regarding delivery and deployment model will help readers better understand the concept of cloud computing.

Cloud computing service model

- Infrastructure-as-a-Service (IaaS) model provides customers with fundamental computing power such as hardware (e.g. servers), operation systems and databases, storage and networks, to deploy and run arbitrary applications. Customers do not manage or control the underlying hardware, but they have control on operating system, storage and limited control of selected networking components (Mell & Grance, 2011).

- Platform-as-a-Service (PaaS) model provides customers with programming languages, libraries, services, and development tools to deploy customer-created or acquired applications onto the cloud infrastructure. Customers do not manage or control underlying cloud infrastructure, but they have control on the deployed application and configuration for application-hosting environment (Mell & Grance, 2011).
- Software-as-a-Service (SaaS) model provides customers with arbitrary applications running on a cloud infrastructure. These applications can be accessible from various client devices, such as PCs, Smart phones or Tablets. Customers do not manage or control the underlying cloud infrastructure.

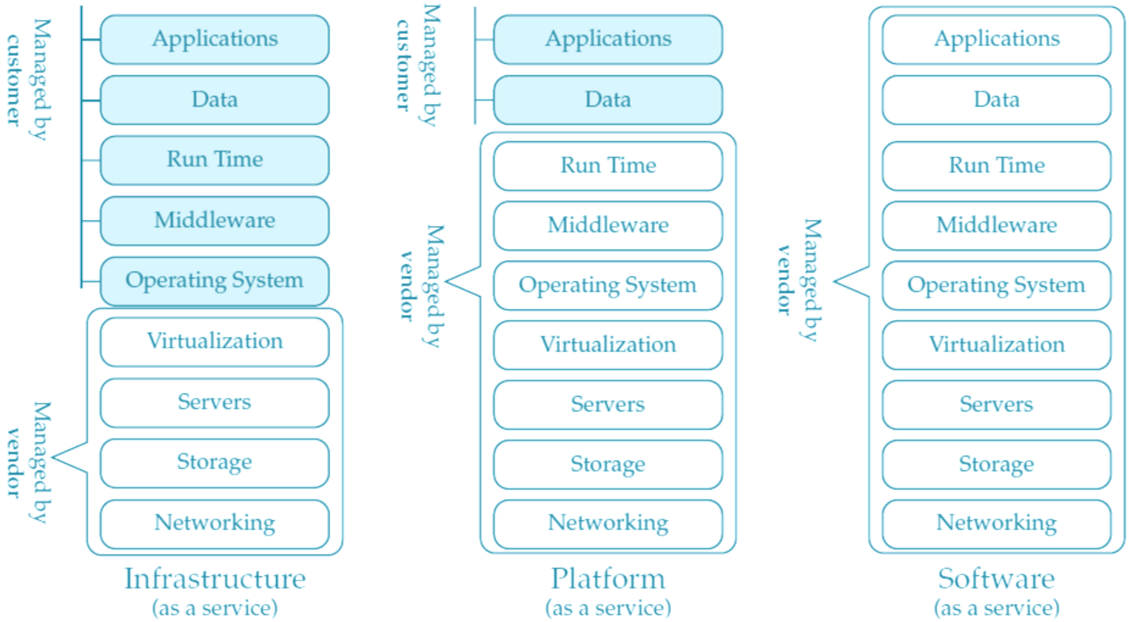

Figure 7 Comparison of vendor and customer responsibilities in different cloud computing service models (P. Zikopoulos, deRoos, Andrews, Bienko, & Buglio, 2014)

Cloud computing deployment model

- Private cloud – Cloud infrastructure that serves a single organization. It may be owned and managed internally, a third-party or combination of them. This solution provides high security level, but results in limited scalability and high total cost of ownership (TCO). This deployment model is always used by large organization.
- Community cloud – Cloud infrastructure shared with serves several organizations with common concerns. This solution keeps relatively high security level but reduces the costs compared to a private cloud solution.
- Public cloud – Cloud infrastructure that designed for open use. It may be owned, managed by any organization(s). In contrast to private cloud, this solution has lower security level but offers higher scalability and lower costs.
- Hybrid cloud – Cloud infrastructure that composited with two or more above cloud infrastructure (private, community or public). The solution used for dealing with cloud bursting takes advantage of scalability and costs benefits through the public clouds while hosting sensitive data on the private cloud.

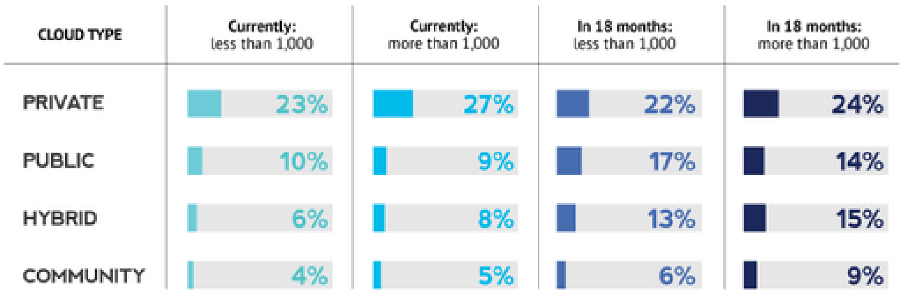

Figure 8 Different businesses vary in the specific types of cloud deployment model (CloudTweaks, 2012)

From the Figure 8, we can see that in business different cloud deployment types are used, while private cloud is the most used type.

2.2.3 The relationship between big data and cloud computing

Big data encompassed the variety and complexity of data and data types, data collection and processing and the value that can be obtained by analytics. This term often requires efficiently and effectively high performance computing power to produce timely results (Talia, 2013). Despite the popularity of Big Data Analytics, it is still general complex, costly, time-consuming and inflexible to put them into practice. Cloud computing has been a revolution for the industry by enabling customers to only pay for the resources and services they use (Assunção, Calheiros, Bianchi, Netto, & Buyya, 2015). The development of cloud computing facilitated the deployment of various novel applications, which results in a tremendous data growth as well as data consumption by these applications (Agrawal, Das, & El Abbadi, 2010). So Cloud computing can be regarded as the source of big data and solution of handling big data. Big Data Analytics services can be implemented via three service model of cloud computing (Talia, 2013). In the automation sector, OEMs always need to get support from external partners in terms of implementation of Big Data Analytics, since they don't have sufficient technical know-how or computing power. Cloud computing provides a possible approach for OEM companies to adopt big data.

2.3 Business trend of Big Data Analytics for OEM

With the development of new technologies the manufacturing industry has transited from "the early adoption of mechanical systems, to support production processes, to today's highly automated assembly lines", in order to fulfil the dynamic market requirements and demands(Lee, Kao, & Yang, 2014). German federal government initiated the concept of Industry 4.0 which described how Internet of things, smart data and smart services will increase digitization of production in future (Buhr, 2015). The adoption of information communication technology and social media networks has increasingly influenced consumers' perception on product and service innovation, quality, variety and speed of delivery. This drives OEM to upgrade its production facilities "with capabilities of self-awareness, self--prediction, self--comparison, self-reconfiguration, and self—maintenance" in terms of boosting efficiency gains and productivity improvements(Lee et al., 2014) . In this trend, the big data that enables fact-based principles for decision-making have received a lot of attention by academia and industries. The main usage of Big Data Analytics for OEM compromises asset and process analytics, energy analytics and cyber security.

2.3.1 Asset and process analytics

Equipped with various sensors, metering devices and connected with industrial network, the heath condition data of OEM's plant and an asset or its critical components is continuously automatically acquired and visualized. The condition of plant and critical assets and machines can be monitored and evaluated in near real-time. At the same time, based on the collected data, mathematic model and machine learning, the data analytics application help the operator or plant manager detect patterns of failure before the actual malfunction event. So when an asset failure is predictable, operation manager can have more time for re-scheduling resources, preparing for spare parts and repair services, adjust production workflow in advance to mitigate the negative impact of unplanned downtimes.

2.3.2 Energy efficiency analytics

These days, economical, efficient production and strict environmental regulations demand a higher level of energy efficiency than ever before for OEM. By collecting real-time energy related data such as electricity usage, water, temperature, pressure and process data, energy analytics application can generate informative reports and analytics to determine discrepancies between baseline and actual energy usage. The energy analytics application can also help benchmark and compare previous performance with actual energy usage. OEMs can use this information to determine whether their plants are operating efficiently and reaching the energy usage target. Therefore, they can then investigate potential area in the plants for energy efficiency improvement, design energy efficiency upgrade plans, or change some energy efficient facilities.

2.3.3 Cyber security analytics

Another area for Big Data Analytics in OEM is cyber security analytics. Within the manufacturing space, Discrete Manufacturing and Process Industries are experiencing fastest pace in innovations and developments, built around connectivity, where men and machine share vast amounts of data from different sources in order to enhance productivity and empower business decisions. This rapidly expanding data interconnectivity, coupled with the rising number and complexity of cyber-attacks targeting industrial control systems, poses new challenges in securing the manufacturing shop-floor. The most common cyber security weakness in industrial control area identified by a research report published by The U.S. Department of Homeland Security includes Improver Input Validation, Credentials Management and Improper Authentication & Access Control (Nelson & Chaffin, 2011). Figure 9 shows the percentage of different industrial control system vulnerabilities. Failure to mitigate the vulnerabilities will leave OEM's industrial control system exposed to increasing cyber incidents, in which could easily cause public reputation loss, environmental impacts, financial loss and even human casualties (Byres & Lowe, 2004). So suitable cyber security technologies such as intrusion detection software, firewall, antivirus software and file integrity checking software together with security mechanisms are crucial for enabling Big Data Analytics.

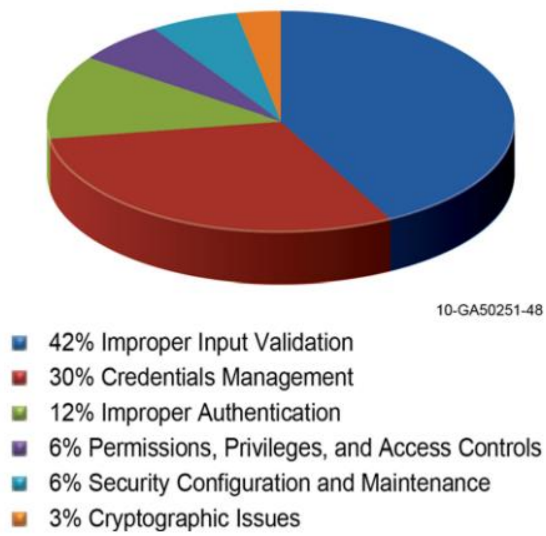

Figure 9 Percentage of 2009-2010 industrial control system vulnerability disclosures from (Nelson & Chaffin, 2011)

2.4 Value network of Big Data Analytics

2.4.1 Evolution of value chain towards a Big Data Analytics value network

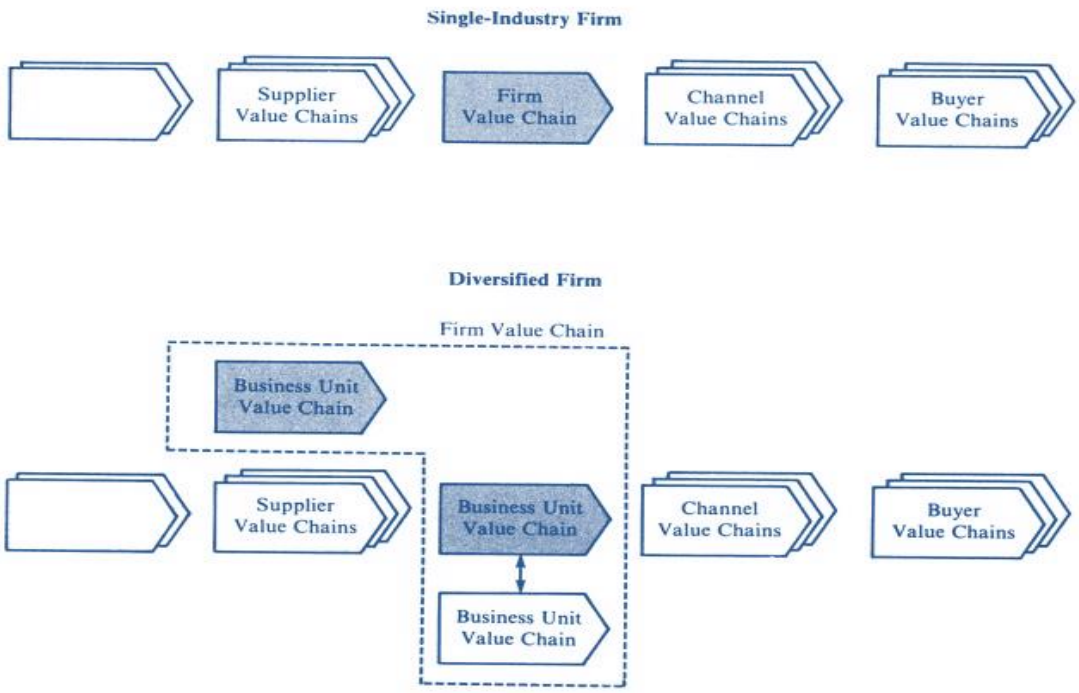

Figure 10 Value system proposed by (Porter, 1985)

In order to address the adoption of Big Data Analytics by OEM, it is very important to identify the involved actors and their value exchange relationship along with various business activities. The basis of value chain concept is a model that describes a full range of activities which are required by a company to develop and manufacture a product or service for a customer (Leimeister et al., 2010). These activities connect a company's supply side (conception, raw materials procurement, inbound logistics, and production processes) with its demand side (marketing, sales, outbound logistics, and final disposal after use) (Böhm, Koleva, Leimeister, Riedl, & Krcmar, 2010; Leimeister et al., 2010). According to Porter (1985), a value chain distinguishes between primary and support activities within and around an organization that ‘design, produce, market, deliver, and support ’a product or service for its customer (Porter, 1985). The primary activities directly generate a value margin for the organization while the support activities are conducted to support the primary activities. In a value chain, several organizations and their internal business units jointly provide a product or service for a market. In order to describe the interrelationship between different companies’ value chains, Porter extended the value chain as a value system, illustrated in Figure 10. In a value system, a company’s value chain links to the value chain of its suppliers (their suppliers all the way back), distribution channels and customers (their customers all the way forward). Linkages connecting different steps enhance the value of a product or service. Figure 10 presents interconnected value chains in a value system. In the conventional businesses activities between industrial automation supplier and OEM, physical products are exchanged between them. The sequential logic in value chain concept has proved useful to perfectly map the vertical sequence of events in the physical world, leading to delivery, consumption, and maintenance of automation product and service (Böhm et al., 2010; Peppard & Rylander, 2006).

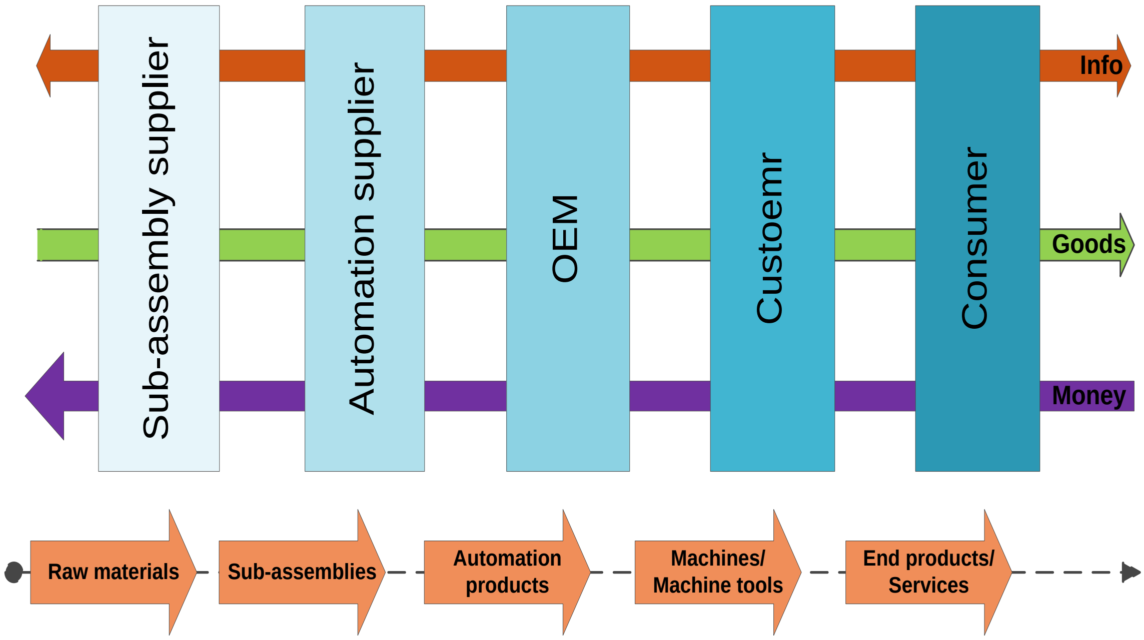

Figure 11 Flows of value chain between automation supplier and OEM adapted from (Nuremberg Chamber of Commerce and Industry, 2014)

In the traditional industrial automation sector, the value chain between automation supplier and OEM can be explained as a system of flows of inputs and outputs, shown in Figure 11. The upstream suppliers deliver goods to downstream customers from which receive money and information. Then the downstream customers alternately act as suppliers to deliver goods to their downstream customers till end customers. End customers then distribute final products or services via machines provided by OEMs.

However, modern manufacturing is not strictly linear process while more and more services are introduced between suppliers and OEMs in the industrial automation sector. The functions and activities among different companies are performed simultaneously rather than sequentially. The interrelationship between companies are becoming more and more complex. Moreover, with the trends of dematerialization and digitization of products and service delivery, besides the tangible value exchanges on the basis of physical products, virtual word made of information become a new way of intangible value creation. Allee argued that intangible value, such as 'customer or external capital (alliance, relationship with customers, suppliers); human capital (personnel's individual capabilities, knowledge, skills, experience); and structural capital (systems and work processes, e.g. business concepts and models, databases, patents, copyrights, etc.)' (De Reuver, 2009), can be generated in business activities (Allee, 2000). Linear model like value chain is no longer suitable for analyzing the value created involving complex alliances, competitors, complementors and other roles in business networks (Peppard & Rylander, 2006). Therefore, a value network is required to understand the complex dynamical value creation and exchanges among companies.

According to Allee's definition, value network can be regarded as a network that contains tangible and intangible benefits exchanged between the partners (Allee, 2000). Tapscott et al. defined value network as a network of commercial service providers and customers connected via electronic media in terms of creating values for their end customers (Tapscott, Lowy, & Ticoll, 2000). De Reuver (2009) defines value network as 'a dynamic network of actors working together to generate customer value and network value by means of a specific service offering, in which tangible and intangible values are exchanged between the actors involved' (2009, P. 12).

Industrial automation sector follows the trend from products to services while services plays a more and more important role in value creation (Nuremberg Chamber of Commerce and Industry, 2014). Automation suppliers offer Big Data Analytics as a service through cloud computing platforms integrated with IT infrastructure, platform and software providers to customers. In this trend, the interdependence between automation suppliers, OEMs and other roles are becoming more complex while new opportunities or business models may be introduced. Value network model appears to be more appropriate for analyzing the linkages between different stakeholders when delivering Big Data Analytics service.

2.4.2 Market roles and actors

Due to an increasing trend towards Big Data Analytics in the industrial automation sector, opportunities to offer Big Data Analytics services and related support services via SaaS gives rise to many new roles in the industrial automation sector. SaaS is always related to other two service delivery model: PaaS, IaaS, which is typically used in the ICT sector. In contrast to this layer model, value network concept can be applied to analyze the market role division regarding Big Data Analytics services in the industrial automation sector from a business perspective(Böhm et al., 2010; De Reuver, 2009). A certain type of market role represents a group of market actors offering similar services to similar customers. According to Böhm et al., in the industrial automation sector, the market actor represents companies or organizations offer or get various services in term of enabling Big Data Analytics services (Böhm et al., 2010). Market actors offering or/and receiving different services related to Big Data Analytics can play several different roles. In this paragraph, we propose that the industrial automation sector can be classified in following market roles, shouwn in Figure 12.

Infrastructure Provider

The infrastructure provider is distinguished into two types in the industrial automation sector. One type provides IT infrastructure including physical servers, database, storage, network connection and firewalls to OEMs. Customers own and operate IT infrastructure. As cloud computing matures, more and more OEMs transit to infrastructure-as-a-Service model that can get virtual hardware at their own usage from IaaS providers. The other type of infrastructure provider offers industrial automation products, such as sensor, drive, motor, PLC, HMI. These automation products are main sources of data for further analytics.

Technical Platform Provider

The technical platform provider provides an technical-oriented environment with necessary supporting components, such as programming languages, libraries, application programming interfaces (APIs), middleware, programming tools as well as services etc. to develop, deploy and host applications for data analytics. Developers of data analytics applications are not responsible for technical, infrastructure related details (Böhm et al., 2010).

Market Platform Provider

The market platform provider builds a business-oriented marketplace where Big Data Analytics services are offered by different roles. On this market platform, companies can market their big data analytic services while OEMs can look for desired analytics services. Beside the function of service presentation and searching, the market plat form can also offer contracting or transaction clearing.

Analytic application Provider

Analytic application provider develops and supplies different data analytics applications for their customers. The applications are hosted and operated by the analytic application provider and are always accessible by business users on the Internet. In order to maximize the performance of the applications, analytic application provider needs to monitor the state of the system, adjust the loading balancing, fix the technical problems, improve and update the features of the applications and prevent the application from unauthorized access or manipulation.

System Integrator

System integrator offers solutions for customers who want to deploy Big Data Analytics services. The system integrator has to smoothly integrate data collection solution, data converting solution and analytic solution via SaaS into the existing IT landscape of the customer (Böhm et al., 2010). In the meantime, the system integrator also offers training and support services. Because of the complexity of the industrial automation, the integrator normally needs to develop customized solution for its customer.

Consultant

The company consultant is employed by different market roles as expertise before introducing Big Data Analytics project. Consultant can provide knowledge about Big Data Analytics on the basis of the customer's business process and specific requirements. Consultant can also offer cost benefit analysis and information security advices regarding Big Data Analytics.

OEM

OEM is the final customer who receives Big Data Analytics services. OEM is the starting point of big data analytic service request and the ending point of service delivery. All value-added services are eventually paid by OEM.

In practice, one market actor plays as one or more roles. The composite actor Big Data Analytics service provider represents that it offers requested services to the System Integrator or OEM who do not necessarily care how they are implemented (Böhm et al., 2010). Therefore, the Big Data Analytics service provider is compromised of the roles Infrastructure provider, Technical Platform Provider, Application Provider and Market Platform Provider. Market actors act as this role may corporately offer services with other roles or on their own. In the industrial automation, traditional automation product suppliers integrates PaaS and IaaS solutions offered by IT companies and build their own SaaS platform to offer Big Data Analytics applications for OEM customers. Siemens is a typical example that acts in several roles in this case. Based on SAP's HANA Cloud platform, Siemens is developing an industrial data analytics platform for its OEM customers. Siemens will offer Big Data Analytics application as well as consulting service, making it both Application Provider and Consultant. On this platform, third-party's applications can be also hosted and sold to OEM, making Siemens both Technical and Market Platform Provider.

Not only traditional industrial companies like Siemens, ABB or Schneider Electric are entering big data trend by leveraging digitalization and data analytics. Several conventional IT players are trying to replace domain know-how with knowledge from data and to enter into traditional industrial automation markets (Siemens AG, 2014). Google, IBM and Cisco all have data analytics business strategy for industrial sector based on their strong analytic capabilities and successful experience gained from consumer markets.

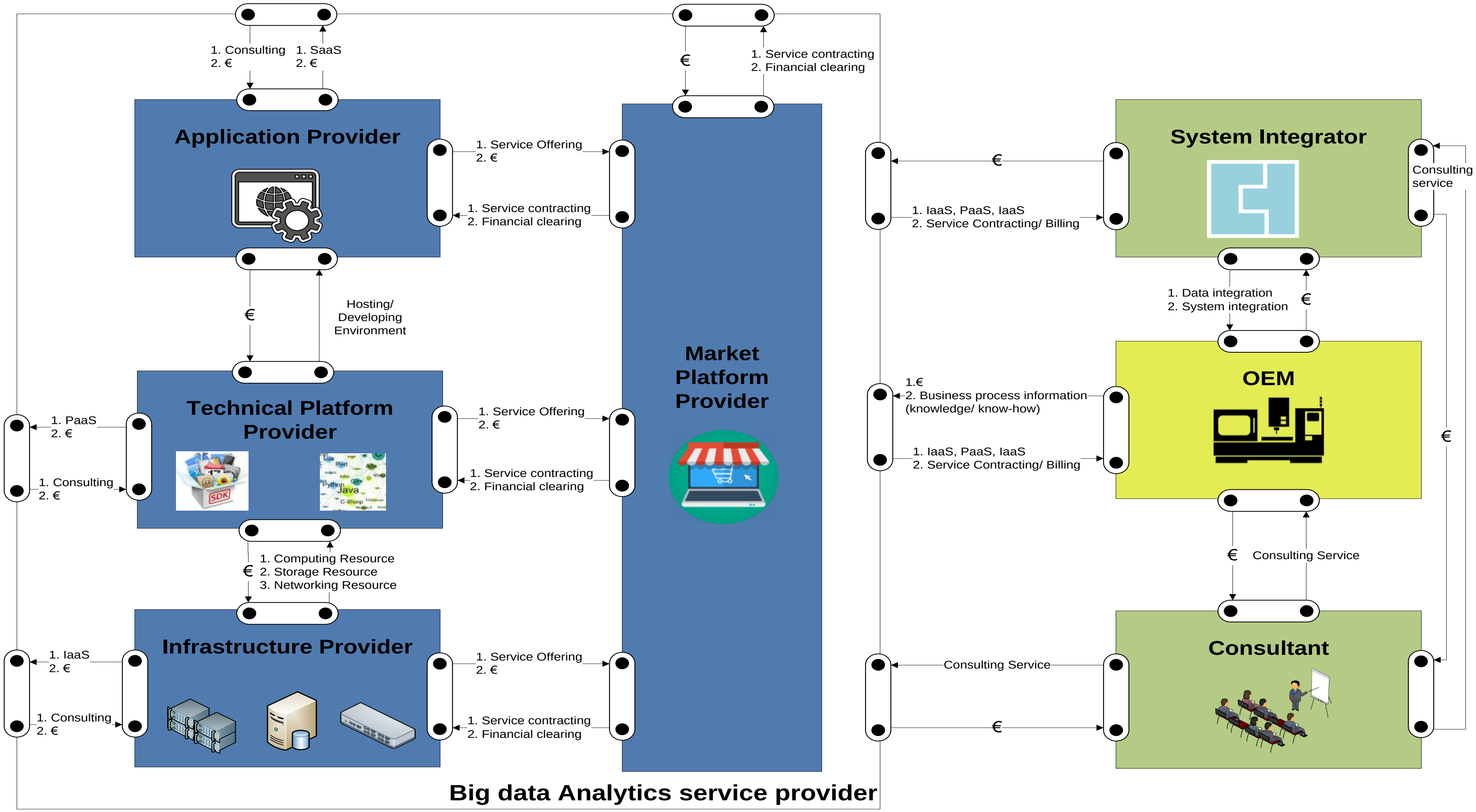

Figure 12 Value network of Big Data Analytics service in the industrial automation sector adapted from (Böhm et al., 2010).

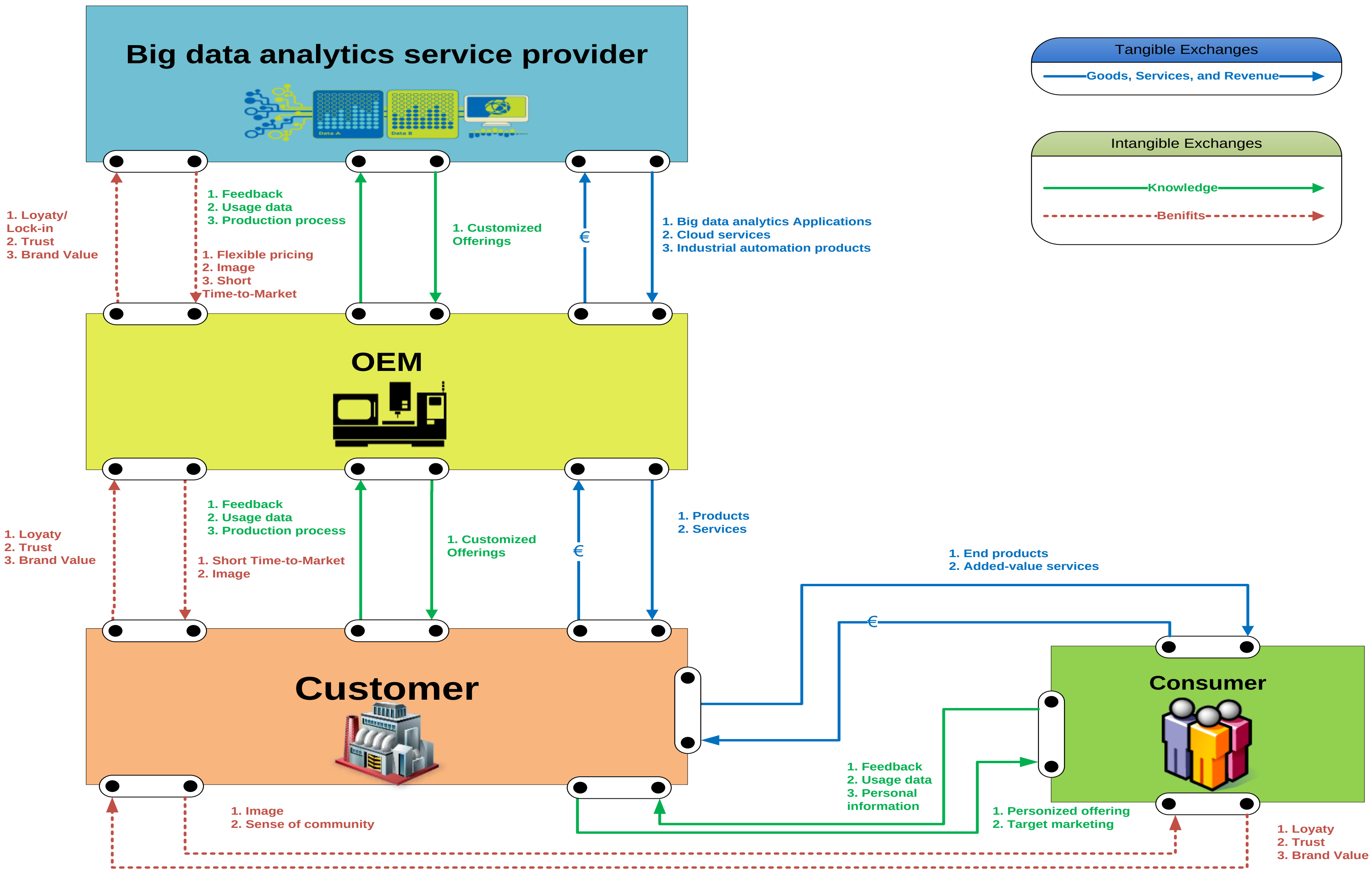

Figure 13 Potential value exchange along with OEM and its customer

2.4.3 Value exchange

According to Allee's value network model, there are two types of economic exchanges: tangible exchange and intangible exchange (Allee, 2000). Tangible exchanges represent physical goods, services and revenue that are contractual in the transaction process. Intangible exchanges represent knowledge and benefits that are not contractual but also essentially important to keep smooth running of contractual exchanges. Figure 12 illustrates the value network of big data service for OEM in the industrial automation sector. In this sector, each OEM has its own special requirement for big data analytic services, so service provider needs to have a deep understanding of OEM's business process and business model in term of selling solutions. The application provider and system integrator in this network will create more monetary value as computing resource is becoming as a commodity.

OEMs have their own end customers who have direct contact with consumers. The individual consumers are the de facto end users who link all industrial products and services to some extent. The continuous challenge of user experience improvement will drive OEM's business. In order to create competitive edge, OEM's customers have to provider new products and services, and response more proactively and quickly to the market. In reverse, industrial products and services offered by OEM's end customers may change the lifestyle of the consumers, e.g. power generation, oil & gas exploration, satellite, electronic computer, etc. Figure 13 illustrates the value exchanges among between various market roles in this network. In this value network, tangible and intangible exchanges go along with various business activities wherein consumers get desired physical and virtual products. Vendors get monetary value as well as knowledge and benefits which are eventually used for creating competitive edge to generate monetary value.

2.5 Conclusion

This chapter answered the first sub research question: "*How does the potential value network look like in the industrial automation sector towards Big Data Analytics for OEM customers?*". The current status of the industrial automation sector and the term of Big Data Analytics have been explained in this chapter by describing various definitions. Due to complexity of big data, OEM companies need to cooperate with other companies and their customers to address the challenges of big data. The growing demand of utilizing big data technologies by OEM companies in the industrial automation sector offers opportunities for integrating partners and customers into a value network. When OEM adopting Big Data Analytics in the industrial automation sector, there are several stakeholders or market roles in the market. Some market roles are still played by traditional IT companies and industrial automation companies while these companies will enter each other's area in term of providing Big Data Analytics services. The potential value network of Big Data Analytics business in the industrial automation sector will create a tendency of competition and cooperation between IT companies and traditional industrial automation companies since all of them have jumped on the analytics bandwagon. The answer to the first sub research question helps understand the involved stakeholders when OEM adopting Big Data Analytics. The next chapter will analyze interrelationship between Big Data Analytics and OEM's business requirements.

CHAPTER 3 MATCH BETWEEN BIG DATA ANALYTICS AND OEM COMPANIES

After addressing the stakeholders in the process of adopting Big Data Analytics, next step is to investigate whether Big Data Analytics can meet OEM companies' demands. Many business leaders and academic experts believe that Big Data Analytics represents a disruptive innovation for effective business processes decision-making on the basis of information (Esteves & Curto, 2013). Before the actual use of Big Data Analytics, it is very important for OEM companies to perceive significant benefits of using Big Data Analytics. Therefore, chapter 3 is to answer: "*How do Big Data Analytics connect the requirements of OEM?*" In this chapter, the benefits come with Big Data Analytics will be investigated in section 3.1. In the section 3.2, the real requirements of OEM in their current business processes will be analyzed. Then, the relationship between the requirements of OEM and the offering of Big Data Analytics will be clear for industrial automation companies and users.

3.1 Benefits from Big Data Analytics

Advanced big data analytics technologies are now being widely used to analyse massive data and extract business intelligence, which may greatly change the way that companies manage their daily operations (IBM, 2014). From industrial automation company perspective, harnessing the data that businesses routinely generate – not only just storing it, but also mining actionable information from it - provides possibility to optimize industry production and process, identify customers' need and develop new added-value services or new business models (Jeseke, Grüner, & Wieß, 2013). From OEM's point of view, it has been generally assumed that leveraging big data will create transparency for production process, support human decision making with automated algorithms for better performance and cost reduction, reduce energy consumption and avoid potential risks (Siemens AG 2012).

Businesses are using the power of Big Data Analytics to extrapolate the maximum valuable insights from massive structured and unstructured data from various sources. The main business benefits in the industrial automation sector include the following aspects: transparency, efficiency improvement, customized production, decision making supporting, new business model.

3.1.1 Creating transparency regarding the production process

Although companies have been utilizing the network-based technologies to business application as they emerged in the last decade. However, the full potential of Internet-based digitalization on machines has yet not been realized across the industry system. The physical world of machines, facilities, fleets, networks, the machines and facilities can be more interconnected and integrated with Big Data Analytics. The most sophisticated data analytics application is useless if the required data is not available or data quality is insufficient. Therefore, establishing cyber-physical systems equipped with digital instrumentation that incorporate the machinery, warehousing systems and production facilities, give the constant remote accessibility of machine data. Only with accessible data, in-depth knowledge about the machines and production processes becomes possible.

Most companies are already struggling with managing a vast amount of data. While good improvements have been made in technological ability to store data, most organizations' ability to manage, analyze and apply data has not kept pace. The data is often unstructured and further processing is required in order to extract the desired information. Besides, as most systems become real-time oriented, data processing and management systems need to adapt to this demand. In the Big Data world, data storage solutions are not restricted to a predefined rigid data model, and data systems are able to process different kinds of structured and unstructured data(EY, 2014). Big Data Analytics provides the possibility of gaining timely insights from the vast amounts of data. Industrial customers can get transparency on product performance and product utilization by the means of digital reports and/or dashboards (Evans & Annunziata, 2012). Connected machinery and manufacturing systems will show that what's happening in the factory to enterprise-level systems and decision makers. For instance, a plant engineer walking the production shop could use mobile device installed with visualization tools to remotely access the real time production information of each machine and reduce the time for decision-making and actions.

3.1.2 Improving operational efficiency

In many cases, Big Data Analytics is not only about getting more data but creating relevant knowledge and delivering it in a very short time span or in a near real-time. According to a survey by BARC Research, the most named Big Data use cases in production includes: reporting and analysis of production processes and efficiency, production planning and optimization, machine monitoring, production asset and process management etc. (Carsten et al., 2015). From a customer perspective, these use cases of Big Data Analytics help customers detect problems, expose deviation and identify further improvement potential regarding their production process, which may achieve the following advantages:

Higher Performance/Productivity:

- Workflow optimization such production or maintenance processes;
- Higher asset availability or increased asset performance due to optimized maintenance cycles or predicting the malfunction before break-down;
- Increased production output quality, e.g. due to more regular/precise calibrations or optimized maintenance cycles;
- Higher asset usability due to more customer specific interfaces and features.

Increased Energy Efficiency:

- Higher efficiency in terms of energy consumption and CO_2 emission;
- More efficient use of scarce or expensive raw materials

Reducing costs:

- Lower non-conformance cost and increase of process efficiency due to the reduced unplanned machine down-time and energy consumption

Businesses, especially industrial businesses have enormous financial loss when equipment or facility fails (Lopez Research LLC 2014). By analysing the performance data collected from different machines in the factory, Big Data Analytics can predict whether a certain machine will breakdown or not. For instance, if OEM customers have equipment which is supposed to run within a certain temperature range, monitoring system and big data analytics based on machine learning can give warning about potential malfunction if the equipment runs out of normal temperature range. OEM can take maintenance or repair action to avoid unexpected malfunction. This proactive and predictive maintenance enabled by big data analytics can save a lot of costs for OEM.

By collecting and analysing sensor data embedded in the industrial automation products, it is possible for the supplier to understand patterns that lead to its equipment failure. This knowledge can help supplier modify and improve its product design. This can lead to very advanced Condition Based Maintenance schemes that allow maintenance activities to be focused on those tasks that yield the greatest return. Better resource planning will be realized for the industrial automation supplier that will avoid unscheduled maintenance services and reduce costs on labour and material.

Reducing risks:

- Risk reduction due to immediate notification regarding the potential risky event;
- Safety improvement by continuously monitoring an asset or production facilities' safety relevant features as well as whether those features are fully functioning and whether a product is handled properly

All these asset availability improvement, process optimization and risk mitigation will together contribute to improving the customer's business operational efficiency.

3.1.3 Segment populations to customize products and services for end users

By analysing the data provided by their customers, the industrial automation suppliers can better understand their customers' needs as well as needs from customers' end customers. Based on this, suppliers can adjust their products portfolio and create more tailored solutions for their customers. Suppliers will also benefit in long-term loyalty of customers based on bilateral trust.

Since businesses also have sales data in their corporate database or opinions, feedbacks, complaints from social network systems like Facebook, Twitter, YouTube regarding their customers and the end users of products and services. With these data, businesses are able to analyse the customer behaviours and satisfaction rate, identify products problems from global complaint trend, track and evaluate service and warranty activities. From foregoing analysis, businesses can better understand their customers' demand and requirement, segment more detailed populations, and then further deliver customized products and individualized services. This will differentia them from their market competitors.

3.1.4 Using automated algorithms to support human decision

Performing more complex analysis often requires sophisticated tools. With the ability to analyse significant amounts of data and to uncover more complex dependencies, it is essential for Big Data Analytics to present the results in a way that can be understood quickly and easily via reporting tools, scorecards or portals. To identify meaningful patterns, visualizations like charts, graphs or maps become the norm rather than spreadsheets. These exploratory analysis and visual analytics tools realized by automated algorithms enable users within a company who don't have absolutely profound knowledge in analytical methods to perform analytical reasoning facilitated by interactive visual interfaces.

In order to reduce the time spent on revising data and analyses the use of automated alerting and monitoring functionalities becomes increasingly popular. People are informed in case of exceptions and do not have to go through standard reports over and over again. Moreover, Prediction and forecasting solutions can be applied which analyse data with the goal to predict future development of key performance indicators, aid users in forecasting the output of technical or economical systems, or to determine likelihood of complex future scenarios. With growing experience, more and more decisions will be made in an automated way as opposed to humans to look at data and draw conclusions. In this case, control, optimization and automation solutions are used that process data continuously using data analytical models and uses the results to feedback information into a control loop e.g. in order to improve stability or optimize the performance. Thus, the use of automated algorithms together with visualized results will support or replace human decision in some extent.

3.1.5 Creating new business model, products or services

Business is about generating value. Traditionally, the underlying businesses models are either about competing on costs reduction, quality improvement or unique features. In the new manufacturing trend, assembling parts into products is no longer the most profitable business (Smart Industry, 2014), while the product related services are becoming a decisive factor for creating competitive edge. A lot of companies are selling their physical products at very low price or lease their products to customers but profits from related services. Companies like Amazon or mobile network operators sell cheap electronic devices such e-readers or smart phones to sell content like books, music or data traffic service. It is more important to sell hardware combined with software and services as a complete solution in the manufacturing industry.

By analysing their business data, companies can create new services or design new products involved with customer use data. Some companies even find that they can profit from their data by reselling it to other organizations (IBM, 2014). One example is a multinational company gained a lot of knowledge from analysing its own manufacturing processes and decided to create a business to provide similar consultancy service other firms. Now the company aggregates machine data and supply chain data for its manufacturing customers and sell analytics application to improve their performance (Brown, Chui, & Manyika, 2011).

For OEMs, new business opportunities may be created when they can acquire their end customers' data through their product. For instances, OEM can provide new industry services, e.g. predictive maintenance, warranty management, etc., for their customers based on sensor-data-driven operation analytics. OEM can also improve equipment quality management based on customers' feeds.

As presented in the previous chapter, Big Data Analytics is enabled by strategic partnerships to generate business and holistically serve customers in a centric-network approach. Companies will more act as a network rather than a single organization. This network-centric business trend enables more opportunities of creating new business models together with new products development and service innovation.

3.2 The business demand of OEM regarding Big Data Analytics

Although there are a lot of benefits that Big Data Analytics can offer for the industrial automation sector, the application is still in the niche phase in which only 13 percent of manufacturing companies are using Big Data Analytics in their daily businesses (Carsten et al., 2015). Before the actual use of Big Data Analytics, it is very important for Big Data Analytics service providers to understand the business demand and requirements of different OEM regarding Big Data Analytics. With all the competition that exists in today's market, OEM companies are taking various actions to create competitive edges. In the following sections, the business demand projecting competitive edges creation will be examined.

3.2.1 Monitor assets and investigate defects

For all OEM companies, it is vital important to monitor the state of their asset and manufacturing facilities. Especially, more and more OEM companies are doing their business in the global markets, which locate their factories in different regions. They are eager to know what is happening in their assets and production equipment from instrument level to management level. Meanwhile, if there is a defect, the OEM companies want to locate the malfunction part, to investigate reason for defects and to implement repair action in a short time. Besides these, end customers operate the machines manufactured by OEM. OEM companies also want to monitor the status of their products remotely concerning warranty service that is essential for improving customer satisfaction. So monitoring the status of assets and investigating defects remotely are OEMs' business demand.

3.2.2 Supply chain management optimization

To maximize profits, all companies want to sell the most products at the relatively lowest price in the larger geographical area. Within the globalization of manufacturing trend, the suppliers for OEMs are around the world. OEMs are also outsourcing some of their production and engineering businesses to suppliers who are transforming from serial producers of predefined parts, components and subsystems into system systems suppliers involved in product development and manufacturing according to OEM specification (Ohl, Geis, & Prosteder, 2012). From this way OEMs can have less capital costs and risks associated with building the subsystems, and more time on developing core competencies. With the benefits of development of supply chain, the supplier relationship management process for OEM companies are transforming from shared social experience such as drinks, diners, meeting, etc., to more quantitative measures to determine the performance of the suppliers. From the assessment, the OEM companies may find potential optimization strategies to improve the supply chain management.

Besides the better supplier management, OEMs want to deliver their products to the customers in a economic, fast and safe way. These products are delivered through various methods, like trucks, trains, ships or planes. Logistic managers of OEM companies need to track the goods for both themselves and their customers. They also want to capture traffic information and vehicle data in real-time to optimize delivery scheduling. If there are unforeseen events such as accidents or inclement weather, they can response and address the issues quickly and effectively. So OEMs want to optimize the whole supply chain that connects upstream suppliers and downstream customers.

3.2.3 Cost saving

While OEMs have always felt price pressures given the "design to specification" nature of projects, this pressure is intensifying for OEMs from industrialized economics that face the competition from emerging markets. All OEMs want to realize costs saving in their business. In practice, they realize these savings through: minimizing upfront investment by outsourcing workload, improved business processes, reduced unplanned facility downtime, waste reduction or elimination, increased energy efficiency (Canadian Manufacturers & Exporters, 2012).

3.2.4 Flexible production for mass customization

Actually a lot of OEM companies already have the capability of customized production for their customers, but the costs still remain relatively high. So the concept of mass customization that integrates the personalization and flexibility of customized manufacturing with low unit cost is attractive for manufacturing business. In the manufacturing industry, the nature of "design to specification” requires OEM companies adopt more customization production at near mass production prices. If OEMs can predict the combinations of features and functionalities that will be sold most, they can use flexible manufacturing systems that can be re-aligned and robots reprogrammed to make small-batch production for mass customization profitable.

3.2.5 Seeking for new sustainable business model

As a lot of products are becoming commodities, OEM companies need to differentiate themselves from their competitors through continuous of innovations. Development of products leads not only to accompanying new features, but also more new and unexpected (cross-sector) services for customers (Smart Industry, 2014). Meanwhile, in the value network regarding Big Data Analytics services, OEMs will increasingly act together with other partners (newcomers and non-manufacturing companies) instead of a single company. This network centric and trans-sector collaboration enable more opportunities and information growth. Therefore, OEMs seek to shift their business model in terms of new revenue stream.

3.2.6 Legislative and ethical compliance

The legislative changes regarding environmental protection, energy consumption, CO2 emission and public health & safety will impact OEMs business. For instance, according to a lot of national and regional regulations, OEMs need to control the greenhouse gas emissions, make the sources of raw material for their products traceable. Not only OEM themselves need to obey the laws, they also need to make sure that the upstream suppliers can meet the requirements of various regulatory regimes. Furthermore, the initial investment to achieve legislative and ethical compliance may be lost as regulations inevitably change, as more asset and facilities are added, new markets are entered, and business models evolve. In terms of compliance, OEMs need information and solutions that be sustainable to fulfil the legal and ethical requirements.

3.3 The correlation between Big Data and OEM business demand

As analysed above, Big Data Analytics can use machine data to make sound, fact-based decisions in terms of achieving transparency in the industrial processes, improved asset availability, efficiency and performance. In order to create competitive edge, OEM companies have some requirements for their businesses operation. These requirements can be fulfilled by diverse benefits of utilizing Big Data Analytics. According to an interview with a business manager of an industrial automation company, the correlation between Big Data and OEM business demand is illustrated in Figure 14. The green cell represents highly correlated OEM’s requirements and benefits of Big Data Analytics. For instance, the asset-monitoring requirement can be achieved through the transparency brought by Big Data Analytics. The yellow cell represents medium correlated OEM’s requirement and benefit of Big Data Analytics, and the grey cell represents low correlated accordingly.

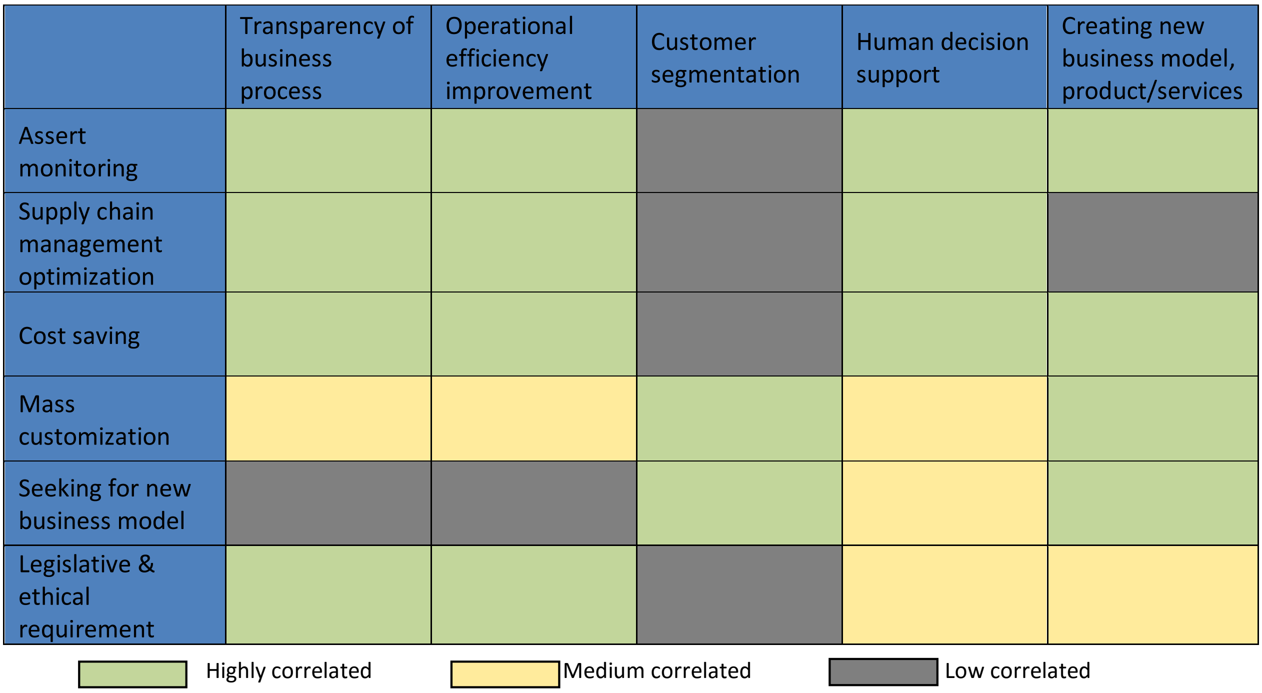

Figure 14 The correlation between Big Data and OEM's business demand

3.4 Conclusion

In order to answer the sub research question: "*How do Big Data Analytics connect the requirements of OEM?*" Chapter 3 analysed the correlation between the benefits of Big Data Analytics and the business requirements of OEM companies. Before adopting Big Data Analytics, OEM companies need to compare their own business requirements with the potential benefits of using Big Data Analytics in order to find a match between these two perspectives. Leveraging Big Data Analytics is to make sound, fact-based decisions in term of achieving transparency in the industrial processes, improving asset availability, efficiency and performance. In order to create competitive edge, OEM companies have some business requirements which include *monitoring assets, investigating defects, supply chain management optimization, saving various costs, achieve flexible production for mass customization, seeking for new sustainable business model, and legislative and ethical compliance*. These requirements can be fulfilled to some extent through using Big Data Analytics. In view of these potential benefits from adopting Big Data Analytics, OEM companies may consider of adopting Big Data Analytics in their organizations. As Big Data Analytics can meet some of OEM companies' business demands, the next step is to investigate the adoption process and influential factors for Big Data Analytics adoption.

CHAPTER 4 INFLUENTIAL FACTORS AND ADOPTION PROCESS FOR ADOPTING BIG DATA ANALYTICS

Previous chapter shows that Big Data Analytics will create new business opportunities for analytics service providers and build up new competitive edge for OEM adopters, at the same time it entails OEMs' a few critical concerns which hinder the quick adoption of Big Data Analytics. In Chapter 4, the following research sub questions "What are the influential factors for the adoption of Big Data Analytics by OEM in the industrial automation sector?" and "How does an adoption framework look like" are answered by exploring relevant factors from literature. This chapter begins with relevant innovation theories regarding OEM's adoption of Big Data Analytics in the industrial automation sector in section 4.1. Subsequently, influential factors for the adoption of Big Data Analytics are identified from the literatures in section 4.2. In section 4.3, the adoption process framework is proposed for further evaluation by means of interviews with sales people and OEM companies.

4.1 Innovation adoption theories

According to Oliveria and Martins, there are many theories of information system innovation acceptance research (Oliveira & Martins, 2011). These theories are developed in specific range which are tailored to particular technologies adoption under different conditions (Wolfe, 1994). In general, the studies of innovation adoption are mainly at two level, individual level versus organizational level.

4.1.1 Theories selection

According to a literature review by Oliveria and Martins, the main innovation theories from the individual level includes the technology acceptance model (TAM) (Davis Jr, 1986), theory of planned behaviour (TPB) (Ajzen, 2011), unified theory of acceptance and use of technology (UTAUT) (Venkatesh & Davis, 2000), UTAUT2 (extended UTAUT model)(Venkatesh, Thong, & Xu, 2012) and Diffusion of Innovation (DOI) (Rogers, 2010). Despite their valuable contribution to individual behavioural research on technology acceptance, the first four models are only applicable for individual level while neglecting the characteristics of organization level (Venkatesh, Morris, Davis, & Davis, 2003; Wolfe, 1994). However, implementing Big Data Analytics for OEM in this research, which are enabled by diverse ITC technologies, is an innovation of information system in an organizational context rather than an individual usage. Thus, given this condition, the abovementioned theories and models are not applicable for this research.

In order to develop an innovation adoption theory at organizational level, a number of studies have attempted to cover as many of organizational attribute in terms of technology innovation as possible. Table 1 shows the different research approach by several researchers in this area. The largely used organizational innovation adoption theories are the Diffusion of Innovation (DOI) theory and the Technology-Organization-Environment framework (TOE) (Tornatzky, Fleischer, & Chakrabarti, 1990) (Oliveira & Martins, 2011). DOI theory, which was proposed in 1962, is frequently used to study the drivers of innovation adoption from both at individual and organizational level (Damanpour &

Gopalakrishnan, 1998; Oliveira & Martins, 2011). DOI has been applied and adapted in various IT innovation research (Eder & Igbaria, 2001; Thong, 1999; Zhu, Kraemer, & Xu, 2003). By including an important attribute: the environmental context, the TOE framework consistent with DOI theory can better explain the organizational innovation adoption in a more specific way comparing to Roger's DOI theory (Ahmad Salleh, Janczewski, & Beltran, 2015; Oliveira & Martins, 2011). The TOE framework has been widely used by various researcher and also combined with other theories e.g. institutional theory as well as DOI theory to study the influential factors of IS adoption (Chong, Ooi, Lin, & Raman, 2009; Soares-Aguiar & Palma-dos-Reis, 2008). In order to study the e-heath adoption in healthcare sector, Yusof et al. designed a new adoption model for analysis. This model includes a important attribute: human without considering the environmental context (Yusof, Kuljis, Papazafeiropoulou, & Stergioulas, 2008). Considering that TOE framework has been empirically tested, it is very useful to also include human factor in TOE framework for this research.

Content of Model	Researcher
1. Individual leader characteristics 2. Internal characteristics of organizational Structure 3. External characteristics of organizational Structure	DOI by Rogers 1962
1. Technical context 2. Organizational context 3. Environmental context	TOE by Tornatzky and Fleischer, 1990
1. Human context 2. Organization context 3. Technical context	HOT by Yusof et al. ,2008

Table 1 Innovation adoption research by different researchers

Even though there are numerous studies on investigating organizational adoption of information system, however, there are little to no literature about the Big Data Analytics adoption. The Big Data Analytics can be considered as an IT innovation. DOI theory and the TOE framework have been demonstrated to be useful and applicable to understand key factors that determine IT innovation adoption at the organisational level by a lot of studies. Therefore, this study can use TOE framework and DOI theory to investigate the organizational adoption of Big Data Analytics. The following sections will elaborate on these two theories.

4.1.2 Diffusion of Innovation

DOI theory investigates from the individual and organizational level with regard to the spread patterns, reasons and rates of new ideas and technology as innovations over time within a particular social system (Rogers, 2010). In the early research of DOI, Rogers segment individuals into 5 categories by different degrees of willingness to adopt innovations: innovators, early adopters, early majority, late majority, laggards (Rogers, 2010). The rate of innovation adoption is impacted by 5 factors: "relative advantage, compatibility, trial ability, observability and complexity " (Rogers, 2010). The first four factors can be considered as drivers for adoption while the last one is considered as barrier for adoption in general.

The innovation process is more complex in organizations that involve a lot of individuals. In the later development of DOI, Rogers also extend this theory to organizational level. According to Rogers, organizational innovativeness is impacted by three perspectives: individual leaders' characteristics, internal organizational structure characteristics, external organizational structure characteristics as showed in Figure 15. Meanwhile, Rogers describes the process of innovation adoption as "an information-seeking and information-processing activity, where an individual is motivated to reduce uncertainty about the advantages and disadvantages of an innovation" (p. 172) (Rogers, 2010) . According to Rogers, this process comprise fives steps: (1) knowledge, (2) persuasion, (3) decision, (4) implementation, and (5) confirmation described in Figure 16 (Rogers, 2010). This theory is applicable for developing the adoption process and identifying related activities in term of Big Data Analytics.

Although many studies have used DOI theory as fundamental theoretical base to examine the factors that influence the adoption of new technologies, researcher continue to develop other theories or combine with DOI theory to explore more explanatory model (Soares-Aguiar & Palma-dos-Reis, 2008).

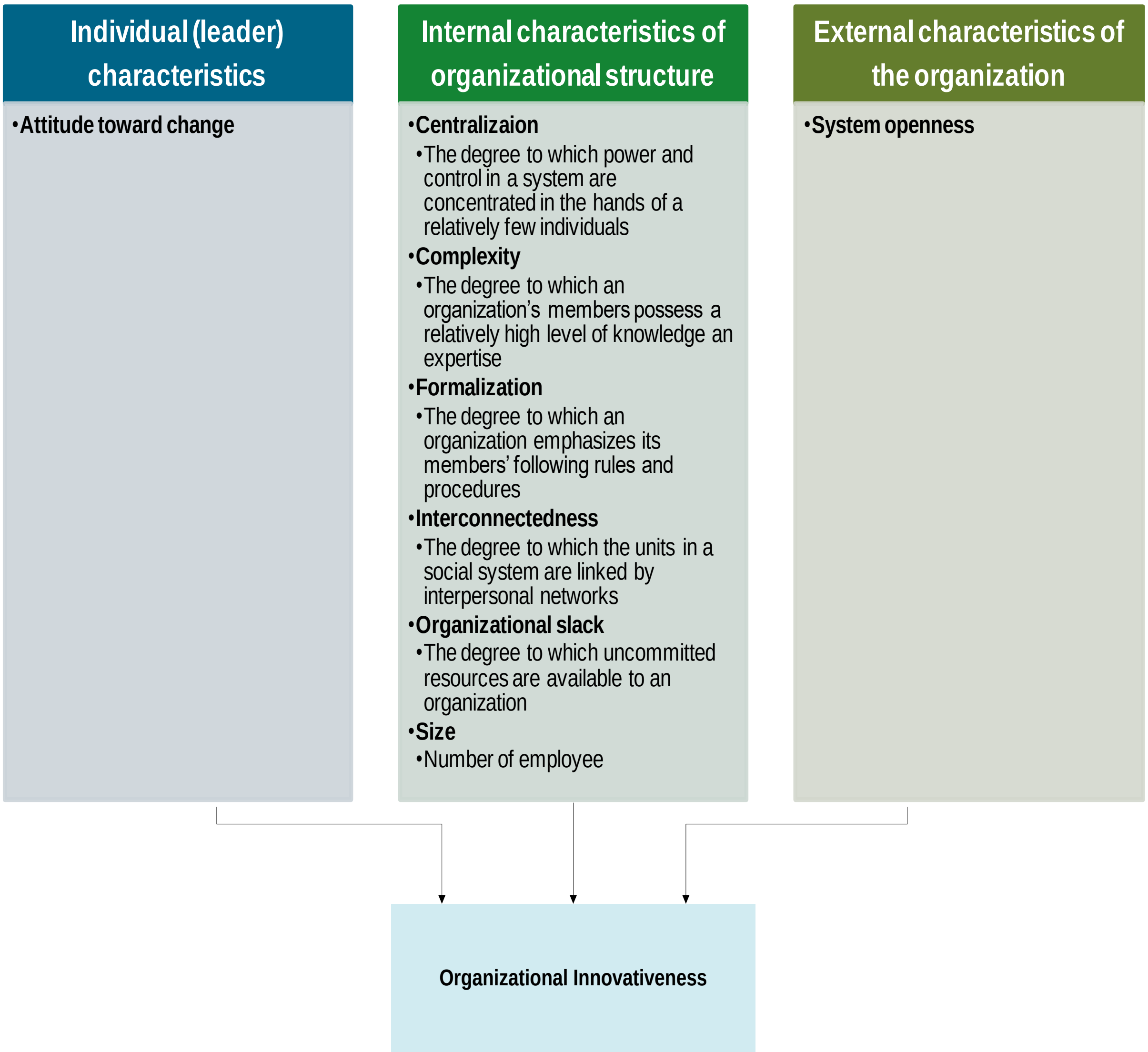

Figure 15 Influential factors of DOI adapted from (Rogers, 2010)

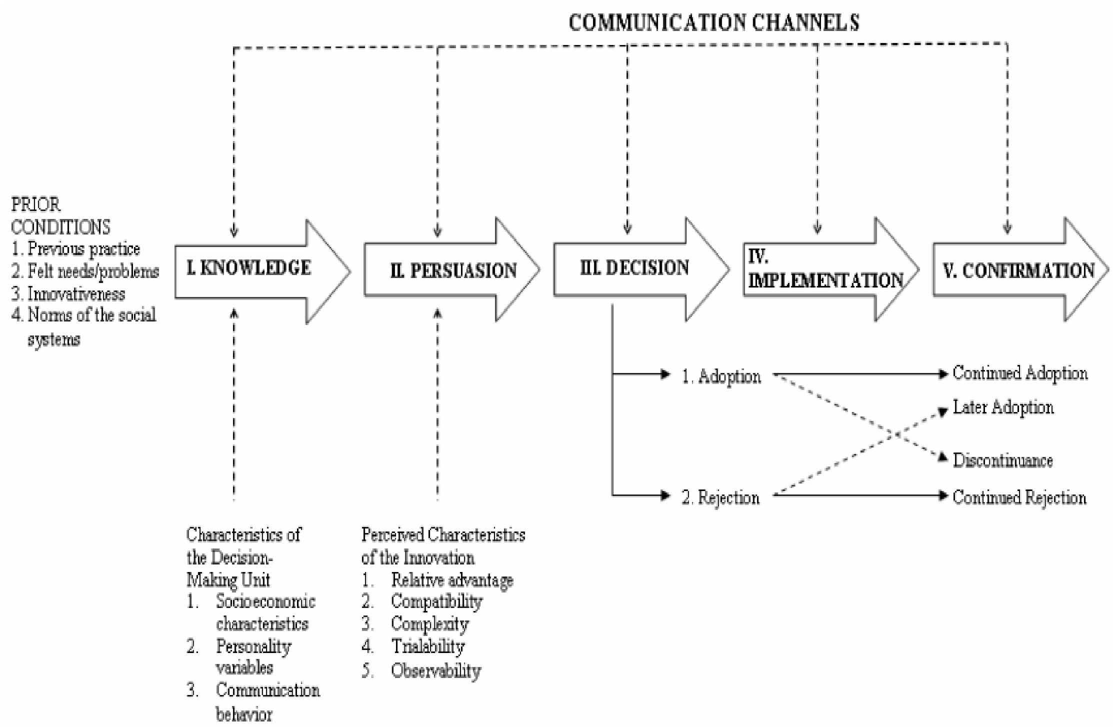

Figure 16 Five stages in the innovation adoption process adapted from (Rogers, 2010)

4.1.3 TOE framework

TOE framework, which is consistent with DOI theory (Oliveira & Martins, 2011), is developed by Tornatzky and Fleischer in 1990. As showed in Figure 17, this framework that includes three perspectives of organizational innovation adoption: the technology, the organization, and the external environment provide an analytical framework for identifying the drivers and barriers for innovation adoption. The TOE framework can be considered as an important extension of DOI theory, which adds the environmental aspect (Oliveira & Martins, 2011) . The TOE framework have also been demonstrated the applicability in diverse sector, especially in IT adoption studies, including Internet, website, open system, e-commerce, e-government, enterprise resource planning, SaaS etc. (Ahmad Salleh et al., 2015; Chong et al., 2009; Soares-Aguiar & Palma-dos-Reis, 2008; Yang, Sun, Zhang, & Wang, 2015).

4.1.4 Conclusion

From the above literature review, the TOE framework can be used as theoretical basis for this research to determine the drivers and barriers for OEM's Big Data Analytics adoption from three aspects of technology, organization and environment. The process model from DOI can be used to develop the adoption framework and related activities to utilize the drivers and mitigate the barriers. These two theories are more applicable to examine all adoption determinants and process phases of Big Data Analytics as an IT innovation.

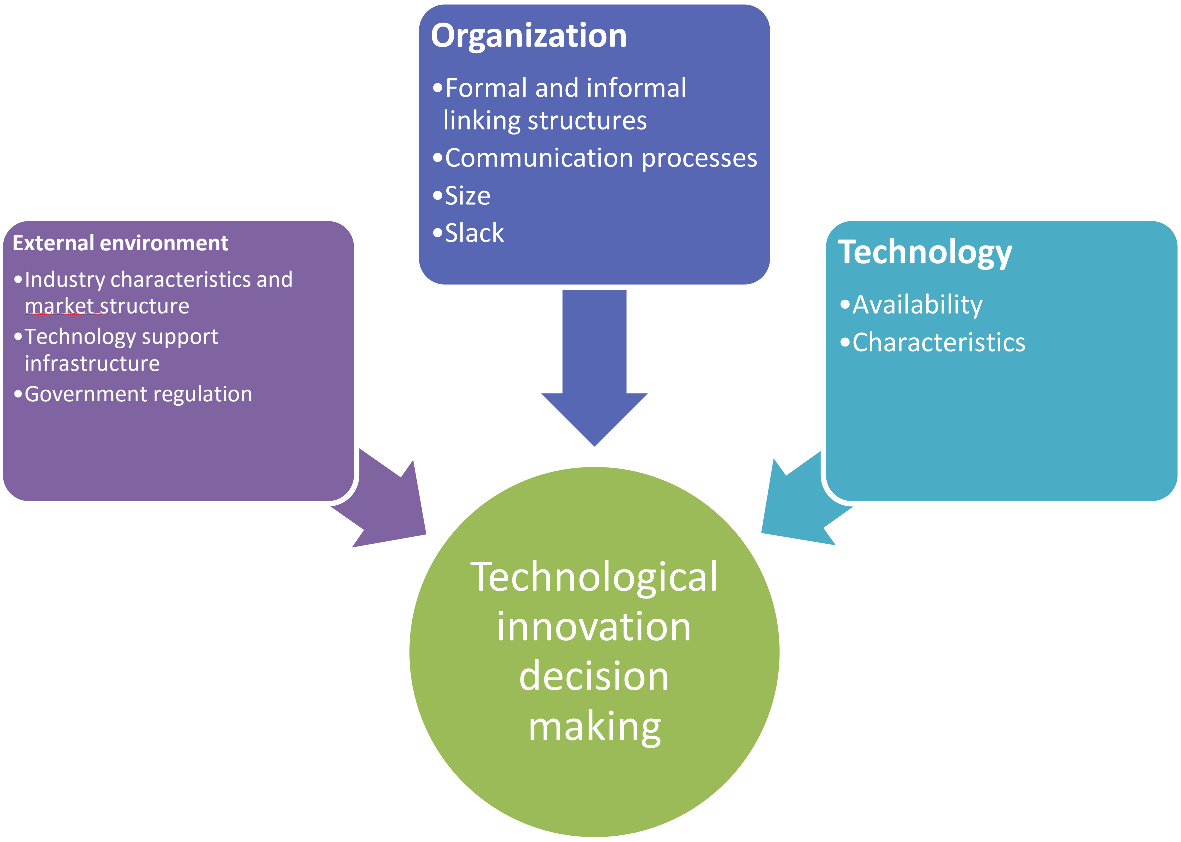

Figure 17 Technology, organization, and environment framework adapted from (Tornatzky et al., 1990)

4.2 Influential factors for adoption of Big Data Analytics by OEM

With the consideration of actual condition of OEM, factors that impact the adoption of Big Data Analytics are categorized into three main perspectives: technology, organization and external environment. Each perspective incorporates several factors that are identified from the literature review regarding Big Data Analytics and will be evaluated by domain expert and OEM customers later on.

4.2.1 Technological aspect

The technological aspect in the TOE framework compromises of available technologies for innovation and the innovation's characteristics that affect innovation adoption (Oliveira & Martins, 2011; Tornatzky et al., 1990). As mentioned above, Rogers argued that the rate of innovations adoption is impacted by 5 factors: "relative advantage, compatibility, trial ability, observability and complexity " (Rogers, 2010). However, several researches on IT innovation adoption suggest that the trialability and observability are found insignificant influencing IT innovation adoption (Premkumar & Roberts, 1999; Sin Tan, Choy Chong, Lin, & Cyril Eze, 2009; Tornatzky & Klein, 1982). The main reason is Big Data Analytics is a new technology with little use cases, so that OEM companies are not able to observe the use of Big Data Analytics or even make a trial of Big Data Analytics. Therefore, trialability and observability factor will be excluded from the technological consideration.

Relative advantage

Relative advantage is defined as “the degree to which an innovation is perceived as being better than either the status quo or its precursor” (Rogers, 2010) . According to a literature review by Jeyaraj et al., relative advantage is identified as the most used factor that motivate organization’s IT adoption (Jeyaraj et al., 2006). If adopters perceive a clear benefit or advantage in using the innovation, the adoption of IT innovation is more likely to be considered as effective and successful (Fichman, 2000; Greenhalgh, Robert, Bate, et al., 2004; Rogers, 1995). By using Big Data Analytics through SaaS, the companies can optimize their enterprise resources, reduce unplanned asset downtime and lower energy consumption without upfront investment for IT infrastructure and technical know-how (IBM, 2014). Therefore, these perceived benefits will encourage OEM to adopt Big Data Analytics via SaaS. Thus, perceived benefits will be a driver for Big Data Analytics Adoption.

Compatibility

Compatibility is defined as “the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of the organization” (Rogers, 2010). It has been identified as an important facilitator that it is necessary for an innovation to be compatible with current work procedure and needs of the organization (Jeyaraj et al., 2006; Sin Tan et al., 2009; Thong, 1999). Big Data Analytics are to be used to support OEM’s decision making regarding business activities, and may also bring some changes to the work procedures and/or practices with OEMs. Therefore, adopting Big Data Analytics needs to be compatible with their current value proposition, past experience and needs of OEMs who don’t need a lot of resources to deal with changes. Otherwise, resistance to change may hinder OEM’s Big Data Analytics adoption. According to DOI theory, the compatibility of an innovation has a positive relationship with its adoption (Rogers, 2010). Thus, perceived compatibility will be a driver for Big Data Analytics Adoption.

Complexity

Complexity is defined as “the degree to which an innovation is perceived as relatively difficult to understand and use” (Rogers, 2010). Innovation’s complexity creates high uncertainty and risks for smooth implementation hence it will have a negative impact on the innovation adoption (Kamal, 2006; Premkumar & Roberts, 1999; Rogers, 2010). If an innovation perceived by an organization as complex tends to be adopted slowly or even rejected by an organization (Bradford & Florin, 2003). On the opposite, the ease of use of an innovation, for instance no requirements of skills for use, is more acceptable by potential users (Meyer & Goes, 1988). Big Data Analytics are relatively new technology for most OEMs. According to a market research survey by Gartner, only 8 percent of companies have really deployed Big Data Analytics application (Kart, Heudecker, & Buytendijk, 2013). So it takes time for companies to understand and get used to Big Data Analytics from the initial adoption. Thus, perceived complexity will be a barrier to Big Data Analytics Adoption.

4.2.2 Organisational aspect

The organisational aspect in the TOE framework compromises of the characteristics and available resources of the organisation (Oliveira et al., 2011; Tornatzky et al., 1990). Since this research only focuses on OEM customer in the industrial automation sector, only the organizational characteristics of OEM will be considered.

Organisational readiness

The organisational readiness refers to the available resources within an organization for adoption, which includes two main aspects: technological readiness and financial readiness (Iacovou, Benbasat, & Dexter, 1995). More resources within an organisation, innovation adoption is more likely to be quick and successful (Damanpour & Gopalakrishnan, 1998; Rogers, 2010).

Technological readiness

Technological readiness is defined as the capability of technological usage and management with an organization, which reflects the level of available technological resources for innovation adoption (Iacovou et al., 1995; Low, Chen, & Wu, 2011; Y.-M. Wang, Wang, & Yang, 2010). Many empirical studies support that technologcial readiness is an important factor on successful IT adoption (Thong, 1999; Zhu et al., 2003; Zhu & Kraemer, 2005). According to Iacovou et al., these technological resources includes tangible resources (physical IT infrastructure) and intangible resources (human resources) (Iacovou et al., 1995). In general, IT infrastructure refers to servers, databases, operation system and deployment platform(Mell & Grance, 2011). Meanwhile, human resources compromises relevant IT skills and technical know-how to implement innovation (Low et al., 2011). Additionally, the IT security which includes cyber security governance mechanism and data share issuse is also included in this research, since it is expected to be a big concern when OEM adopts Big Data Analytics.

IT infrastructure

For Big Data Analytics adoption, the application is implemented through SaaS model, which don't require upfront investment for computing resoures which would reduce the risk and costs for OEM. The main IT infrastructure requirement for Big Data Analytics includes sensors & meters for data collection, computer, industrial network connection and Internet connection.

Human resource

Big Data Analytics is considered as a new emergence technology for the industrial automation sector. Implementing Big Data Analytics will require new IT skills and knowledge. Besides, the help and support for end users who actually intensively use Big Data Analytics application would increase the acceptance of new innovation, since "ease-access-to-support" can be also perceived as "ease of use" by users(Klein & Sorra, 1996). The availability of analytics experts and experience with SaaS model would reduce the risk for OEM during the adoption.

Data security

IT security refers to the level of how access is controlled and data is protected. As Big Data Analytics focus on processing data from OEM enabled by numerous ICT technologies, a lot of OEM's data will be tranferred and shared with the Big Data Analtics service provider. The location storing data and the ownership of the data will be an important factor that cannot be igorned. Even if private cloud deployment model can be used, OEM would still have big conern regarding the security of data flow. The capability of securing the data is considerd to be relevant to Big Data Analytics adoption through SaaS (Boyd & Crawford, 2012; Janssen & Joha, 2011). Thus, data security with regard to technical readiness will be a barrier to the adoption of Big Data Analytics.

Financial readiness

Financial readiness refers to the availability of financial resources within an organization to spend on innovation adoption, in other words, budget constraints. (Iacovou et al., 1995; Molla & Licker, 2005; Oliveira & Martins, 2011). Enough financial support has been demonstrated to be an important positive factor for successful IT adoption by a number of empirical researches (Jeseke et al., 2013; Manyika et al., 2011; Sin Tan et al., 2009; Soares-Aguiar & Palma-dos-Reis, 2008). Thus, enough financial resource will be a driver of Big Data Analytics adoption

Top management support

Top management support refers to “the extent of top management understanding the importance of the IT function and resource support assigned by top management” for Big Data Analytics adoption (Premkumar & Roberts, 1999; Ragu-Nathan, Apigian, Ragu-Nathan, & Tu, 2004). Within most of OEM, top management controls enterprise resources and makes decisions on business operation. Therefore, they directly or indirectly influence the adoption of IT innovation in the organization(Ghobakhloo, Sabouri, Hong, & Zulkifli, 2011). The main support from top management for IT adoption includes providing resources, i.e. financial funding and human resources, as well as stimulating an enterprise culture towards IT adoption (Low et al., 2011; Wu, 2011). Previous studies on IT adoption have found that top management support is an important factor that positively drives IT innovation adoption (Oliveira & Martins, 2011; Premkumar & Roberts, 1999; Yang et al., 2015). Thus, top management support will be a driver of Big Data Analytics Adoption

Organisational structure

According to the DOI theory, organisational innovativeness is impacted by the internal organisational structural characteristics, including “centralisation, complexity, formalisation, interconnectedness, organisational slack and size”(Rogers, 2010). Due to the complexity of organisational structure, in this study, characteristics of OEM’s organisational structure only incorporate with company size.

Company size

Company size refers to the organizational size of OEM. Previous studies has showed that the more formalised and centralised organization (often larger company) is, the more difficult to make innovation adoption decision (Kennedy, 1983; Y. Wang, Chang, & Heng, 2004). But they will be better equipped to implement actual innovation adoption after making adoption decision, since it is able to allocate more organizational resources and take risks (Premkumar & Roberts, 1999; Rogers, 2010). Researchers consider size as an adoption facilitator consistently related to an organisation’s propensity to IT innovation (Damanpour & Gopalakrishnan, 1998; Rogers, 2010). Thus, company size is a positive influential power on Big Data Analytics adoption.

4.2.3 Environmental aspect

The environmental aspect in the TOE framework refers to the environment in which the organisation operates its business (Tornatzky et al., 1990). The environmental aspect includes the business trends of organisation’s industry, competitors, partners, macroeconomic, and regulatory environment (Iacovou et al., 1995; Oliveira & Martins, 2011). In this study, the industry is limited to the industrial automation sector that have high technology orientation and creative industry sectors. The main environmental factors include competitive pressure and marketing effort.

Competitive pressure

Competitive pressure refers to the extent of perceived pressure by companies from the markets, including direct competitors and indirect market disruptors (Low et al., 2011). For many companies, pressures to keep up with competition, survive in the dynamic market and promoting services to customers force companies to adopt new IT technologies (Premkumar & Roberts, 1999; Ragu-Nathan et al., 2004; Sin Tan et al., 2009). A number of empirical studies have found that the more intense competition in the industry, the higher adoption rate is likely to be in companies (Bradford & Florin, 2003; Brandyberry, 2003; Thong, 1999). For OEMs, especially whose business focus on low added-value products are facing intensive competition from emerging market (Nuremberg Chamber of Commerce and Industry, 2014). The adoption of Big Data Analytics by OEMs would provide potential benefits including automated decisions for real-time processes, detection of malfunctions, manufacturing yield improving, operation cost reduction (Russom, 2011). These benefits would create competitive edge for OEMs. Thus, perceived competitive pressure is a positive influential power on Big Data Analytics adoption.

Marketing effort

Marketing effort refers to the effort made by vendors in promoting their products, services or even just their own public image. Besides the self-awareness of innovation adoption from adopter side, the supplier's activities, especially marketing activities also play as important influential factor to innovation adoption (Frambach & Schillewaert, 2002). According to Dos Santos and Peffers, the marketing effort is considered as a very important role in the first few years after the introduction of a technology innovation(Dos Santos & Peffers, 1998). As Big Data Analytics for OEM is a relatively new technology in the industrial automation sector, marketing effort are needed from Big Data Analytics service providers to increase OEM's awareness about big data. Thus, marketing effort is a positive influential power on Big Data Analytics adoption.

4.2.4 Conclusion

On the basis of the TOE framework, this research identified several factors that influence the adoption of Big Data Analytics by OEM from Technological, organizational and environmental aspects in the literature reviews. Figure 18 presents the expected role of each factor to Big Data Analytics adoption. In the following chapters, these factors will be evaluated by sales people from industrial automation company and representatives of OEM companies.

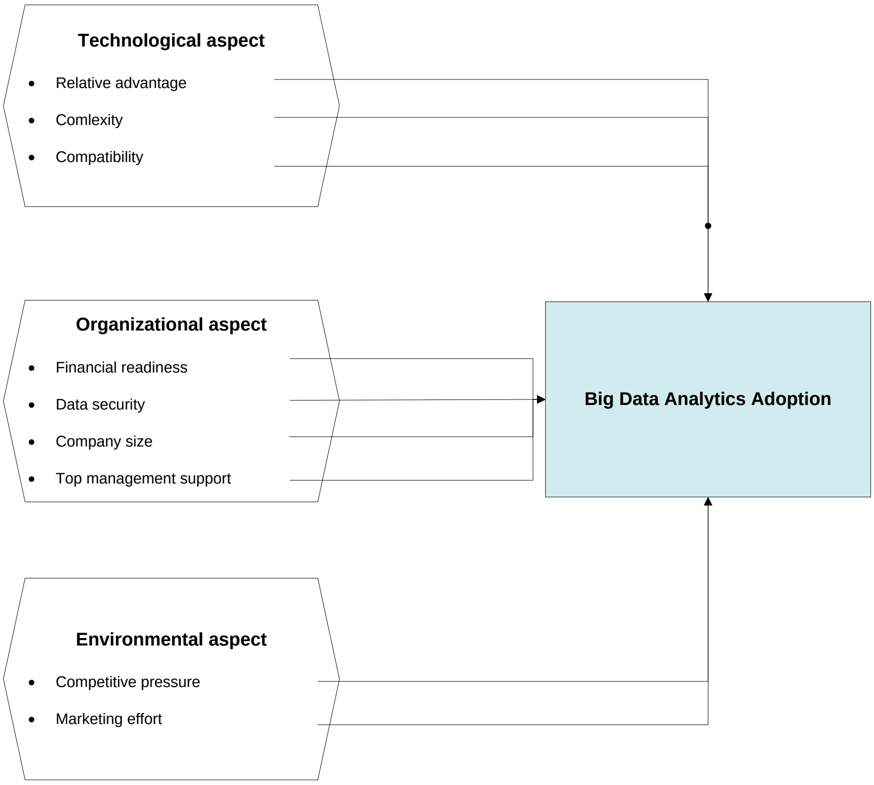

Figure 18 Influential factors for Big Data Analytics adoption by OEM

4.3 Adoption process framework

4.3.1 Adoption process theory

After addressing the influential factors for adopting Big Data Analytics by OEMs, the adoption process regarding Big Data Analytics as an innovation will be analyzed. In 1957, George Beal and Joe Bohlen proposed a framework which describe five steps of the individuals adopting new ideas or innovations (Beal & Bohlen, 1957), including:

- **Awareness stage**

  In this stage, an individual simply becomes aware of a new idea or an innovation. He or she may hear about the existence of the idea, or only knows the name of the innovation as a buzzword, but lacks details or in-depth knowledge about it.

- **Interest stage**

  In this stage, the individual wants to more information about the innovation or product. They want to know whether this innovation may help him/her in some ways.

- **Evaluation stage**

  In this stage, the individual mentally examines the innovation on the basis of obtained information from previous stage, trying to determine whether it will really impact his/her work.

- **Trial stage**

  In this stage, if the individual is interested in certain possibilities offered by the innovation, the individual actually experimentally uses the innovation in a small scale to test if reality matches expectations.

- **Adoption stage**

  After testing and perceiving certain benefits, the individual is satisfied with the innovation and adopts it in large-scale.

Each individual appears to go through all these fives, but the rates and time at each stages are different depending upon the characteristics of individual and innovation itself. This five-step framework refers to the adoption of innovation by individuals.

The Diffusion of Innovation Theory by Everett Rogers describe 6 steps of technology adoption process by an entity (Rogers, 2010), shown in Figure 19. The entity involved can be an individual or a group such as a community or an organization (Deibel, 2011). The specific phases includes:

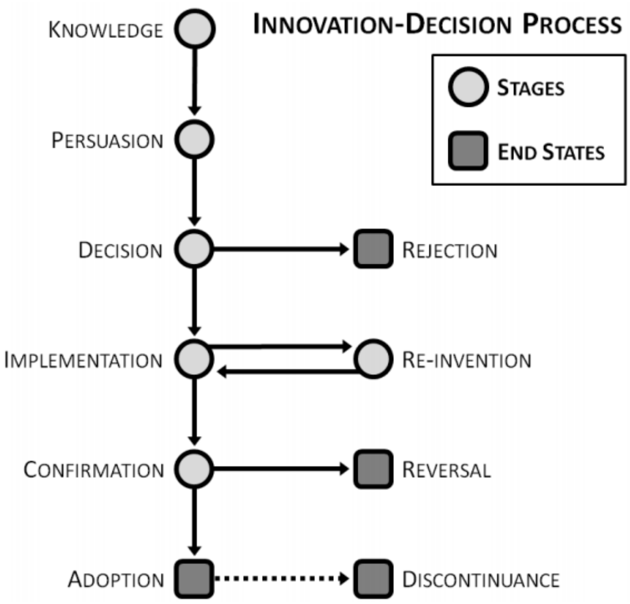

Figure 19 Rogers's innovation adoption process model (Deibel, 2011)

- **Knowledge stage**

  At this stage, an individual becomes aware of a new technology or innovation from media, Internet or someone who has already used the technology.

- **Persuasion stage**

  At this stage, the individual shows interest in the innovation and wants more information about the innovation or product such as: features, costs, reviews, etc. He begins to consider himself as a potential user and think about whether or not to use this technology.

- **Decision stage**

  At this stage, the individual makes decision on adopting the innovation or rejecting based on his criteria and gathered information.

- **Implementation stage**

  At this stage, the individual or the organization integrates the innovation into regular use. This can be time-consuming step. For the entity involved, changes of his habits or organizational structure may occur. The innovation will be also evaluated in this stage, in which more information about the innovation may be obtained. During the regular use process, a re-invention that adapts or modifies the original innovation by the entity may also occur in terms of improvement and/or optimization.

- **Confirmation stage**

  After implementation, the entity is fully satisfied with the innovation and confirms the full adoption. Another possibility is a reversal of the original decision on the use of this innovation.

- **Discontinuance stage**

  After adoption, the entity does not always continue to use the innovation because of various reasons such as unaffordable costs, incompatible features, limited expectation, etc. The entity may also want to abandon the use and replace with another technology.

Conner and Patterson proposes a total of 8 stages that an organisation or a person would go through towards a change goal, illustrated in Figure 20 (Conner & Patterson, 1982). The authors suggest a series of phases along the change process: Preparation, Acceptance and Commitment. In the Preparation phase, the potential change is published and advertised in terms of reaching Acceptance phase, which is reached when the “disposition threshold” is crossed. When the “commitment threshold” is crossed, the people in the organisation can be taken from Acceptance phase to Commitment phase. Each stage indicates a critical juncture, in which commitment may be lost from the individual. If one stage is completed successfully, it is possible to advance to the next stage. If not, the downward arrows shows the results and the desired change fails.

Since there are few large-scale Big Data Analytics use case in the industrial automation sector, the adoption process theories mentioned above will be used for guiding the practical adoption process of Big Data Analytics.

4.3.2 Adoption process framework for Big Data Analytics adoption

In this section, a framework describing a number of phases in the Big Data Analytics adoption process by OEM companies is proposed. The process contains the following phases: *Awareness phase, Strategy phase, Knowledge phase, Trial phase, Implementation phase, Operation Phase*, presented in Figure 21.

Awareness phase

In this phase, OEMs companies are aware of Big Data Analytics concept. They will get to know this idea from various media like newspapers, magazine, TV shows, radio, the Internet, trade show, consultancy reports, vendor’s marketing activities or word of mouth.

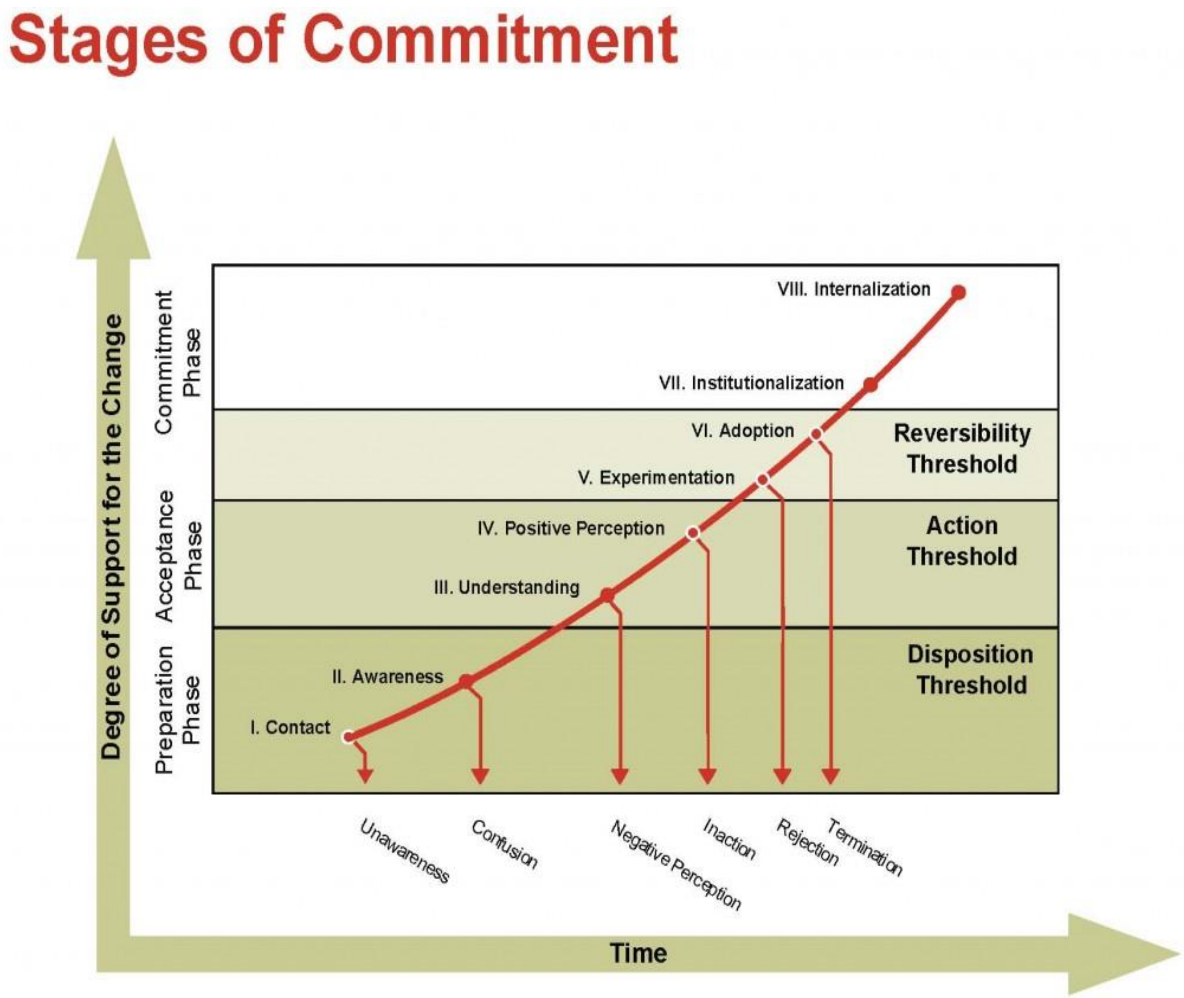

Figure 20 Conner and Patterson 's adoption process model (Conner & Patterson, 1982)

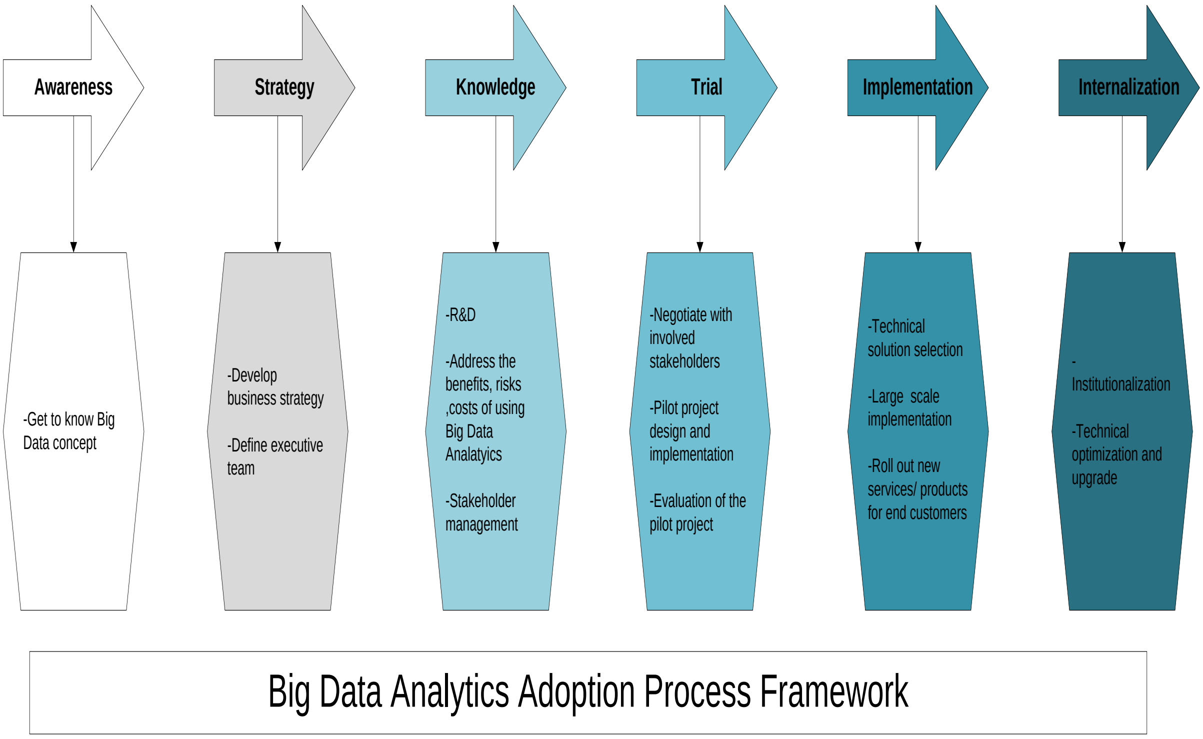

Figure 21 Proposed Big Data Analytics adoption process framework

Strategy phase

In this phase, in response to the Big Data concept as a irreversible trend, the management group of OEMs will allocate in-house resources to investigate the value and benefits as well as risks of early and late adopting Big Data Analytics in their business. The new possibilities derived from Big Data Analytics in their business are analyzed. Based on this information, the management team of an OEM company will make decision on whether or not initiating Big Data as a strategy for its daily business operation. If Big Data strategy is decided, an initiative plan will also be made to implement the strategy.

Knowledge phase

In this phase, research and development activities are conducted to generate in-depth knowledge regarding Big Data Analytics. OEM will either develop their own knowledge about using Big Data Analytics or cooperate with external partner(s). In some cases, the industrial automation companies can offer a turn-key platform for Big Data Analytics purpose, OEMs need to sign contracts to manage the stakeholders for R&D. Meanwhile, OEM needs to research on the choices of enabling technologies, vendor selection, the cost of benefits analysis and potential business case development, etc. In this phase, data governance issues about the location of data storage, the ownership of data and data management mechanism will be studied, since the data is the core asset and starting point of Big Data Analytics activities.

Trial phase

In this phase, OEM will use an experiment case or pilot project characterized with small-scale and low-budget use. Along with the on-going test case, OEM can gain more knowledge about using Big Data Analytics and evaluate whether the practical outcome meets the expectations. In the end of this phase, the management team of OEM, especially large companies, often makes decision on whether the functions of selected solutions are suitable for Big Data Analytics, or whether selected solution regarding Big Data Analytics is worth of being widely popularized in its whole organization.

Implementation phase

In this phase, the use of Big Data Analytics will be used on a large scale with more supporting resources, affecting more individuals within OEM companies. More IT infrastructure and sensors need to be installed, replaced or updated for acquiring and analyzing more data. The organizational structure of OEM may be changed since some new business process will be introduced. OEM can also develop new products, services or business models for its end customers, and prepare for roll-out.

Internalization phase

In this phase, Big Data Analytics related organizational structure, management mechanism will be adjusted and institutionalized to full maturity level. The pre-defined Big Data Analytics will be optimized and upgraded according to the practical business needs. New services offering and business models will be delivered to OEM's customers, from which new stable revenues contributed the development of OEM. The Big Data Analytics becomes embedded in OEM distinctive capability.

Since the study focus on the adoption process of utilizing Big Data Analytics, the downward arrows shown in Figure 19 representing unsuccessful phases are excluded in this proposed adoption process framework. However, it is always possible that OEM will have a lot of problems which they cannot overcome in each adoption phases, they may decide to stop the adoption of Big Data Analytics in any phase.

4.4 Conclusion

This chapter has analyzed the potential influential factors that will impact the Big Data Analytics adoption by OEM companies based on the literature review and desk research. Afterwards, an adoption process framework for adopting Big Data Analytics is proposed, which compromises six phases: Awareness phase, Strategy Phase, Knowledge phase, Trial Phase, Implementation Phase and Internalization phase. With the initial design of the adoption process framework, the influential factors and their impact in different adoption process have been further verified through qualitative analysis by conducting interviews with field experts in the sequential chapter.

CHAPTER 5 DATA COLLECTION AND ANALYSIS

This chapter elaborates the data collection and analysis method of this study to evaluate the influential factors for Big Data Analytics adoption and adoption process framework. After relevant data was gathered through desk research and literature review during the early phase of the research, the influential factors and adoption process framework were generated. Further, this model has been evaluated through qualitative interviews with filed experts, sales force and OEM customers in cooperation with a multinational engineering company (hereafter, Company X) [2]. In the section 5.1, the qualitative approach for data collection is elaborated. The respondent selection for conducting interviews is elaborated in the section 5.2. The data collection procedure from interviews regarding sampling technique and questionnaire development is explained in the section 5.3. Finally the qualitative analysis method on the basis of gathered data is discussed in the section 5.4.

5.1 Qualitative research approach

After identifying the influential factors and developing an adoption process framework, the next step is to design the research in a way that necessary data can be collected and analyzed to evaluate the adoption framework. The objective of this research is to explore the adoption of Big Data Analytics by OEM in the industrial automation sector while the practical use of Big Data in the industrial automation sector is still at the initial development level. With the nature of rather limited literature concerning Big Data Analytics adoption, little studies regarding the industrial automation sector can be found in academia. A qualitative study is usually undertaken by researchers to explore an substantial area about which is not yet much know(Strauss & Corbin, 1990). Qualitative research "seeks to discover and to describe a phenomenon, a process, the perspectives and worldviews of people involved, to understand the meanings of actions of involved people"(Denzin & Lincoln, 2009; Merriam, 2002). This aim is aligned with the objective of this research that is to identify the attitudes, opinions and perceptions from the real or potential users of Big Data Analytics. Therefore, a qualitative research approach was conducted in this study.

The data for the final analysis was obtained from semi-structured interviews using open-ended questions. The reasons for opting in-depth interviews for this research have four counts. Firstly, there are rather limited documents or interactions where adopting Big Data Analytics in the industrial automation sector is displayed. Desired data regarding people's attitudes, beliefs, behavior and the meaning of the actions attached to them on Big Data did not exist and needed to be generated. Secondly, in cooperation with Company X dedicated to providing industrial automation products, in-depth interviews with the field experts in this research can be relatively easily carried out in this research to gain insights about the adoption of Big Data Analytics and investigate the solutions to the research problems. Thirdly, an individual interview is the widely used method for collecting data on the perceptions, opinions and understandings from group of people who have common interest(Ritchie, Lewis, Nicholls, & Ormston, 2013). Face-to-face interviews designed with open-end questions allow the researcher to gather information as much as possible and explore the relevant information for detailed analysis. Meanwhile, due to the time limitation of this research, the semi-structured interviews can define the boundaries and themes of the research for the

[2] In consideration of confidential business information, this company requested anonymity in this research report. Therefore, the names of the engineering company and relevant OEM customers are not mentioned in this report.

researcher and interviewees for further investigation. Lastly, this research can be combined with previously mentioned engineering company's business development research for offering Big Data Analytics services in the industrial automation sector. For these reasons, this research adopted a qualitative research using in-depth individual interview to gain insight about Big Data Analytics adoption.

According to Merriam, the design of a qualitative research can be described by an interpretation process consisting of four phases: formulating a research problem, sample selection, data collection and analysis, and writing up the findings (Merriam, 2002). This research will follow these steps to conduct the evaluation of the influential factors and proposed adoption process model in the Chapter 4.

5.2 Sample selection

5.2.1 Respondents selections

In the beginning of the research, the respondents were planned to be selected from two different types of field experts: sales team from the industrial automation company and the representatives of various OEM companies from different industries. Since the Big Data Analytics projects were still infrequently implemented in the industrial automation sector in the Netherlands, there were rather limited information or reference cases regarding this topic. However, the respondents of the sales and services teams from Company X, who have different functional roles ranging from sale representatives, service engineers to team managers, have frequent interaction with OEM companies at different business management and operation levels. Therefore, they had direct information on the OEM market trend regarding big data. They were invited to participate in the interview sessions. The selection of the respondents was based on several criteria including:

- *The respondents should have in-depth knowledge about the businesses of various OEM customers in the industrial automation sector.*
- *The respondents should cover some senior position of the organization.*
- *The respondents should have already discussed with OEM companies regarding their big data strategies, or have been involved in the big data projects.*
- *The respondents can provide significant information to evaluate the adoption process framework.*

Another respondent group, the OEM companies were planned to be interviewed directly by the researcher to get more information in responding to the research questions. Due to the protection of confidential business information, most representatives of the OEM companies cannot be directly interviewed by the researcher in this study. However, the sales representatives, who have already discussed with some OEM companies, can provide useful information on the perceptions, thoughts and strategies of OEM companies regarding big data. The selection of the OEM respondents was based on the following criteria:

- *The OEM companies are located in the Netherlands.*
- *A number of OEM companies should be selected from different companies across OEM market in the industrial automation sector.*
- *The respondent should have clear vision on his company's business and IT landscape.*
- *The respondent should been involved in the decision-making process regarding Big Data and business analytics strategy.*
- *The respondents can provide significant information to evaluate the adoption process framework.*

5.2.2 Interview sample

The respondents from various functional roles and different companies specialized in different industries can differentiate from each other, so that a diverse range of information can be gathered. Due to confidentiality agreements between the respondents, all gathered acquired information was processed anonymously. There are 12 interview sessions conducted in the end, comprising of 7 interviews with sales and services team in Company X and 5 indirect interviews with OEM companies via sale managers. The respondents are presented in Table 2.

Type	Respondent code	Industry sector	Main product portfolio	Functional Role
Company X	**Sales A**	Industrial automation	All industrial automation products	OEM sales
	Sales B	Industrial automation	All industrial automation products	OEM sales
	Sales C	Industrial automation	All industrial automation products	OEM sales
	Sales D	Industrial automation	All industrial automation products	OEM sales
	Sales E	Industrial automation	Industrial services	Service sales specialist
	Sales F	Industrial automation	Industrial services	Field service manager
	Sales G	Industrial automation	Industrial services	Industrial service team lead
OEM Companies	**Customer A**	Food & Beverage	Bakery Machine	Business manager
	Customer B	Food & Beverage	Poultry processing machine	CTO
	Customer C	Machine Tools	Engineering consultancy and training services	Technical consultant
	Customer D	Oil & Gas	Oil & Gas exploration operation platform supplier	Production manager
	Customer E	Metallurgy	Steel	Maintenance Manager

Table 2 Overview of interview respondents.

5.3 Data collection process

5.3.1 Interview preparation

The data collection process from interviews were conducted to understand the factors influencing the adoption of Big Data Analytics and evaluate the adoption process framework proposed in the chapter 4. In order to conduct the interviews in an efficient and flexible way, the researcher in this study gave a brief introduction on Big Data Analytics for all the respondents from Company X in a group meeting before starting the actual interviews. Later on, two questions schemes translating the research questions into observational questions were designed to guide the interviews for two respondent groups. The systematic procedure of this interview is described as followed:

a) **Research Introduction**

Sales respondents: The researcher introduced the basic information of this study for respondents to better understand the content of interview. Meanwhile, the confidentiality agreement was discussed for practical purpose.

OEM respondents: The sales representatives or the researcher introduced the basic information of this study for respondents to better understand the content of interview. Meanwhile, the confidentiality agreement was discussed for practical purpose.

b) **Respondent background information**

Sales respondents: The respondents' company information, contact information, functional role and focus business responsibilities were documented.

OEM respondents: The respondents' company information, contact information, functional role and focus business responsibilities were documented.

c) **Current situation**

Sales respondents: The respondent was asked to describe the market trend and business development regarding big data in his focus industry sectors or regions. If there are relevant projects on Big Data in his business, the respondent was asked to provide more information about these projects.

OEM respondents: The respondent was asked to describe the market trend of their core business. The respondent was asked to describe the level of awareness relevant business strategies regarding big data concept in his own organization. If there are relevant big data projects within his organization, the respondent was asked to provide more information about these projects.

d) **Influential factors**

Sales respondents: The respondent was asked to enumerate the potential drivers for OEM companies to adopt Big Data Analytics, relevant concerns before adopting Big Data Analytics or barriers to hinder smooth adoption of Big Data analytics solution.

OEM respondents: The respondent was asked to enumerate the perceived drivers to adopt Big Data Analytics, relevant barriers to adopt Big Data Analytics or risks during the implementation of Big Data analytics solution.

e) **Model Evaluation**

Sales respondents: The respondent was asked to provide feedback on the proposed adoption process framework and assign the influential factors shown in Figure 17 to different adoption phases.

OEM respondents: The respondent was asked to provide feedback on the proposed adoption process framework and assign the influential factors shown in Figure 17 to different adoption phases. The respondent was also asked to indicate in which phase his organization is regarding adopting Big Data Analytics.

f) **Closing**

Sales respondents: The respondent can share additional information and ask questions that he thought was relevant to this study.

OEM respondents: The respondent can share additional information and ask questions that he thought was relevant to this study.

These two interview protocols can be found in Appendix A and Appendix B.

5.3.2 Interoperability

In order to attract as many respondents as possible, a brief presentation regarding big data in the industry sectors was organized for sales teams dedicated to industrial automation products, services and solutions within *Company X*. Afterwards, an invitation letter with the relevant interview questions to participate in the interview session was sent to the whole sales teams which already have an overview of big data concept in this research. Then, the interview session was arranged and conducted. Before the execution of individual interview, the possibility for further interview with OEM companies was discussed with sales respondent. Since it was difficult to conduct direct interviews with OEM customers who have never had any discussion with sales representatives regarding big data solution, some interviews for OEM companies were conducted to ask sale representatives to answer questions from the point view of OEM companies. All interview sessions with sales were conducted through face-to-face meetings. Each interview session lasted between 50 to 120 minutes while integrated interviews were relatively longer. The locations where interview sessions were held are at the office building of Company X in Den Haag from August to September.

After selecting the final respondents, the first interview was conducted to test the effectiveness of getting desired information by following the interview protocol. Afterwards, interview techniques were slight adjusted by the researcher for better time management. Then, all interviews were smoothly conducted and were fully audio-recorded with respondent signed agreement. The researcher also wrote notes during the session. All collected information during the interviews was processed and translated into formal transcripts that contained a summary of discussed subjects during the interview session. The accuracy and quality of each the interview description is guarded by respondent's review after the interview.

5.4 Data analysis approach

All information gathered from interviews was translated into formal transcripts that contains a lot of textual data. The next step was to extract the concepts for analyzing the textual data:

Step 1. Open coding

The first step was a detailed process in which almost every line of text was read again and coded in term of reducing the data. Since a set of focus issues were pre-defined in the interview questions, this step had a clear framework guiding the initial open coding process. After listening to the recorded audio and reading the transcripts, the related concepts with the whole transcripts from the interviews were clustered into a set of codes. This step reduced the redundancy of original data, yet covered as many meaningful codes as possible.

Step 2. Category identification

After the whole transcripts were coded, these codes were then compared and clustered into related themes, and were eventually put into the TOE categories. Various codes were reduced to 3 representative categories that cover all segmented text. These codes describing the influential factors were analyzed and determined as drivers or barriers. The category identification was indented to understand the influential factors regarding Big Data Analytics adoption.

Step 3. Constructing linkage

After codes from the full text were assigned with TOE frame, the various codes were linked to different adoption phases within the whole adoption process. This will create the final adoption process framework.

5.5 Conclusion

This study has chosen a qualitative research approach to evaluate the concept from desk research and literature review in this research project. The data input for further qualitative analysis was acquired from the semi-structured face-to-face interview with open-ended questions. This interview approach allows the respondents provide information for the researcher as much as possible in an efficient way. The interviewed respondents were pre-selected and divided into two groups comprising of the sales respondents and OEM customer respondents. Two types of interview schemes were designed and conducted for data collection. The textual data gathered from those interview sessions were transcribed and analyzed through the thematic coding approach.

CHAPTER 6 ADOPTION PROCESS FRAMEWORK EVALUATION

This chapter is to present the analysis results from the interviews and to answer the sub research question 3 and 4: What are the key factors that influence the adoption of Big Data Analytics from an OEM's perspective? How does an adoption process framework look like when OEM customers want to utilize Big Data Analytics in the industrial automation sector? In the section 6.1, the current situation regarding Big Data Analytics is elaborated. The influential factors for Big Data Analytics adoption are elaborated in the section 6.2. The adoption process framework is evaluated in the section 6.3.

6.1 Current situation in the industrial automation

From the results of the interviews, most OEM companies only showed interests in Big Data Analytics They all know the importance of Big Data Analytics in the Industry 4.0 trend. However, most OEM companies have not adopted any practical big data solutions, thus they can be considered as non-adopters. Only three organizations were found to have been actually developing knowledge for further business cases or pilot projects. Shown in the second column of Table 3, respondents mentioned the desired Big Data Analytics solutions for OEM companies. The desired Big Data Analytics activities are primarily related to the asset analytics, energy use analytics and process analytics, which are presented in Table 3. The option in the third and fourth column represent whether OEM companies want to improve their current business or to develop new product and services. As we can see that the utilization of Big Data Analytics by OEM companies tend to improve current business activities.

Asset Analytics

For the asset analytics, OEM companies want to achieve the continuous local and/or remote acquisition and analysis of asset statuses, mainly install-based production facilities at their manufacturing departments. Then the analyst experts can calculate the overall equipment efficiency and provide the plant / system operator with important indicators regarding efficiency enhancing measures. OEM companies also want to determine the overall equipment efficiency (OEE) of their manufactured machine which are installed at their customers' sites for product improvement. Comprehensive analysis options form the basis to increase the OEE Figures and maintenance planning thus the efficiency in operation. The predictive maintenance is highly preferred by OEM companies, for instance the maintenance department of the company could better schedule their operation and maintenance planning by anticipating when a certain asset or a machine is expected to break down.

Energy Analytics

For the energy analytics, OEM companies want to Big Data Analytics provide energy usage measures which can change their energy consumption behavior in order to reduce energy costs through less energy consumption. However, energy use data from meters is not yet extracted and analyzed on a regular basis as companies do not have capabilities or in-depth knowledge for analysis. They doubt the actual saving in contrast to potential high investment for getting energy consumption data.

Process Analytics

For the process analytics, OEM companies desire that Big Data Analytics could enable the traceability of the entire process from the beginning such as gathering the information of raw material sources, production planning, until the end such as product delivery to the customers. For instance, in the food and beverage industry, according to the regulations in the Member States of the European Union and the United States, the carcass of animal meat must be marked with a health mark in order to conduct the necessary inspection activities to establish compliance with legislative requirements.

Respondent code	Desired /Adopted Big Data Analytics solution	Current business improvement	New product or service Development
Sales A	Asset Analytics (Machine condition monitoring + Remote service)	❖	
Sales B	Process analytics		❖
Sales C	Asset Analytics (Machine condition monitoring+ Predictive maintenance)		❖
Sales D	Asset Analytics (Machine condition monitoring)	❖	
Sales E	Asset Analytics (Predictive maintenance +) Energy analytics	❖	
Sales F	Machine condition monitoring	❖	
Sales G	Predictive maintenance + Process analytics+ Energy analytics	❖	
Customer A	Asset Analytics (Predictive maintenance)	❖	❖
Customer B	Process analytics		❖
Customer C	Asset Analytics (Machine condition monitoring)		❖
Customer D	Asset Analytics (Machine condition monitoring + Remote service)	❖	
Customer E	Asset Analytics (Machine condition monitoring)	❖	

Table 3 Overview of desired Big Data Analytics application.

6.2 Influential factors for adoption

Results from interviews with field experts showed three main drivers and two main barriers for Big Data Analytics adoption proposed under TOE framework in the chapter 4. One factor is not considered as important parameter. Table 4 shows the distribution of various drivers selected by the respondents during the interview sessions. More frequently mentioned by the respondents, more influential the factor will be. *The relative advantage*, *top management support* and *competitive pressure* were perceived as the main drivers for adopting Big Data Analytics by interviewees.

Drivers	Respondents
Perceived benefits	10
Easy to use	0
Capable to integrate with current internal process	4
Enough financial budget	2
Data security	0
Top management support	8
Company size	0
Competitive pressure	8
Vendor's marketing effort	6

Table 4 Drivers for Big Data Analytics adoption

Meanwhile, two main barriers were also found to hinder the adoption of Big Data Analytics. These are lack of perceived benefits and Data security, shown in the table 5.

Barriers	Respondents
Unclear perceived benefits	7
Not easy to use	0
Not easily capable to integrate with current internal process	2
No enough financial budget	0
Data security	8
Lack of top management support	5
Company size	2
Competitive pressure	0
Vendor's marketing effort	0

Table 5 Barriers for Big Data Analytics adoption.

6.2.1 Technological factor

The most dominant driver factor for Big Data Analytics adoption is clearly perceived benefits through leveraging Big Data Analytics. A lot of respondents expressed a positive interest or belief in generating new business value by analyzing large datasets. However, the majority of the respondents also emphasized that OEM companies would only consider adopting Big Data Analytics when they are able to clearly see the benefits, especially when they can refer to a practical use case. OEM companies want adoption case from other companies that have with similar business that have already adopted Big Data Analytics. If the reference cases show significant benefits, OEM companies will be more convinced by Big Data Analytics concept.

> *"If we can help OEM company analyze the data from their production process, I believe that some valuable information and insights will be gathered and help the business." [Service sales specialist, Sales E]*

> *"We want to develop new functionality in our product as an unique selling point based on Big Data Analytics, so we decide to co-develop the new machine with our partner." [Business manager, Customer A]*

In contrast, unclear perceived benefit is the most dominant barrier towards the adoption of Big Data Analytics. Findings show that in many interview sessions, respondents mentioned that the advantages of big data are widely known through media and Internet, but the perceived benefits for them are still vague. The reasons for vague perceived benefits are found in two categories. Firstly, OEM companies have little domain know-how regarding Big Data, so they do not know how to use the large amount of data. On the other hand, since Big Data Analytics is a new area, the adoption is long-term process. The costs of upfront investment and the return of investment (ROI) are not clear for OEM companies, since they do not have quantitative information for this theme. So most OEM companies do not dare to conduct as early adopters for Big Data Analytics.

> *"How much should I invest for Big Data? …When can I see the financial benefits? These are not clear for me. How can I play with it? " [Production manager, Customer B]*

Therefore, combined with the above driver and barrier that describe the relative advantage of Big Data Analytics from two sides, the relative advantage can positively influence the adoption of Big Data Analytics.

A second technological factor mentioned in the interviews was the compatibility of integrating with current internal business process. Since the realization of Big Data relies on various information communication technologies and analytics requires special skills, end users need time to adapt their work to get familiar with new Big Data Analytics application. Therefore, it is very important that new Big Data Analytics application can be integrated with current information system or business operation process. If analytic application is not developed to be easily integrated with existing business process, end users may spend a lot of time for learning, or even reject the use of Big Data Analytics application. This may slow down adoption progress and the expectations of using Big Data Analytics will fall short.

The complexity of Big Data Analytics was not found to be significant during the interviews. One plausible explanation for this is that Big Data Analytics is a new area, all OEM companies need to learn using Big Data Analytics from scratch. Therefore, it is difficult to assess the ease-of-use of Big Data Analytics.

6.2.2 Organizational factor

From the interview analysis, an important organizational factor influencing the adoption of Big Data Analytics was top management support. During the interviews, the majority of respondents admitted that the successful adoption of Big Data Analytics relied on the strong support from the management team that can allocate enough financial resources and personnel related to big data firms. According the some respondents, a few top managers of OEM companies initiated the innovation based on Big Data Analytics so they are already on the way of adoption. In contrast, a lot of companies' managers think that high investment is needed to implement Big Data Analytics as an immature technology. These managers want to focus on their current business rather than taking risk, so these companies have not adopted Big Data Analytics. Therefore, top management support is an essential driver facilitating Big Data Analytics.

> *"I have an OEM customer owned by a world-famous venture capitalist who believes in a bright future of big data. This company puts a lot of efforts on big data innovation, e.g. investigating the implementation of big data in processing line product." [OEM Sales, Sales B]*

Another important factor confirmed by the respondents was the data security. Most respondents expressed their concerns with regard to security which hindered the adoption of Big Data Analytics. According to the interviews, the security issues in Big Data Analytics mentioned by respondents includes the availability of the application, confidentiality of data and integrity of information. These concerns were found to be common in the non-adopters. Although the OEM companies who are developing knowledge on leveraging big data also had concerns regarding security issues, they believe they will eventually find proper solutions to safeguard the use of Big Data Analytics.

Both financial readiness and company size were only mentioned twice in the interviews as influential factor. Enough financial resources were confirmed the positive influence of adopting Big Data Analytics by two respondents which is consistent with a number of empirical researches (Jeseke et al., 2013; Manyika et al., 2011; Sin Tan et al., 2009; Soares-Aguiar & Palma-dos-Reis, 2008). Therefore, financial readiness is a positive factor for adoption Big Data Analytics.

However, the feedback from two respondents on company size with regard to Big Data Analytics adoption was conflicting with each other. One respondent though large company will have more resources for utilizing big data while the other argued that sluggish decision-making process in large company inhabited the adoption of Big Data Analytics. Therefore, the company size is considered as an factor which have not been determined yet due to the small sample size.

6.2.3 Environmental factor

A lot of studies showed competitive pressure driving companies to adopt new technologies or innovations (Bradford & Florin, 2003; Brandyberry, 2003; Thong, 1999). In this study, the majority of respondents confirmed that OEM companies tend to actively seek new technology innovation like Big Data Analytics under competitive pressure, which is consistent with previous study. OEM companies are facing market pressure including costs reduction and product innovation.

> *"The market competition in the food & beverage industry is rather intensive. Once there is new machine with new feature rolled out on the market, companies are always willing to try new features. They seek for all possibilities of cost reduction. If big data can help them, they will follow up." [OEM Sales, Sales B]*

Yet, findings from the interviews have shown that marketing effort was a driving factor for the adoption of Big Data Analytics. Since Big Data Analytics is a new service in the industrial automation sector with limited use case, it is very difficult for Big Data Analytics service providers to promote this new service to OEM companies. Accordingly, OEM companies only consider big data as a buzzword, but cannot link this concept with their own business. Lack of practical business cases with regard to Big Data Analytics dented OEM companies' confidence on Big Data Analytics. Therefore, marketing effort from Big Data Analytics service providers is an essential factor for adopting Big Data Analytics.

6.2.4 Main influential factor

Concluded from the interview analysis, within TOE framework, *relative advantage*, *top management support*, *data security* and *competitive pressure* from the market are considered by respondents as the main factors that influence the adoption process of Big Data adoption. Meanwhile, *the compatibility, financial readiness* and *marketing effort* also influence Big Data Analytics adoption. The complexity seems to be insignificant to utilize Big Data Analytics. The above conclusion is shown in Figure 22 below.

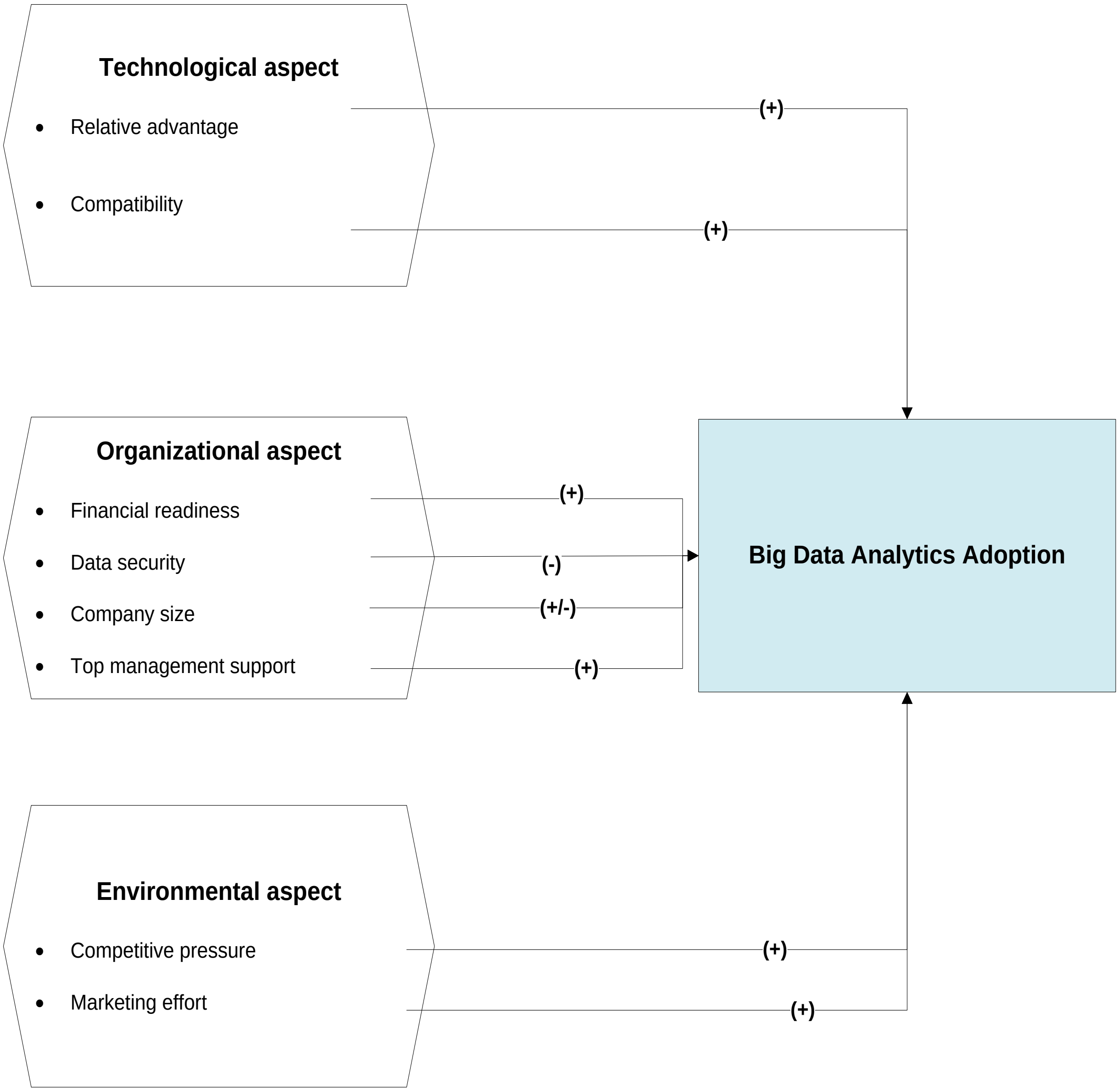

Figure 22 Influential factors of Big Data Analytics adoption

6.3 Evaluation of adoption process framework

During the interviews with respondents, diverse feedback and suggestions with regard to the proposed adoption process framework were received. The respondents were asked to link the influential factors to different adoption phases. The evaluation and adjustment of adoption process framework were based upon this empirical data. No drastic changes occurred during the finalization of proposed adoption process framework. More important is the impact of different influential factors to different adoption phases. This section elaborates more in more detail on the interactions between influential factors and different adoption phases.

Awareness phase

The awareness phase represents a pre-Big Data Analytics environment. In this stage, OEM companies have a low awareness of Big Data Analytics or its value across much of the business. There is no real top management support, although there are a few people that get to know big data and spread the concept through the company on a small scale. In this phase, the *competitive pressure and the marketing effort* are significant factors that influence OEM companies. Big Data Analytics service providers need to take efforts to spread the Big Data Analytics concept and its benefits for OEM companies.

Strategy phase

In the strategy phase, in response to the big data concept as an irreversible trend, OEM companies start investigating Big Data Analytics. One executive sponsor, usually the chief information officer (CIO), or the chief technology officer (CTO) or one business sponsor is first on board. But companywide support is missing. The executive sponsor will assign a team to explore big data around experimentation. Staff might start desk research on this concept and take part in conferences and expositions to collect more information. The new possibilities derived from Big Data Analytics in their business are analyzed. Afterwards, more executive sponsors are engaged, and then together explore the top business problems to solve and define the business strategic objectives regarding Big Data Analytics. On the basis of the findings from the interviews, in this phase, *relative advantage, top management support and competitive pressure* play major roles that positively influence this phase. Marketing effort from Big Data Analytics service providers also positively influence the perception of OEM companies with regard to big data. According to the interviews, currently most OEM companies are in this phase.

Knowledge phase

In the knowledge phase, research and development activities are conducted to generate in-depth knowledge regarding Big Data Analytics. The OEM company explores some kinds of analytics at a department or line-of-business level either by themselves or cooperating with external partner(s). The information about the required financial costs, risks and technological know-how on Big Data Analytics might be addressed for top management's further decision-making. Some respondents think the knowledge phase is a critical phase before the real implementation in which top management support, and marketing effort contributes to generate more knowledge with regard to Big Data Analytics. Meanwhile, data security may create prejudice and concerns on Big Data Analytics in the perception of some top management members, which might hinder the progress to the next phase. There are also some interest conflicts between management teams on the goal of Big Data Analytics. According to some respondents, this phenomenon is quite common in the companies in which managers always argue on cost containment and competitive edge. It is vital to eliminate prejudice and create positive image for top management on Big Data Analytics in this phase through appropriate information. According to the interviews, Customer A, Customer B and Customer C are in this phase. They have collected some data and put some effort in the R&D department regarding Big Data Analytics.

Trial phase

In the trial phase, the OEM company establishes a team to start an experiment case or pilot project characterized with proofs of concept (PoC) that will become production ready in small scale. This pilot project might be implemented in the OEM company or at their customers' place. Technical specifications of Big Data Analytics are realized in this phase. More executive sponsors show interest in the proofs of concept and become involved in this phase, since new products, services or business models may be developed for its end customers. According to the respondents, r*elative advantage* and *compatibility* are the main influential factors, since the real wins in the PoCs become visible for OEM companies in the end phase of the project. The OEM company often uses these two criteria to assess the gains from the implementation of pilot projects and make decision on whether the selected solutions regarding Big Data Analytics is worthy of being widely popularized in its whole organization. Experience and knowledge gained in this phase are sent back to knowledge phase for OEM companies to redefine Big Data Analytics strategy. Moreover, the OEM company wants to see tangible benefits in a relative short period, otherwise they might stop the pilot project. For instance, the return of investment for the respondent-*Customer B*'s customers is from six to eighteen months on average. Therefore, the trial phase needs to be short. In addition, financial readiness is also a very important influential factor. Some respondents emphasized that companies are not able to get past the prototyping because they are lack of necessary funding.

Implementation phase

In the implementation phase, the use of Big Data Analytics is extended to a larger scale with more supporting resources, affecting more individuals within OEM companies. More IT infrastructure and sensors need to be installed, replaced or upgraded for acquiring and analyzing more data. In the trial phase, one organization may have been driving big data effort while more departments are brought on board in the implementation phase. The way how OEM companies do business may be changed and the organizational structure with OEM company may be transformed since some new business processes will be introduced. Some internal cultural and political issues may be involved. Departments may begin to fight against each other for their particular vision, e.g. data ownership, data governance, etc. These internal issues may stop Big Data Analytics from becoming pervasive in the OEM companies (Halper & Krishnan, 2013), which is significant in large companies. Therefore, a solid plan and roadmap on implementing Big Data Analytics with executive management support is vital important. Hence, *top management support, company size* and *data security* are the main influential factors in this phase. OEM companies tend to spend a long period in this phase.

Internalization phase

In the internalization phase, the OEM company uses Big Data Analytics at a mature level. Executives view Big Data Analytics as a competitive differentiator and de facto standard for doing business within the OEM company. Innovation around Big Data Analytics becomes the core value and culture of the organization. Big Data Analytics programs are conducted as budgeted and planned initiative. Collaboration between internal departments is harmonious. The capability of Big Data Analytics will be continuously optimized and upgraded. Meanwhile, the OEM company continuously looks for new service offerings for their customers on the basis of Big Data Analytics, from which stable revenues contributed to the development of OEM. The Big Data Analytics becomes embedded in OEM distinctive capability. In this phase, Big Data Analytics is fully institutionalized and integrated with the daily business activities of the OEM company. In the mature phase of leveraging Big Data

Analytics, competitive pressure is the main influential factor that may change the mindset of OEM on Big Data Analytics.

Synthesis on framework

From the above analysis of the information from the respondents, the influential factors based on TOE framework can be linked to different proposed adoption phases, shown in the Figure 23. The arrows in the Figure 23 represent different adoption phase in term of adopting Big Data Analytics. The hexagons represent the key actives conducted by OEM companies in the different adoption phases. The eclipses in green, purple and orange color respectively represent different influential factors allocated in different adoption phases. It is also important to point out that Big Data Analytics adoption is not a sequential process, rather a continuous process which OEM companies move one phase to next phase. It is possible that OEM companies iterate back from Trial phase to Knowledge phase or Strategy phase when the adoption activities are problematically conducted. In this case, OEM companies might redefine their business strategies on utilizing Big Data Analytics. By using this framework, Big Data Analytics service providers can gauge where their potential OEM companies are in term of Big Data Analytics. They can be aware of the influential factors in different phases and design related business strategies to carefully handle related matters.

6.4 Conclusion

This chapter answered the sub research questions: "What are the key factors that influence the adoption of Big Data Analytics from an OEM's perspective?" and "How does an adoption process framework look like". Firstly, this chapter described how current Big Data Analytic is in the industrial automation sector. The desired Big Data Analytics of OEM companies includes asset analytics, process analytics, and energy analytics. Secondly, the influential factors based on TOE theory have been evaluated. Most perceived influential factors for Big Data Analytics adoptions by respondents in the interview sessions includes relative advantage, top management support, data security and competitive pressure as the main factors that influence the adoption process of Big Data adoption. On the other hand, the compatibility, financial readiness and marketing effort also greatly influence Big Data Analytics adoption. The evaluation of the Big Data Analytics adoption process framework can be referred to the result of representation shown in the Figure 23. The feedback and evaluation of all respondents have linked the most important influential factors above to different adoption phases. This framework can be used as guidance for both Big Data Analytics service providers and OEMs to deal with the issues related to the applying Big Data Analytics.

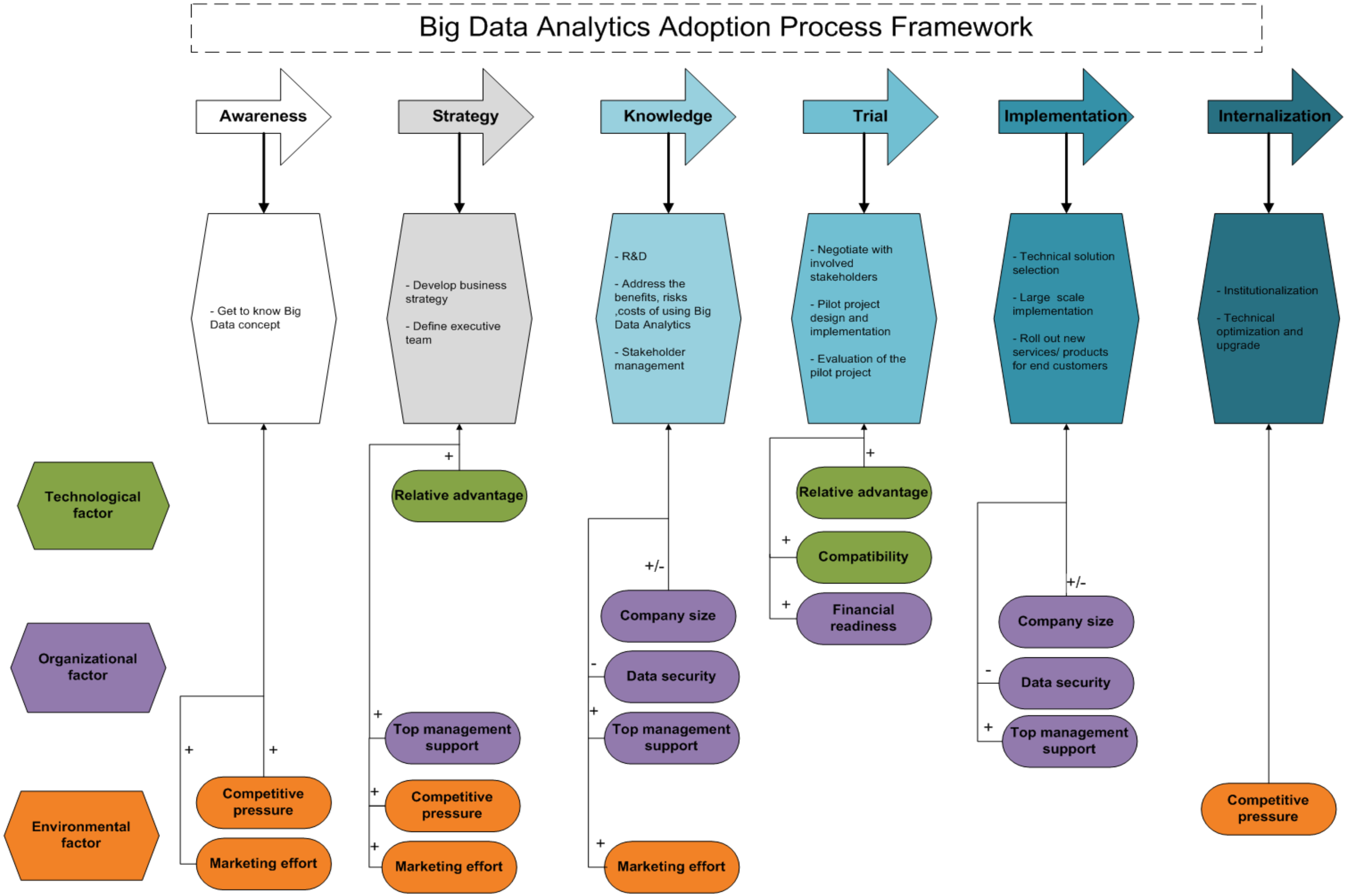

Figure 23 Complete Big Data Analytics adoption process framework

CHAPTER 7 CONCLUSIONS AND REFLECTION

This last chapter of this report concludes and reflects the results of this research findings by qualitative analysis outlined in the chapter 5. The main research findings will be discussed in section 7.1. A reflection on the theoretical implications of the research findings will be described in section 7.2. The societal contribution of this research will be described in section 7.3 through the recommendations for Big Data service providers and OEM companies. Furthermore, research limitations will be discussed in the 7.4, followed by a number of future research directions in section 7.5. Finally, a reflection on the research process will be presented in section 7.6.

7.1 Research findings

The main objective of this research was to develop an adoption process framework by investigating the adoption process of OEM companies sector leveraging Big Data Analytics in the industrial automation. On the basis of this objective, the main research question was formulated: "*Which technology adoption framework can support OEM companies in the industrial automation sector to adopt Big Data Analytics by means of the Software-as-a-Service concept?"* Accordingly, several sub research questions were formulated in the beginning of the research and answered in the previous chapters. The answers to the sub-questions have led to solve the research main question. The correlation between the business requirements and the advantages of using Big Data Analytics can help OME companies make decisions on whether adopting Big Data Analytics for their business and define their specific objective in term of using Big Data Analytics. Then OEM companies can use the proposed adoption process framework presented in Figure 23 to understand the influential factors regarding Big Data Analytics adoption in different adoption phases. They also need to consider the steps need to be taken in order to fully adopt the Big Data Analytics. They can also check the position of their own organization in the whole adoption process. They can design business strategies accordingly in order to enhance the drivers and overcome the barriers to progress to the next adoption phases. In this section, the answers to the sub research questions will be called back and outlined below.

> ***RQ1: How does the potential value network look like in the industrial automation sector towards Big Data Analytics for OEM companies?***

Due to complexity of big data, OEM companies need to cooperate with other companies and their customers to address the challenges of big data. The growing demand of utilizing big data technologies by OEM companies in the industrial automation sector offers opportunities for integrating partners and customers into a value network. These companies and customers will play several market roles in this value network in term of collaboration, including:

Infrastructure Provider provides IT infrastructure and industrial automation products;
Technical Platform Provider provides technical-oriented environment;
Market Platform Provider provides business-oriented marketplace aggregating Big Data Analytics services;
Analytic application Provider offers data analytics applications;
System Integrator offers Big Data Analytics as a service;
Consultant provides expertise and consultancy services regarding Big Data Analytics;
OEM receives Big Data Analytics service offerings;

Customer receives product and service offerings.

Some market roles are still played by traditional IT companies and industrial automation companies respectively while these companies may enter each other's conventional business area through competition and/or collaboration in term of providing Big Data Analytics services. Some companies may play several market roles in the value network. When OEM companies adopt Big Data Analytics, relationship between different market roles are established and new potential business model may be created in this network. Tangible value such as financial transactions, IT infrastructure and sensors etc., and intangible value, such as knowledge, trust etc., are exchanged in this value network which will lead to continuously collaborative value.

RQ2: How does Big Data Analytics connect the requirements of OEM companies?

Before adopting Big Data Analytics, OEM companies need to compare their own business requirements with the potential benefits of using Big Data Analytics in order to find a match between these two perspectives. Leveraging Big Data Analytics is to make sound, fact-based decisions in term of achieving transparency in the industrial processes, improving asset availability, efficiency and performance. In order to create competitive edge, OEM companies have some business requirements which include *monitoring assets, investigating defects, supply chain management optimization, saving various costs, achieve flexible production for mass customization, seeking for new sustainable business model, and legislative and ethical compliance*. These requirements can be fulfilled to some extent through using Big Data Analytics, shown in Figure 14. In view of these potential benefits from adopting Big Data Analytics, OEM companies may consider of adopting Big Data Analytics in their organizations.

RQ3: What are the main factors that influence the adoption of Big Data Analytics from an OEM's perspective?

According to the interviewees, *the relative advantage*, *top management support* and *competitive pressure* were perceived as the main drivers for adopting Big Data Analytics by OEM companies. On the other hand, the compatibility, financial readiness and marketing effort by Big Data Analytics service providers also greatly influence OEM companies' Big Data Analytics adoption.

RQ4: How does an adoption process framework look like when OEM companies want to utilize Big Data Analytics in the industrial automation sector?

In this study, a Big Data Analytics adoption process framework for OEM companies is developed. The adoption process framework contains three main elements: the adoption phases, key activities and influential factors in each phase respectively, shown in Figure 23. The adoption of Big Data Analytics by OEM companies will experience several phases, including *Awareness phase, Strategy phase, Knowledge phase, Trial phase, Implementation phase, and Internalization phase*. In each phase, there are some main activities will be conducted by OEM companies in order to progress to the next adoption phase. Meanwhile, different influential factors concluded from the previous research question will have different impact in different adoption phases.

Awareness phase

The awareness phase represents a pre-Big Data Analytics environment. OEM companies have a low awareness of Big Data Analytics. In this phase, the *competitive pressure and the marketing effort* are two significant factors that influence OEM companies.

Strategy phase

In the strategy phase, OEM companies start investigating Big Data Analytics. A team will be assigned to explore big data around experimentation. Business development strategies concerning Big Data Analytics will be defined. In this phase, *relative advantage, top management support and competitive pressure* play major roles that positively influence OEM's attitude on Big Data Analytics. According to the interviews, currently most OEM companies are in this phase.

Knowledge phase

In the knowledge phase, research and development activities are conducted to generate in-depth knowledge regarding Big Data Analytics. The financial costs, risks and technological know-how on Big Data Analytics will be addressed for top management's further decision-making. According to the interview results, knowledge phase is considered as a critical phase before the real implementation in which top management support and marketing effort contributes to generate more knowledge with regard to Big Data Analytics. Meanwhile, data security may create prejudice and concerns on Big Data Analytics in the perception of some top management members, which might hinder the progress to next phase.

Trial phase

In the trial phase, OEM company establishes a team to start an experiment case or pilot project characterized with proofs of concept (POC) which will become production ready in small scale. In this phase r*elative advantage* and *compatibility* are the main influential factors for Big Data Analytics adoption. Experience and knowledge gained in this phase are sent back to knowledge phase for OEM companies to redefine Big Data Analytics strategy. In addition, financial readiness is also a very important influential factor. The trial phase needs to be relatively short for OEM companies to really perceive the benefits from adopting Big Data Analytics.

Implementation phase

In the implementation phase, the use of Big Data Analytics is extended to larger scale with more supporting resources, affecting more individuals within OEM companies. Hence, *top management support, company size* and *data security* are the main influential factors in this phase. OEM companies tend to spend a long period in this phase.

Internalization phase

In the internalization phase, the OEM company use Big Data Analytics at mature level. In this phase, Big Data Analytics is fully institutionalized and integrated with the daily business activities of the OEM company. Innovation around Big Data Analytics becomes the core value and culture of the OEM companies. In this phase, competitive pressure is the main influential factor that may change the mindset of OEM on Big Data Analytics.

7.2 Scientific contribution

This study has some theoretical contributions to existing literature on organizational big data adoption. First of all, the existing literature on big data adoption is rather limited. The empirical study on organizational adoption of Big Data Analytics by OEM companies provides in-depth insights of organizational technology adoption in the industrial automation sector. Meanwhile, the study on OEM companies can be considered as a case within the organizational technology adoption and assimilation research domain.

Secondly, this study applied value network analysis approach to understand the various market roles involved for adopting Big Data Analytics as a service in the OEM companies. The findings of the study confirmed the usefulness of value network theory.

Thirdly, while many studies on the basis of the Technological-Organizational-Environmental framework only focused on 'adoption' as a unique dependent variable (Nam et al., 2015), this study integrated TOE with the DOI theory to investigate the influential factors in the domain of Big Data Analytics adoption. This study has confirmed the applicability and usefulness of the TOE framework and the DOI theory to investigate the adoption influential factors from three perspectives in the big data research domain. In addition, this study has proved the significant relevance of several existing influential factors for Big Data Analytics adoption from the TOE framework and the DOI theory, such as: relative advantage, top management support and competitive pressure.

Fourthly, most of the existing studies in the literature examined in IT innovation adoption are "adoption versus non-adoption"(Jeyaraj et al., 2006; Nam et al., 2015), this study integrated the processes of innovation adoption with differential effects of TOE and DOI factors. The findings of this research allow us to clearly understand the influence of different factors in different organizational innovation adoption phases. The final adoption process framework makes advancement in the big data adoption research domain.

7.3 Societal contribution

Prior to this research, there is little understanding in the adoption of Big Data Analytics by OEM companies in the industrial automation sector. This study provides an understanding in the value network of delivering Big Data Analytics service, factors influencing organizational Big Data Analytics adoption by OEM companies and their adoption process on the basis of existing theories and empirical results from the interview sessions. The adoption process framework can be employed by OEM companies or industrial automation companies which would like to offer Big Data Analytics as a service for their clients to deepen and widen the understanding around Big Data Analytics adoption as to accelerate the transition period. In order to ensure smooth implementation and assimilation of Big Data Analytics by OEM, the results of this study can guide the design of promotion strategies both for OEM companies and industrial automation companies. Any progress in utilizing big data in the industrial automation sector can be considered as societal contribution. In addition, this study provides some managerial implications for OEM companies and industrial automation companies.

Recommendations to OEM companies

This study offers a useful tool for OEM companies to assess whether their business requirements can be potentially achieved through Big Data Analytics before they make decision on the adoption of Big Data Analytics. After they decide to adopt Big Data Analytics, they can use the adoption process framework to assess the position of their adoption process and design strategies towards enhancing the positive factors associated with Big Data Analytics adoption and mitigating the negative factors accordingly.

It is found that the relative advantage, top management support and marketing pressure are the most expansive factor in overall adoption phases. Managers of OEM companies need to adjust management practices at different adoption phases. For instance, in several phases, relative advantage plays a very important role, employees or mangers of OEMs need to collect successful use cases from other organizations or internal department to show the benefits of using Big Data Analytics. Top management support is found also very important in the Big Data Analytics adoption.

Therefore, management of OEM companies needs to ensure the support and commitment to allocate sufficient financial and human resources for Big Data Analytics adoption. Top Management support may also influence the perception within the organization to use Big Data Analytics. Therefore, top management is advised to actively encourage the use of Big Data Analytics, reward innovation on Big Data Analytics, etc.

Recommendations to industrial automation companies

The findings from this research also help the industrial automation companies develop their marketing strategies in term of offering Big Data Analytics as service. Since most OEM companies are still in the initial phase of adopting Big Data analytics, such as the awareness phase or strategy phase, the industrial automation companies need to design some marketing strategies to foster the adoption of Big Data Analytics by OEM companies.

Develop demo case for reference

According to the interviews, one of the reasons that OEM companies hesitate to adopt Big Data Analytics is that it is difficult for OEM companies to find relevant use case as reference. Sometimes, OEM companies are lack of funding for implementing experiment project. Therefore, they cannot clearly understand the relative advantage of Big Data Analytics. Hence, industrial automation companies as the Big Data Analytics service provider are advised to invest in cooperating with OEM companies to develop pilot project to gain more use case for further promotion. The industrial automation are also advised to set up more workshop, showcase center to present the application of Big Data Analytics in different industry.

Set up flexible offerings

OEM companies have various requirements for Big Data Analytics while Different organizational size also have different financial capability. The industrial automation companies need to set up flexible offering in term of Big Data Analytics for OEM companies to choose.

Tackle security concern

From the study, it is found that data security is the main barrier for Big Data Analytics adoption by OEM companies. The industrial automation companies is advised to demonstrate their capability of providing secure and reliable data protection solution for Big Data Analytics solution. Adequate information security and privacy measures need to be implemented in order to guarantee a secure data and information exchange in the value network.

7.4 Research limitation

It is very important to reflect the limitation of the study in term of the evaluating the findings of this research.

First of all, the major limitation of the research projects is the chosen qualitative data collection method through interviews. Although the face-to-face interviews provide more in-depth information than surveys, processing the information from interview participants were prone to biases. The responses from the OEM sales team and representatives of OEM companies could be biased due to their different interests in promoting Big Data Analytics to be adopted, gained domain experience, understanding of big Data, or other reasons. In addition, single responses from each organization were collected in this research may also lead to response bias which also lowered the validity of the research. Qualitative research approach caused a lot of bias in investigating the Big Data Analytics adoption phenomenon.

Secondly, the data sample size for both the industrial automation companies and OEM companies is relatively small due to the limited time for research execution and limited external business connection, especially the limited representatives of OEM companies. The data sample only covered a limited range of OEM companies in different industry sectors. In addition, the Big Data Analytics adoption as a phenomenon in this research is changing all the time while the process of studying. This resulted that the research findings cannot be always generalized for all types of organizational Big Data Analytics adoption. The research findings only provide a periodic understanding of Big Data Analytics process at this moment.

Thirdly, this study did not cover all potential influential factors for Big Data Analytics adoption identified from the existing literature on IT innovation adoption due to the limited research time, small sample size and qualitative approach.

7.5 Future research

In responds to the findings and limitations of this research study as mentioned above, further research could emphasize more in the validation of the adoption process framework.

First of all, in this study the adoption process of Big Data Analytics is described on the basis of the OEM companies located in the Netherlands. Future research can focus on Big Data Analytics adoption process in other sectors and other regions to clarify and confirm the completeness, reliability and validity of this study.

Secondly, it would be interesting to conduct a quantitative research approach to examine the factors that influence the Big Data Analytics adoption by OEM companies with larger sample size. More other influential factors identified from the existing literature can be included to assess the influential degree of various factors. In addition, the quantitative research method can also investigate the interrelationship between these influential factors for Big Data Analytics adoption.

Thirdly, with a larger sample size, a quantitative research method can be used to assess the extent of influence of different factors in different adoption phases.

Finally, since there are many individuals with the organizations adopting Big Data Analytics. Further research may introduce the individual factors in the organizational context in the TOE framework to study the individual adoption process within the organization. This can be considered as the modification of the TOE theory.

7.6 Research reflection

In the final section of this research report, I would like to provide a brief personal reflection on my research process. The early stage during the conceptualization of the study area was the most remarkable affair in this research. Searching for the right research direction and shaping a solid research design were considered as a cumbersome process. Although big data concept is rather popular at this moment, the study on the adoption of big data, especially in the industrial automation sector was a relatively new area. There were little scientific papers supporting this topic. At the start of this study, many theories in the field of innovation adoption and white paper, business report were studied. After constructing the initial adoption process framework, interviews were designed and tested in order to be smoothly conducted for evaluation of adoption process framework. Before I conducted the interview sessions, I made a public presentation for OEM sales department with Company X concerning the concept of big data and its application in the various sectors to attract more potential respondents for the interviews. The audience showed great interest in my study, and most of them became the respondents. Although big data is a new area in the industrial automation sector, the OEM sales team had a broad network that connected technical experts and OEM companies. Therefore, I had the opportunity to approach enough respondents. Overall, this research project was carried out roughly according to the initial project planning. The knowledge and skills that I gained from the Master programme of Systems Engineering, Policy Analysis and Management helped me a lot in a qualitative research study.

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APPENDIX A

Interview Protocol – OEM Account Manager

RESPONDENT INFORMATION

Name of participant :

Telephone :

E-mail address :

Job position :

Area of responsibility :

SECTION 1- INTRODUCTION

Dear Sir/ Madam,

My name is Yi Yin and I am currently conducting a Master thesis research project together with Delft University of Technology and Company X. The main objective of this research is to gain insights on the adoption of big data analytics by OEM customers in the industrial automation sector. The research study is conducted to provide answers to the following questions:

> *Which type of OEM can gain more benefits from big data analytics adoption? What are the influential factors for OEMs to adopt big data analytics solution? What are the adoption process regarding big data analytics solution?*

I would like to invite you to be part of this research. Your knowledge and experience in this area will assist me in providing recommendation to improve the dispersion of big data analytics adoption, especially within the industrial automation sector. Your cooperation in an interview session will be greatly appreciated and will lead to a better understanding on how this matter takes place in practices. In order to conduct the interview smoothly and protect your information, herewith there are some guidelines:

Interview guidelines

- Duration: interview will take about an hour
- Focus: the focus of this interview will be on familiarity with big data & big data analytics solutions, company perspective, decisions and/or implementations within company, timeframe involved, choices for specific implementations and risks related to big data analytics solution implementations.
- Recording Confidentiality:
  I would like to ask your permission to make recording during our conversation. For the sake of source reliability and being an aid during data analysis, this interview session will be fully recorded.
  The content of this interview will be processed anonymously and be only used for this research.
  All individuals and company names will not be mentioned in the final research report.

Participant signature	[Place]:
	[Date]

Section 2 Current Situation question

2.1 Do you know whether or not there is a OEM customer already adopted or interested in any big data analytics application?

[If not, go to the questions on the next page]

[If yes]

2.2 If so, what kind of analytics applications do the OEM customer need or desire to adopt in order to achieve a business objective regarding industrial automation?

2.3 What characteristics are attracted to customer organization that have adopted Analytics or interested in adopting analytics?

2.4 Which essential factors facilitate big data analytics adoption in this company? Please choose important factors which you think.

Technological factors:

- ❑ Perceived benefits
- ❑ Easy to use
- ❑ Capable to integrate with current internal process
- ❑ Other factor

Organizational factors

- ❑ Available Industrial network and sensors
- ❑ Enough budget
- ❑ Data security
- ❑ Top Management support
- ❑ Company size
- ❑ Other factor

Environmental factors

- ❑ Competitive pressure from the market
- ❑ Vendor's marketing effort
- ❑ Other factor, please mention

[If not]

2.5 Why have OEMs not yet adopted big data analytics?

2.6 Do you think whether OEMs have considered adopting big data analytics? Can you elaborate on that?

2.7 Which essential factors inhibit big data analytics adoption in an OEM customer?

Technological factors such as

- ❑ Perceived benefits
- ❑ Easy to use
- ❑ Capable to integrate with current internal process
- ❑ Other factor

Organizational factors

- ❑ Available infrastructure, such as industry network, sensors, etc.
- ❑ Financial budget
- ❑ Data governance issue
- ❑ Top Management support
- ❑ Company size
- ❑ Other factor, please mention

Environmental factors

- ❑ Competitive pressure from the market
- ❑ Vendor’s marketing effort
- ❑ Other factor, Please mention

Other aspect, please mention

Section 3 Model evaluation

Conceptual adoption process model

3.1 In which adoption phase(s) do OEM customer have most difficulties to progress in term of technological factors? What kind of actions are required to take?

3.2 In which adoption phase(s) do OEM customer have most difficulties to progress in term of organizational factors? What kind of actions are required to take?

3.3 In which adoption phase(s) do OEM customer have most difficulties to progress in term of environmental drivers and barriers? What kind of actions require to be taken?

3.4 Based on your experience and knowledge, is there any adjustment applicable to this adoption model?

APPENDIX B

Interview Protocol – OEM Customer

RESPONDENT INFORMATION

Name of participant	:
Telephone	:
E-mail address	:
Job position	:
Area of responsibility	:
Industry sector	:

SECTION 1 - INTRODUCTION

Dear Sir/ Madam,

My name is Yi Yin and I am currently conducting a Master thesis research project together with Delft University of Technology and Company X. The main objective of this research is to gain insights on the adoption of Big Data Analytics by OEM customers in the industrial automation sector. The research study is conducted to provide answers to the following questions:

> *Which type of OEM can gain more benefits from Big Data Analytics adoption? What are the influential factors for OEMs to adopt Big Data Analytics solution? What are the adoption process regarding Big Data Analytics solution?*

I would like to invite you to be part of this research. Your knowledge and experience in this area will assist me in providing recommendation to improve the dispersion of Big Data Analytics adoption, especially within the industrial automation sector. Your cooperation in an interview session will be greatly appreciated and will lead to a better understanding on how this matter takes place in practices. In order to conduct the interview smoothly and protect your information, herewith there are some guidelines:

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- Recording Confidentiality:
  I would like to ask your permission to make recording during our conversation. For the sake of source reliability and being an aid during data analysis, this interview session will be fully recorded.
  The content of this interview will be processed anonymously and be only used for this research.
  Any individual and company names will not be mentioned in the final research report.

Participant signature	[Place]:
	[Date]

Section 2 - Current Situation question

2.1 Have your company adopted any Big Data Analytics applications or does your company want to adopt any Big Data Analytics solution in your company?

[If no, skip this page and go to the next page starting from question 2.7]

[If yes, go from question 2.2 to 2.6 and skip the next page]

2.2 Which Big Data Analytics application is your company currently using? In which area?

2.3 What kind of Big Data Analytics applications does your company need or desire to adopt regarding your business?

2.4 How does your company select vendors, specifically for Big Data Analytics? Are there any selection criteria?

2.5 Which essential factors do facilitate Big Data Analytics adoption in your company?

Technological factors:

- ❑ Perceived benefits
- ❑ Easy to use
- ❑ Capable to integrate with current internal process
- ❑ Other factor

Organizational factors

- ❑ Available Industrial network and sensors
- ❑ Enough budget
- ❑ Data security
- ❑ Top Management support
- ❑ Company size
- ❑ Other factor

Environmental factors

- ❑ Competitive pressure from the market
- ❑ Vendor's marketing effort
- ❑ Other factor, please mention

2.6 What concerns or risks do you perceive/ anticipate during the adoption of Big Data Analytics in your company?

[If no]

2.7 Why have your company not yet adopted data analytics application?

2.8 Have you consider Big Data Analytics for the manufacturing process in your company? What kind of data analytics applications do your company need or desire to adoption in order to achieve a certain objective?

2.9 Which essential factors inhibit data analytics adoption in your company?

Technological factors:

- ❑ Perceived benefits
- ❑ Easy to use
- ❑ Capable to integrate with current internal process
- ❑ Other factor

Organizational factors

- ❑ Available Industrial network and sensors
- ❑ Enough budget
- ❑ Data privacy and security
- ❑ Top Management support
- ❑ Company size
- ❑ Other factor

Environmental factors

- ❑ Competitive pressure from the market
- ❑ Vendor’s marketing effort
- ❑ Other factor, please mention

Section 3 - Model Evaluation questions

3.1 Can you please elaborate on the different time phases of your project regarding Big Data? Which phase is your company in now? How you think the following model describing the adoption process?

Technology

3.2How does your organization define the technical objectives and requirements regarding Big Data Analytics?

3.3 What are the most important technical issues or difficulties in adopting Big Data Analytics in your organization?

3.4 In which adoption phase(s) does your company have most difficulties to progress in term of technological factors? What kind of actions are required to take?

Organization

3.5 How would you describe the availability of individual analytical talents in your organization?

3.6 What is the attitude of business leadership in your company on supporting Big Data effort?

3.7 In which adoption phase(s) does your company have most difficulties to progress in term of organizational factors? What kind of actions are required to be taken?

Environment

3.8 How does your organization define your own focus competitive edges in your market?

3.9 How does the vendor's marketing effort influence your purchasing decision?

3.10 In which adoption phase(s) does your company have most difficulties to progress in term of environmental factors? What kind of actions are required to be taken?

Section 4 - Closing

4.1 Are there any other things you would like to ask or share regarding this study?

4.2 Would it be possible for me to contact you after this interview by email if I have further questions?