THE ACCEPTANCE OF BIG DATA ANALYTICS FACTORS IN THE SMART SUPPLY CHAIN PERFORMANCE AMONG MALAYSIAN SMALL AND MEDIUM-SIZED ENTERPRISES (SMEs)

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DECLARATION OF ORIGINAL WORK

I hereby declare that this thesis with the title

"THE ACCEPTANCE OF BIG DATA ANALYTICS FACTORS IN THE SMART SUPPLY CHAIN PERFORMANCE AMONG MALAYSIAN SMALL AND MEDIUM-SIZED ENTERPRISES (SMEs)"

is the result with my own research except as the cited in references

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DEDICATION

I would like to express my appreciation to my beloved family and friends, who were always encouraging and supportive as I worked on the research. In addition, my supervisor, Mrs. Nor Ratna Binti Masrom, and panel, Ts. Dr. Nurulizwa Binti Abdul Rashid, supervised my research, and course mates assisted me in completing the research path.

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ABSTRACT

Big Data Analytics (BDA) plays a vital role in achieving the target of the company in Smart Supply Chain performance (SSCP). The acceptance of big data analytics in Malaysian SMEs has becomes major barrier. This is because the SMEs in Malaysia are still left behind in how to integrate the big data analytics and have a lack of strong awareness of applying effective big data analytics to smart supply chain performance. Although, some of Malaysian Small and Medium-Sized Enterprises (SMEs) now realize the value of the adoption of big data analytics, but some of the SMEs are not actively using it. Therefore, this research is to study the acceptance of big data analytics on the smart supply chain performance and aim to determine the relationship between the dependent and the independent variables (adoption of BDA acceptance and the impact on smart supply chain performance). This research was conducted by using a quantitative method. This research will be focus on the employees who are working in the SME company who is in the work position of executive-level and above as they take more responsible in decision making. The data was collected from 120 respondents through a questionnaire design using Google Forms and an online platform. Therefore, the result from the Multiple Regression Analysis and Pearson's Correlation Coefficient showed that both variables in this study had a significant and strong relationship together. In conclusion, through this research, it is hoped that it can provide the guideline to the SMEs for them to know the criteria that are needed for employees to apply and use the big data analytics on the smart supply chain in their work which can produce an effective and efficient way of doing business.

Keywords: *Big Data Analytics, Smart Supply Chain Performance, SMEs.*

ABSTRAK

Analisis Data Besar (BDA) memainkan peranan penting dalam mencapai sasaran syarikat dalam prestasi Rangkaian Bekalan Pintar (SSCP). Penerimaan analisis data besar dalam PKS Malaysia telah menjadi penghalang utama. Ini kerana PKS di Malaysia masih ketinggalan dalam cara mengintegrasikan analisis data besar dan kurang kesedaran yang kukuh untuk menggunakan analisis data besar yang berkesan kepada prestasi rantaian bekalan pintar. Walaupun beberapa Perusahaan Kecil dan Sederhana (PKS) Malaysia kini menyedari nilai penggunaan analisis data besar, tetapi sesetengah PKS tidak menggunakannya secara aktif. Oleh itu, penyelidikan ini adalah untuk mengkaji penerimaan analisis data besar ke atas prestasi rantaian bekalan pintar dan bertujuan untuk menentukan hubungan antara pembolehubah bersandar dan bebas (penggunaan penerimaan analisis data besar dan kesan ke atas prestasi rantaian bekalan pintar). Kajian ini dijalankan dengan menggunakan kaedah kuantitatif. Penyelidikan ini akan memberi tumpuan kepada pekerja yang bekerja di syarikat PKS yang berada dalam jawatan di peringkat eksekutif dan ke atas kerana mereka lebih bertanggungjawab dalam membuat keputusan. Data dikumpul daripada 120 responden melalui reka bentuk soal selidik menggunakan Borang Google dan platform dalam talian. Oleh itu, hasil daripada Analisis Regresif Berganda dan Pekali Korelasi Pearson menunjukkan kedua-dua pembolehubah dalam kajian ini mempunyai hubungan yang signifikan dan kuat bersama-sama. Kesimpulannya, melalui penyelidikan ini, diharapkan dapat memberi garis panduan kepada PKS untuk mereka mengetahui kriteria yang diperlukan untuk pekerja mengaplikasi dan menggunakan analisis data besar pada rantaian bekalan pintar dalam kerja mereka yang boleh menghasilkan cara yang berkesan dan cekap menjalankan perniagaan.

Kata Kunci: *Analitis Data Besar, Prestasi Rangkaian Bekalan Pintar, PKS.*

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LIST OF ABBREVIATIONS / SYMBOLS

BD	=	Big Data
BDA	=	Big Data Analytics
SC	=	Supply Chain
SSC	=	Smart Supply Chain
SSCP	=	Smart Supply Chain Performance
SMEs	=	Small and Medium Enterprises
RBV	=	Resources-Based View
SPSS	=	Statistical Package for Social Science
IV	=	Independent Variables
DV	=	Dependent Variables
H	=	Hypothesis
P	=	Personalization
IG	=	Information Governance
SCW	=	Supply Chain Warning
IL	=	Innovation and Learning

CHAPTER 1

INTRODUCTION

1.1 Introduction

The purpose of this chapter is to explore the acceptance of big data analytics factors in the smart supply chain performance among Malaysian Small and Medium-Sized Enterprises (SMEs). This chapter will also cover the research background, problem statement, research questions, research objectives, research scope, the significance of the study, limitations of the study, and operational definition.

1.2 Background of Study

Small and Medium Enterprises (SMEs) have played an increasingly important role in Malaysia. If compared to other large companies, SMEs were more resilient during the Asian Financial Crisis 1998-1999. The establishment of the National SME Development Council (NSDC) in 2004 was an important event in recognizing the importance of SMEs to the Malaysian economy. In addition, small and medium enterprises (SMEs) are a common type of business in Malaysia. 97.3 percent of the 662,939 businesses were small

and medium enterprises (SMEs). Then, Micro-enterprises account for more than three-quarters of all SME establishments, followed by 20% of small businesses and 3% of medium-sized businesses (Malaysia, 2014). Thus, Malaysia has a smaller number of medium-sized businesses and leaving a gap in the middle. Thus, the contribution of SMEs to output and employment, as well as productivity and performance in innovative activities, are often used in evaluating the performance.

Moreover, the result of the increase in the use of information technology nowadays which is growing rapidly by customers and the global economy has prompted firms to find innovative ways to produce and deliver value to consumers through supply chain management (SCM) (Seth, et al., 2006). In addition, consumer behavior, the industry environment, and market uncertainties have all influenced the way services in businesses operate. Therefore, companies will be more effective if they collaborate with other companies to improve their capabilities. With this, they can reduce costs and develop higher quality products by leveraging the added value in services for their customers.

Next, to improve the smart supply chain performance, firms have used Big Data Analytics of structured and unstructured data, as well as leveraging firm performance to optimize the business through innovation. As such, Big Data technology has become ingrained in business operations and strategies to anticipate and meet the needs of today's modern customers. In addition, responsiveness flexibility to customer service, and greater reliability of Big Data Analytics have enabled service organizations to improve the performance components of the smart supply chain.

Furthermore, the application of Big Data Analytics in logistics and supply chain operations is critical. This is because effective and fast supply chain decisions are essential to optimize its overall performance. Moreover, the bullwhip effect of supply chains that generate inefficiencies between distribution channels, can be solved by Big Data analysis. According to Gunasekaran, et al., (2017), Big Data's predictive analytics capabilities are not fully defined, which can limit its impact on supply chain performance. By implementing Big Data Analytics (BDA) techniques, many businesses have gained a

competitive advantage in the long run and are able to increase productivity in markets around the world to analyze and manage their data (Wamba, et al., 2017).

Lastly, to always remain competitive in the global market, companies must master their Big Data (BD). These companies should be proficient in managing, processing, and analyzing 5V data-related dimensions using Big Data Analytics (BDA). It is an emerging new technology as a comprehensive approach to generating relevant ideas to create long-term value to track the value of their performance, as well as generate an advantage in competitiveness (Wamba, et al., 2017).

1.3 Problem Statement

Many kinds of research have been done on the acceptance of big data analytics in the smart supply chain performance. Yudi Fernando, et al., (2018) stated that BDA will gives an impact on data security practices on service supply chain performance. Big Data Analytics has a strong correlation with a company's and able to manage the data security. Also, it gives positive impact to the service supply chain innovation and performance. Then, big data analytics has a wide range of applications in supply chain demand forecasting including customer behavior analysis and trend analysis applications, and research opportunities (Mahya Seyedan & Fereshteh Mafakheri, 2020). According to L Tamym, et al., (2020), supply chain management in industry 4.0 in big data can improved the data-driven decision-making including the improvement of business efficiency and effectiveness in a new way from the vast amount of data. Rakesh D. Raut (2021) stated that big data analytics gives challenges to Indian manufacturing supply chains. For example, the most significant barriers are the lack of top management support and financial support and the lack of skills and procedures.

It shows that big data analytics has a good impact on smart supply chain performance. L Tamym, et al., (2020) stated that BDA can improve data-driven decision-making in a new way from the large volume of data. It is a reality that big data can enhance end-to-end visibility in smart supply chain processes and develop more flexible and sustainable logistics/supply chain strategies. Therefore, the attempt to strengthen supply chain analytics, skills has become a key priority for all supply chains (Tiwari, Wee & Daryanto, 2018). In addition, organizations create a large amount of data for supply chain operations. Also, these many types of data can be collected in unstructured, structured, and semi structured formats from homogeneous or heterogeneous sources.

However, there is some research that gives the negative impact of big data analytics on the smart supply chain performance. According to N Chbaik, et al., (2022), the fourth industrial revolution led to a new era in the automation industry that transformed it into an autonomous decision-making machine. Thus, Big Data Analytics is also

described as one of the technical foundations of industry 4.0, as it affects all equipment and supply chain operations. With this, it can make activities more accessible and controllable by leveraging complex logistics models to make smart decisions in real-time quickly. So, the availability of data in both unstructured and structured formats has led to security and privacy issues derived from various sources related to large amounts of data. In addition, the existing solutions of the security are often insufficient to handle the complexity and diversity of Big Data. Thus, most businesses do not have a systematic approach to ensuring proper data access mechanisms (Kshetri, 2014). As a result, service organizations lack the data analysis tools and procedures that are needed to gain relevant insights to guide strategy, as well as in improving the business performance (Yiu, 2012, Manyika et al., 2013).

Moreover, Mahya Seyedan & Fereshteh Mafakheri (2020) stated that big data analysis provides demand forecasting, including customer behavior analysis in a smart supply chain performance. Therefore, due to this mixed method, the availability of real-time data and information, and the use of big data analytics may cause some behavioral difficulties for Malaysian SMEs. For example, low estimates and overly high estimates. Any variation from normal operating procedures is referred to as underestimation or overestimation in this context. This can lead to higher inventory costs and higher supply chain risks. Individuals may also worry about losing their jobs as a result of technological advances that are taking place. Thus, these behavioral difficulties may lead to the acceptance of statistically significant but irrelevant relationships in the future. So, due to cultural shift, the implementation of big data analytics causes difficulties in such behaviors (Arunachalam, et al., 2018).

In conclusion, it is important to make the data useable to achieve better operational performance in the value creation process to obtaining a competitive advantage in supply chain performance. Thus, this research is to find out the acceptance of big data analytics in the smart supply chain performance among Malaysian SMEs.

1.4 Research Question

A research question focuses on research, identifies the theory and approach, and guides all the study, analysis, and reporting phases. The following research question is being addressed in this study:

i. What is the acceptance factors of big data analytic among manufacturing firms?

ii. What is the relationship between big data analytics factors with smart supply chain performance among manufacturing firms?

iii. What is the most significant factors of big data analytics in the smart supply chain performance among manufacturing firms?

1.5 Research Objective

The research's objective was to determine the acceptance of big data analytics in the smart supply chain performance among Malaysian SMEs. The following are the research objectives:

i. To identify the acceptance of big data analytics factors that influence the smart supply chain performance among manufacturing firms.

ii. To measure the relationship between big data analytics factors with smart supply chain performance among manufacturing firms.

iii. To determine the most significant factors of big data analytics in the smart supply chain performance among manufacturing firms.

1.6 Scope of Research

The research scope is the distribution of questionnaires to analyze the acceptance of big data analytics factors on the smart supply chain performance among Malaysian SMEs. The targeted respondent will be focused on employees in Malaysian small and medium-sized (SMEs) businesses who hold executive-level or above positions. This study focuses on respondents in job positions since they are more accountable for decision-making.

This research will be utilizing the resource-based view (RBV) theory. This study discovered that the resource-based view (RBV) hypothesis has become the dominant paradigm in strategic planning. So, it can help us to understand how firms create efficient results. Moreover, it provides us with broad information on how efficient manufacturing is and how it is managed.

1.7 Significant of Study

1.7.1 Practical Contribution

This research helps companies better understand the acceptance of big data analytics in the smart supply chain performance among Malaysian SMEs. According to Abla Chaouni Benabdellah, et al., (2016) big data is high-value, high-volume, high-diversity, high-velocity, and high-precision data that requires new data processing techniques to enable deeper observations of decision-making and process automation that can speed of data collection or in transferring data. So, it is believed that this model will provide practitioners with clear instructions for continuing to implement effective execution. Using these big data analytics on smart supply chain performance helps companies in improving their business efficiency and effectiveness for company success. From here the benefit of using this platform is can improve their speed and visibility.

1.7.2 Theoretical Contribution

Resource-Based View (RBV) theory also acts as a theoretical foundation. This theory can sustain the management of a smart supply chain by focusing on big data analytic practices. Also, this research will be discussing on the connections between BDA and SSCP in Malaysian SMEs. The ability to alter big data analytics in a smart supply chain by monitoring performance. This study is intended to provide information and recommendations for SMEs. As a result, this research will help SMEs in identifying critical aspects that have been proven to either continue with the big data analytics process in the smart supply chain to strengthen organizational capabilities or discontinue the big data analytics process in the smart supply chain performance.

1.8 Limitation of Study

Their researcher faces various limitations and restrictions while conducting this research. For example, a restricted number of respondents, time limits for completing the data collection, and faced a limited geographic area to do this research. Moreover, the researcher also has some limitations on respondent honesty. Whether the respondent answered the questionnaire regarding their own experiences and knowledge or not. Thus, this research only focuses on SMEs Malaysian respondents, but the results are more focused on SME respondents from other industries too. Lastly, the most and one of the limitations that researchers face was the short time in collecting the data collection about the acceptance of big data analytics in the smart supply chain performance among Malaysian SMEs.

1.9 Operational Definition

A) Big Data Analytics (BDA)

This research will go over big data analytics (BDA). It has a lot of data to find the hidden patterns and other features. In today's technology, we can analyze data and get results faster. However, more traditional business intelligence solutions are less efficient and slower. The term "Big Data" has become popular in recent decades to describe the rapidly growing amount of data generated in various fields regularly. Thus, big data can be defined as a set of data that cannot be collected, managed, stored, or evaluated by an organization's IT systems over some time (Addo-Tenkorang R & Hello P.T., 2016). Big Data analysis has been able to assist businesses with strategic sourcing with supply chain network design and the design decisions in product development (Wang, et al., 2016). BDA is a new technology that takes a holistic approach to data processing, management, and analysis that enables these businesses to process, manage and analyze data-related dimensions. It can generate relevant ideas to monitor performance, create long-term value and create a competitive advantage (Wamba, et al., 2017). In addition, it can improve data-based decision-making and find new approaches to business using large data sets to increase their efficiency and effectiveness.

B) Smart Supply Chain Performance (SSCP)

This research will go over the smart supply chain performance. As traditional supply networks become more intelligent with more devices that improved so much in terms of increasing the capabilities and the intelligent of decision-making. Then, the new smart supply chain (SSC) offers previously unimagined cost-cutting and efficiency-improvement options (Lifang Wu, et al., 2016). Moreover, a "smart supply chain" is a new integrated business system that encompasses everything from local, isolated, and single-

company to supply chain-widely in smart implementations. Most of the features can be present in a smart supply chain, including technologies like the Internet of Things (IoT), smart machines, and intelligent infrastructure. In addition, their capabilities are so wide in interconnectivity in real-time communication, as well as across all supply chain stages with intelligent decision making, fully enabling data collection. Also, to better in serving customer with efficient and responsive processes (Lifang Wu, et al., 2016).

1.10 Chapter Summary

Finally, this section summarizes the description of the research analysis. The background of the study was focused on the current situation status of Small and Medium Enterprises (SMEs) in Malaysia by completing the research's background. There are also have statements on why this research is being conducted. In addition, three research questions and objectives have been presented in this chapter. The purpose of this research is to investigate the impact of big data analytics factors in the smart supply chain performance among Malaysian Small and Medium-sized Enterprises (SMEs). Moreover, there are various limitations to doing this study, such as a restricted number of respondents, time limits, and respondent honesty. The importance of this study is that it provides information on the acceptance of big data analytics in the smart supply chain performance among Malaysian SMEs. It will also assist the firm to understand the effects of producing their competitive advantage in their organization.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter looked at the issues, problems, concepts and points of view research that will be done in the field. Then, the literature review and appropriate theoretical model will be examined in this chapter. The definition and measurement of big data analytics (BDA) and smart supply chain performance (SSCP) will be covered in this chapter. Including the adoption on Malaysian SMEs will clearly state here. Aside from that, the correlations between variables like BDA and SSCP are well-defined. Also, the research hypothesis will be developed. Thus, a research framework will be utilized to describe the theory of the important variables and how they were connected together in this study.

2.2 Big Data Analytics (BDA)

Big data is a term used to describe a volume of data that is too large for traditional database software tools in acquiring, managing, storing and analyzing. In recent years, BDA techniques is a method to gain a competitive advantage for businesses. It has received a lot of attention from academics and decision makers out there (Dubey, et al., 2016). BDA from Industry 4.0 emphasized as a separate macro approach, but critical to the success of industry 4.0. Similarly, BDA is credited with advances in various aspects of Industry 4.0, including smart logistics, smart grids, smart factories, customer analytics, smart cities, smart homes, product life cycles, smart transportation systems, etc. (Chauhan et al., 2016). Also, Marshall, et al., (2015) emphasized the importance of BDA to organizations to address key problems and find new ideas. Market-leading companies invest in BDAs to gain a competitive advantage and outperform their competitive performance (Marshall, et al., 2015).

Product/data quality (Shen, et al., 2019), energy efficiency (Kumar, et al., 2018), supply planning (Arunachalam, et al., 2018), part defect detection (Abrahams, et al., 2015), supplier defect detection (Almohriet, al., 2019), demand forecasting (Blackburn, et al., 2015), and testing of new manufacturing processes are all advantages of BDA's capability for manufacturing (Tan, et al., 2015). Big data seeks learning patterns and resources to analyze additional data obtained from various sources for knowledge dissemination (De Camargo Fioriniet, al., 2018). The BDA system can be used to develop sustainable policies as well as knowledge. So, the performance of SME projects can be drastically altered by BDA -based production setups. BDA is a new strategy for SME growth that relies on analytics tools to help them make better decisions about the market and the needs of their customers. This will also help them in increasing their market competitiveness (Sen, et al., 2016). BD is currently a term widely used to represent the expansion and availability of structured and unstructured data as well as important to business and society. So, more information can lead to more accurate analysis that can

lead to more confidence in decision making. Then, better judgment can lead to increased operational efficiency, cost savings, and risk reduction for SMEs.

2.3 Smart Supply Chain Performance (SSCP)

The new SSC promises tremendous prospects for cost reduction and productivity improvements as traditional SC become increasingly intelligent with more products embedded with sensors and greater communication, intelligent decision making, and automation capabilities. The goals are to investigate the existing state of SSC in management as well as the remaining difficulties. Following this trend, smart supply chain is as a new interconnected business system that encompasses everything from local, isolated and single-company applications to supply chain-wide smart implementations. In addition, most of the features would be present in a smart supply chain, including the technologies like the Internet of Things (IoT), smart machines, and intelligent infrastructure. It has capabilities like interconnectivity in the real-time communication across all supply chain stages with fully enabling data collection and intelligent decision making. Also, be an efficient and effective processes to better in deal with customers (Lifang Wu et al., 2015). Figure 2.1shows the architecture of the supervision system equipment in the SSC from Nabil Chbaik. et al., (2022).

"Getting the right item in the right amount at the right time with the right place for the best price in the perfect position to the right customer" is what supply chain management (SCM) is all about (Mallik, 2010). However, most genuine SC are known for having several mismatch problems and supply-demand, such as overstocking, stockouts, and delivery delays. It has long been become an attractive research topic in the business management literature due to the complexity, uncertainty, and other aspects involved (Wong, et al., 2012).Because the value of information is such an important topic when dealing with demand unpredictability, there has been a lot of research that suggests that sharing information is a major supply chain performance motivator (Ali, et al., 2019).

From this, a company can enable efficient material and information flows by taking advantage of the knowledge available and sharing it with other stakeholders in the supply chain to improve the coordination.

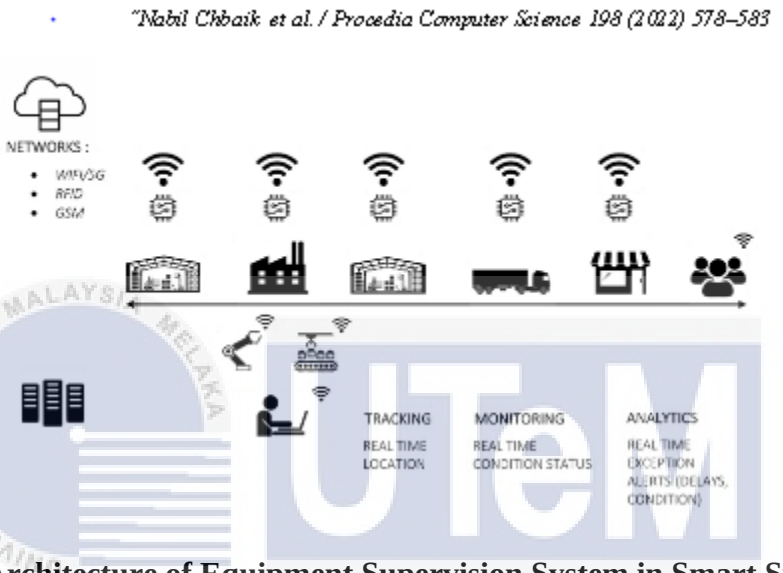


Figure 2.1: Architecture of Equipment Supervision System in Smart Supply Chain

(Source: Nabil Chbaik, et al., 2022)

2.4 Small and Medium Enterprises (SMEs)

SME's (Small and Medium Enterprises) are the backbone of any emerging country's economy. Aside from that, SMEs are companies or businesses that are linked to people' entrepreneurial activity. Because of different countries have varied criteria for designating SMEs, there are several definitions and meanings of SMEs. They are difficult to define. In addition, various criteria have been utilized to define criteria for SMEs, particularly in terms of countries, sizes, and sectors. Furthermore, SMEs have been defined in numerous nations in terms of the number of employees, management structure, and capital investment restriction. SMEs are often referred to as the "informal sector," which

is thought to include a wide range of economic activities. In Malaysia, the definition of SME is a manufacturing company with less than 200 full-time employees and a sales turnover of less than RM50 million. SMEs are critical to the development and expansion of the employment and business sectors. In general, the SMEs sector is divided into three categories, which are micro, small, and medium businesses. The micro SMEs are the smallest of the three categories.

Furthermore, SMEs are the most common type of business in Malaysia. Small businesses are frequently judged on their performance. Examining its importance to output and employment, as well as its productivity and performance in innovative activity. For example, data is regarded as a company's most valuable asset in today's environment, and the use of BD is not limited to global corporations. Then, the enterprises from both large corporations to small and medium-sized businesses (SMEs), are looking for innovative ways to use the data. To make rapid and precise decisions, SMEs may now take use of the massive amount of data available to improve their business's functionality. According to several scholars, big data is a paradigm shift for improving corporate processes, hence there is a need for it.

2.5 Acceptance of BDA on SSC

In the context of Industry 4.0, BDA may help improve every interaction, including the SSC strategy, which includes sensors, smart products, radio-frequency identification (RFID), and so on. Because some supply chain operations generate data. So, BDA is clearly the most important tool for gaining a competitive edge in the gains in innovation, competition, and productivity to discover that market structure had an impact on BDA adoption (Wang, et al., 2016). Then, information sharing in the supply chain benefits both large companies and small businesses, as well as SMEs performance (Chen, et al., 2019). Thus, the demand and procurement management are heavily reliant on data analytics (Inamdar, et al., 2020).

Besides, by successfully controlling the flow of suppliers, the SSC idea conclusively performs the overall logistic chain from customer to client, regardless of their location. These controls are concerned with both cost savings and quality requirements.

On the other hand, the data security and data reliability are remains important and concerns in the integration of smart technology into the supply chain. These issues coexist with procedural infrastructure issues, policy complexity and cost volatility. As a result, it will achieve a critical logistics flows at all state of transparency, in order to assure the fast and secure movement of money, product and information (Nabil Chbaik, et al., 2022).

The goal for supply chain management has always wanted to be cheaper, faster, and better for their performance. From there, supply chains are getting increasingly uncertain, complex, costly and vulnerable. Also, supply networks must become much smarter to deal effectively with the mounting difficulties. Furthermore, the new update of the supply chain seeks to create a large-scale intelligent infrastructure for trying to merge data, information, products, and business processes together. It will take full advantage of advancements in areas such as semiconductor, computer science, and other engineering technologies. So, it's no surprise that there are numerous instances of SSC applications, such as smart transportation management systems and smart factories.

2.6 The Impact of BDA on SSCP

2.6.1 Personalization (P)

In today's highly competitive marketplaces, more and more businesses are realizing that their ability to meet customers' increasingly individualized needs in a timely manner will decide their overall viability. The product cycle in an intelligent supply chain can be integrate to the whole of value chain. Then customers will be treated as integral components of the supply chain system. Thus, the intelligent system, which is based on Industry 4.0, will connect with clients throughout their lives and classify them based on

numerous interactions. After that, provide them with dependable and individualized service options (Witkowski).

In addition, the degree to which consumer needs are addressed and measured by the customization indicator. So, the product and service personalization can give customer satisfaction in the three second-layer indicators that make up the personalization. Personalization of products is a horizontal extension of traditional products. It assesses whether the smart supply chain can meet customers' basic demands while also providing them with distinctive products. Thus, the term "service personalization" refers to the process of keeping consumers through the analysis of customer service data. This is because customer satisfaction relates to how satisfied customers are at each stage of the smart supply chain performances (Yongping Xie, et al., 2020).

2.6.2 Information Governance (IG)

An intelligent smart supply chain's primary attribute is "intelligence." An intelligent supply chain needs to make sure that all players produce high-quality processes and data in the SC process in order to do the filtering, analysis, information collection, and transfer across the entire process. In this instance, a strategy is required to increase the information value while reducing the effects associated with its generation and distribution along the supply chain. Other than that, information from governance encompasses transaction management, rule creation, information life cycle management, and information security of data flow management in an intelligent supply chain. The purpose of governance information is to assure the reliability information security and reliability. This is to make information exchange and transfer quicker and more convenient (Yongping Xie, et al., 2020).

According to Kooper, et al., (2011), the core of an intelligent supply chain is based on information governance. Then, information controllability, information sharing, and information sensitivity are the three second-layer indicators that make up this indicator.

The responsibility to maintain the data safe and reliable is referred to as information controllability. Next, the amount to which critical information is accessible to supply chain members is referred to as information sharing. The information sharing among supply chain partners is critical for enhancing the smart supply chain performance. In the process of supply chain management, the information of sensitivity refers to the reliability of information exchange and the ease of information transfer.

2.6.3 Supply Chain Warning (SCW)

An intelligent supply chain places a greater emphasis on early problem detection and resolution. Then, it will be able to reduce risks and expenses across the entire process. As a result, an intelligent supply chain allows SC stakeholders to acquire real-time production, sales, and inventory information based on the demands of upstream and downstream businesses. Therefore, a simulation model is used by an intelligent supply chain to run it through the supply chain performance system for any individual order. This is done to quickly identify the system process that initiates the virtual ordering process first. This virtual procedure enables the system to detect a supply chain disruption and issue an early warning signal. The supply chain warning strategy ensures that supply chain processes are stable and also that intelligent manufacturing is supported. (Yongping Xie, et al., 2020).

Furthermore, in an intelligent supply chain, a supply chain warning is present. Every step in the supply chain requires early notice. The supply chain warning system then includes three secondary indicators, which are controlled cost, risk management, and quality management. Risk management is a supply chain management process in which businesses adopt effective strategies to reduce hazards. A controlled cost is the ability to set a predetermined target for the cost of each supply chain. Finally, quality management refers to management actions like command and control that are used to achieve quality goals.

2.6.4 Innovation and Learning (IL)

For a competitive advantage, innovation and learning provide value to a product or service. Next, the industry 4.0's technology wave enables organizations to thrive and grow in a never-ending learning environment. The ability of members to innovate and learn is used to evaluate the intelligent supply chain's innovation and learning potential. As a result, the rate of adoption of new technologies of new services, and this innovation and learning capability will enhance the effectiveness and minimize the overall cost of information transmission between each supply chain link, as well as make a contribution to the performance of the other aspects of intelligent supply chain.

Moreover, innovation and learning play a vital role to drive the intelligent supply chains. the It consists of three secondary indicators, which are the members' innovation ability, the new technology adoption rate, and the new service development intensity. The ability of supply chain members is to continuously develop and explore a new product, processes, and services in order to respond the changing needs quickly is referred to as an innovation ability. Then there's the adoption rate of new technology, which relates to how quickly new technologies are accepted, integrated, and used in the supply chain. Lastly, the intensity with which member firms in the supply chain efficiently blend the information resources and consumer engagement to increase the service quality for customer needs is referred to as the development intensity of new services.

2.7 Theoretical Framework

The researcher focuses as a reference on resources-based view (RBV). Figure 2.2 shows the theoretical model of the research that is obtained from Yongping Xie, et al., (2020). The intelligent smart supply chain performance measurement can be classified into the following indicators, namely, personalization, information governance, supply chain warning, and innovation and learning. Besides, the framework below also shows the impact of smart supply chain performance (SSCP) on big data analytics (BDA) acceptance.

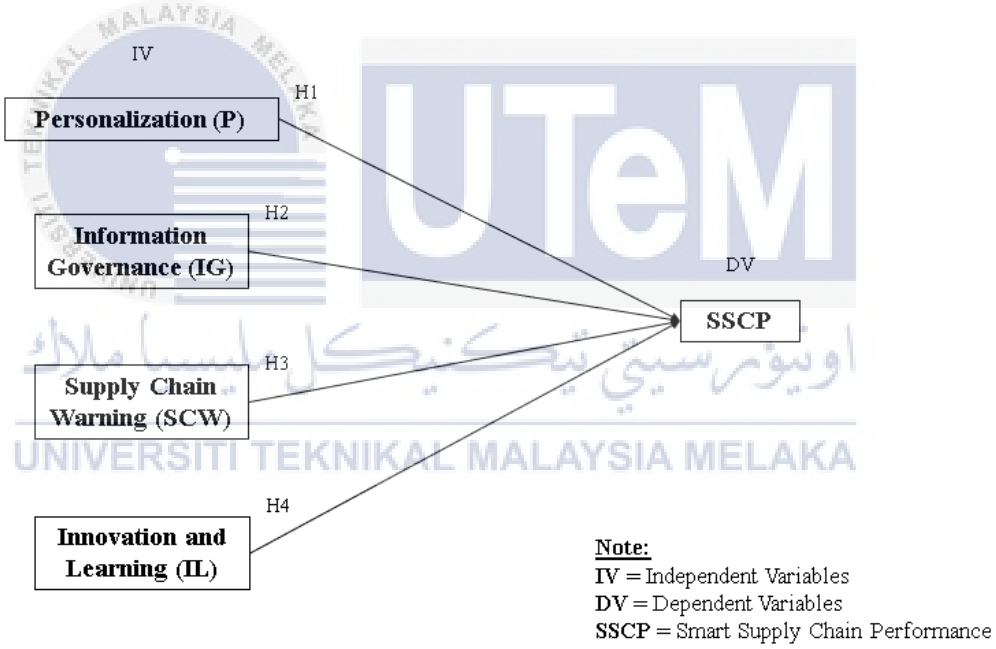


Figure 2.2: Theoretical Framework

(Source: Yongping Xie, et al., 2020)

2.8 Conceptual Framework

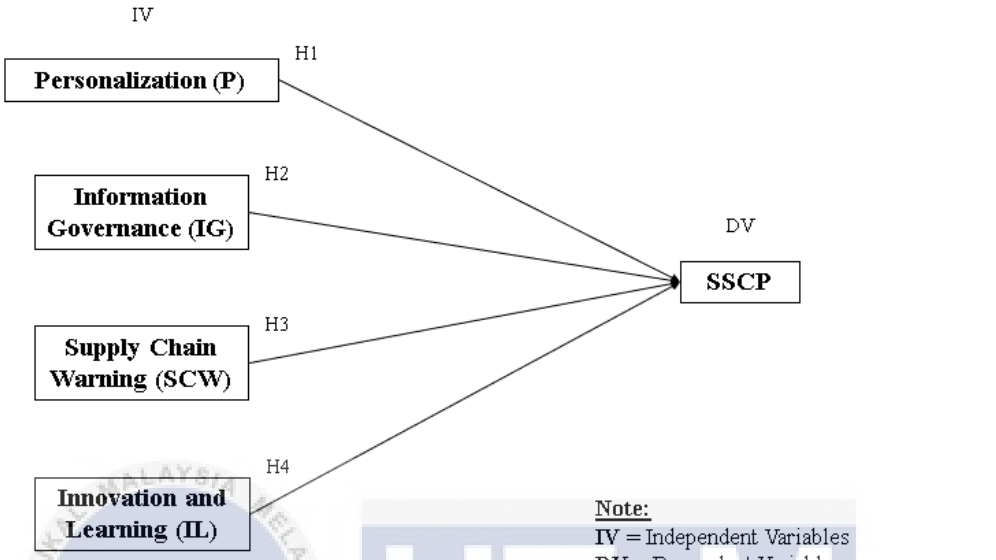


Figure 2.3: Conceptual Framework

(Adopted from: Yongping Xie, et al., 2020)

Figure 2.3 shows the conceptual model of the research. Based on indicator framework from Yongping Xie, et al., (2020). The framework shows the relationship between dependent and independent variables, which are the acceptance of big data analytics (BDA) and smart supply chain (SSCP) as a dependent variable, while the independent variables are between personalization, information governance, supply chain warning, and innovation and learning. Therefore, the aim of the research is to study the acceptance of big data analytics factors in the smart supply chain performance among Malaysian SMEs.

2.9 Hypothesis Testing

Based on the research framework in Figure 2.2, there were 4 hypothesis which could be constructed according to the proposed framework. The hypothesis is:

Personalization (P)

H_1: There is a significant relationship between personalization and smart supply chain performance.

Information Governance (IG)

H_2: There is a significant relationship between information governance and smart supply chain performance.

Supply Chain Warning (SCW)

H_3: There is a significant relationship between supply chain warning and smart supply chain performance.

Innovation and Learning (IL)

H_4: There is a significant relationship between innovation and learning and smart supply chain performance.

2.10 Chapter Summary

The literature reviews that are being covered in this research topic are about the acceptance of big data analytics in the smart supply chain performance among Malaysian SMEs. Furthermore, in this chapter, the researcher examined the definition of BDA, SSCP, SME and adoption of BDA on SSCP, all of which are based on previous research. Also, the researcher received the studied conceptual framework from Yongping Xie, et al., (2020), but modified it to suit the research variables, which included four independent variables and one dependent variable. Both variables have been covered in the research framework. Lastly, the researcher developed the hypothesis testing to utilize the relationship between the independent variables and the dependent variables.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

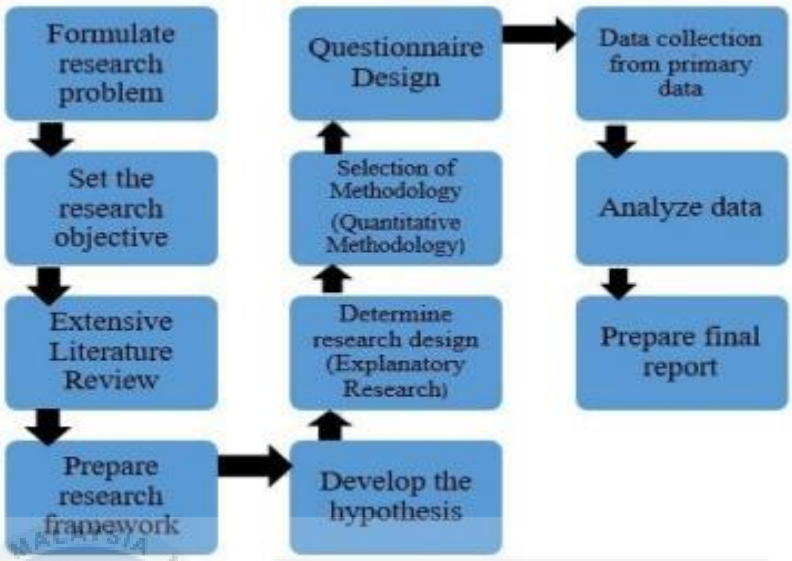
The methodology discussed in this chapter was mainly focused on the research technique used. In addition, the researcher highlighted the data collection approach used in order to meet the research goal. For example, researchers gather data from primary, secondary, and information sources, as well as data relevant to the study. Aside from that, the research design, methodological choices, data sources, and research strategy were all explored in this chapter in order to fulfil the research goal. The data analysis tool is used to use the link between dependent and independent variables in order to improve the coherence and accuracy of the research.

3.2 Research Design

This research study deliberates the relationship between big data analytics and smart supply chain performance in SMEs. The framework for collecting and analyzing the data to fulfill the research objectives and satisfy the research goals was collect from the research design, which provided a logical justification for selecting the data sources, data collection processes, and data analysis methodologies (Saunders, et al., 2016). The importance of research design is that it allows for a smooth transition between various methods approaches. Furthermore, it is crucial and the work resulting is as competent as feasible, in term of providing a complete information with the least amount of effort, time, and money (Innam, 2016). In short, it is a strategy for carrying out the proposed research. There are four types of research designs, such as exploratory, descriptive, explanatory, and evaluative (Saunders, et al., 2016). However, in this study, the researcher has selected descriptive research as the research design. Lastly, this design shows the primary and secondary data that were examined from the present and previous studies.

3.2.1 Descriptive Research

The descriptive research design was important to examine about the systematically information to describes the situation, population and phenomenon of this research study. It can be considered as a concept of observing and evaluating the function, item and behavior without affecting it in any manner. As the name implies, work is done on descriptive research to answer a series of questions in order to address a new concern that have not been addressed previously. The major goal of these investigations is to formulate a question or establish operational hypotheses for a larger investigation. In addition, descriptive research can assist researchers in observing the relation to acquire a better understanding of the study. The following Figures 3.1 shows the stages of research process.



Figures 3.1 Stages of Research Process

3.3 Methodology Choice

Methodology choices may be classified into three types, which were quantitative methods, qualitative methods, and mixed methods. Various types of the research studies need to use the appropriate methods of their research. In this study, the researcher believes that the quantitative method was the suitable method that can be used to carry out the data collection compare with the other two method. Furthermore, quantitative methods may be used to the study to be link between the acceptance of BDA factors in the SSCP of Malaysian SMEs. Then, the data will be gathered by the researcher using a questionnaire.

3.3.1 Quantitative Research Design

A quantitative method was suggested by Bayley, et al., (2015) because it includes viewpoints such as the sample test, hypothesis tests, and statistics that are important for data collecting. Quantitative research is also the process of collecting and evaluating numerical data in order to investigate the phenomena. Furthermore, according to Saunders, et al., (2016), quantitative data was used in conjunction with a deductive strategy that focused on validating the hypothesis with data. It can be used to find the patterns and averages, make forecasts, test for coincidences, and extrapolate results to a bigger group (Pritha Bhandari, 2020). The quantitative research will be used by the researcher to investigate the relationship between the acceptance of BDA factors in the SSCP of Malaysian SMEs. Then, to prove that this research study was purely quantitative, the researcher was used the reliable questionnaire to collect the primary data.

3.4 Data Sources

The data collection methods were centered on obtaining the information required to achieve the objectives. The platforms for collecting primary and secondary data are known as data sources. This is where it can group the study data together through statistics, observations, and figures. In this study, both data sources have been used by researchers to conduct the research.

3.4.1 Primary Data

According to Kassu Jilchs, (2019), specified primary data are more reliable and have a higher level of confidence in the decision-making process, with reliable analysis being directly linked to event occurrence. The material a researcher obtains for a specific study aim is referred to as primary data. As a result, primary data play a significant part in this study because of its relevance. Primary sources, such as surveys, experiments, questionnaires, personal interviews, or observations that are not filtered by the second party, make up the original work (Saunders, et.al., 2016). The method for this study can then be acquired by using the online questionnaire approach to distribute questionnaires to each respondent one by one. Then, an online questionnaire can be constructed using a seven-item likert scale. Each argument was graded on a five-point scale, with 1 indicating "strongly disagree" and 7 indicating "strongly agree." The Linkert-Scale is shown below:

Table 3.1: Linkert-Scale Survey

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
1	2	3	4	5	6	7

3.4.2 Secondary Data

Most researchers have always relied on secondary data to gather information for their studies. Secondary data is inquiring about information that has already been used in previous literature. They can be assessed for more or specific data, clarity, or inference (Saunders, et. Al., 2016). According to Johnston (2017), secondary data was material obtained by someone else for the researchers' purposes. In addition, Saunders, et al., (2016) describes that journal, articles, internal documents, novels, and government publications online is a secondary data source. The researchers identified the data related to research in this study through a famous strategy of collecting the secondary data, which is google scholars.

The greatest technique to convey background and historical information about a specific topic is to use secondary data to expose other people's points of view, opinions, and conclusions. The researcher analyzed data and knowledge related to the research issue by reading articles papers and journals. To meet the research objectives purpose, the researcher collected secondary data from Google Scholar web page and library databases such as Emerald Insight and Science Direct to support the research.

3.5 Location of Research

Malaysia is a country in southern Asia that is located near the island of Borneo and is part of the Malay Peninsula. As a result, the investigation was carried out in Malaysia, since Malaysia has a large number of Small and Medium-sized Enterprises (SMEs). The location of this research will be particular on SMEs Malaysia firm whose employees are at the executive level or higher.

3.6 Research Strategy

The plan to respond to the investigator's query was referred to as a research strategy. The research strategy is significant because it allows researchers to plan the flow and structure of their studies. The research strategy determines the overall direction of the study, as well as the method by which it is carried out. Research strategies are included experimentation, ethnography, archival research, action research, survey, grounded theory, case study, and narrative inquiry (Saunders, et al., 2016). The research technique discovered that the research strategy is the research main introduction (Bryman, 2018).

According to Saunders, et al. (2015), the proper research method must be decided based on research questions and aims at the tendency of the study's information. Thus, it is accessible resources, along with logical support for research, as well as the duration of the research. Then, examine and apply the key to the data. According to Yin (2016), a research method should be determined based on three factors, which are the degree of control on real-life behavior occurrences, and the amount to which the researchers are focused on current or historical events. Some of the most prevalent research methodologies utilized in trade and management are theory, study, and participatory inquiry (Collis & Hussey, 2015).

3.6.1 Survey Strategy

In this study, the researcher has selected to use the survey strategy as the research strategy. The survey strategy enables the researcher to obtain quantitative data by examining descriptive and constructive statistics, as well as inferencing statistics, in order to collect quantitative data and establish a possible relationship between variables (Saunders, et al., 2016). The survey method was to collect data from an interview sample

via a response from a distribution form. A survey approach can be used to demonstrate and implement human behavior (Ponto, 2015).

In order to acquire quantitative data, the questionnaire is used in the survey strategy. Questionnaires are quantitative data that allow researchers to collect a large amount of information and data from a large number of people. The survey strategy is appropriate for the researcher to use in order to collect data and analyze the acceptance of BDA factors in the SSCP among Malaysian SMEs. Thus, a deductive technique involving an online Questionnaire is commonly coupled with a survey tactic. The web questionnaire portrays a Google Form as a survey form that can be accessed, filled out, and submitted online by any respondent. In this situation, the survey approach proved to be an effective way for the investigator to examine the relationship between data collecting and analysis in this study.

3.6.2 Questionnaire Design

In order to collect data for this study, a questionnaire will be given to personnel who are working in positions of executive level and above in manufacturing firms. The researcher will create a questionnaire to gauge the acceptance of big data analytics in the smart supply chain performance. The survey study's questionnaire design is divided into three sections. The questions on this page are set up in a close ended multiple choices format.

The questionnaire is separated into three sections (Section A, Section B and Section C). The first section of the questionnaire focused on the demographic profile of the respondent, such as ownership, job tittle, department, and working experiences. The purpose of the first section was to determine the general characteristics of respondents. The second section focuses on the acceptance of the big data analytics (BDA). The final section of the questionnaire focused on the impact of smart supply chain performance among Malaysian SMEs.

The Linkert Scale was represented by 1: “Strongly disagree”, 2: “Disagree”, 3: “Somewhat disagree”, 4: “Neutral”, 5: “Somewhat agree”, 6: “Agree” and 7: “Strongly agree”. The table below shows the research design questionnaire. The Linkert-Scale is shown in Table 3.1.

Table 3.2: Questionnaire Design

SECTION	CONTENT
A	Demographic Background • Ownership • Job Tittle • Department • Working Experiences
B	Assessment of Independent Variables • The acceptance of Big Data Analytics (BDA) (personalization, information governance, supply chain warning, and innovation and learning).
C	Assessment of Dependent Variables • The impact of Smart Supply Chain Performance (SSCP) among Malaysian SMEs.

3.7 Pilot Testing

According to Eldridge, et al., (2016), the objective of a pilot testing is most commonly emphasized in research. The progress assumed in the construction of a future extensive test, venture, or development. A pilot study is conducted to replicate all of the procedures of the main study and to validate the feasibility of the study by evaluating the participants' inclusion and exclusion criteria, intervention preparation, storage and testing of the instruments used for measurements in the study, and researcher and research assistant training (Benger,, et al., 2016).

According to Dikko, (2016), using a questionnaire in a pilot context can help with interpretation of the questions and reduce the risk of misunderstandings in the research agreement. The pilot test may uncover inaccuracies and flaws in the questionnaire and allowing it to be revised before being disseminated to respondents. In order to construct a final survey questionnaire, the pilot test would collect recommendations and information from respondents. A minimum of 20 people had been recruited for the pilot test due to time constraints.

3.8 Sampling Design

A sampling design is a method of making a decision that is representative of the entire population by using a subset of the population. The sampling process is used to define the research's target population, determine sample size and sampling strategy, and select the best method (Crossman, 2019). For this investigation, sampling probability was used as the sampling design. The sampling population, sampling technique, and sampling size are all examples of sampling design approaches.

3.8.1 Sampling Population

The study's target population is Malaysian small and medium-sized enterprises. The individuals who work in Malaysian SMEs and are in executive-level or higher positions are included in the sampling frame. Moreover, small and medium-sized businesses have made up 98.5 percent of all businesses in Malaysia (907065). (SME Cooperate Malaysia, 2020).

3.8.2 Sampling Technique

Probability sampling and non-probability sampling are the two types of sampling procedures. The researcher will utilize probability sampling as the sample technique in this investigation. In order to answer the research question, the researcher will use probability sampling, which requires the researcher to make an assumption based on the sample. There are some number of sampling probability approaches, which are cluster sampling, multi stage sampling, stratified random sampling, simple random sampling and systematic random sampling. The most appropriate for this study is simple random sampling. This has been selected since it is easy to identify the possibility of the sample.

Furthermore, simple random sampling, which is incorporated in the probability sample, is used to keep the target population under control. According to Mark Saunders, et al., (2016), simple random sampling is a technique which involves a computer or a random number table to select a sample from a target population at random. An online random number generator could be used to make sample selection easier.

3.8.3 Sample Size

Krejcie and Morgan (1970) choose the sample size for this study. Small and medium-sized businesses have made up to 97 percent of all businesses in Malaysia based on Department of Statistics, Malaysia (DOSM). A total of 384 sample sizes were utilized according to the sample size chart from Krejcie and Morgan (1970), with a population size of 98,190 to responding the questionnaire survey in Johor. The sample size was kept small due to time restrictions and the need for extremely precise data.

Note

N is population size.

S is sample size.

N	*S*	*N*	*S*	*N*	*S*
10	10	220	140	1200	291
15	14	230	144	1300	297
20	19	240	148	1400	302
25	24	250	152	1500	306
30	28	260	155	1600	310
35	32	270	159	1700	313
40	36	280	162	1800	317
45	40	290	165	1900	320
50	44	300	169	2000	322
55	48	320	175	2200	327
60	52	340	181	2400	331
65	56	360	186	2600	335
70	59	380	191	2800	338
75	63	400	196	3000	341
80	66	420	201	3500	346
85	70	440	205	4000	351
90	73	460	210	4500	354
95	76	480	214	5000	357
100	80	500	217	6000	361
110	86	550	226	7000	364
120	92	600	234	8000	367
130	97	650	242	9000	368
140	103	700	248	10000	370
150	108	750	254	15000	375
160	113	800	260	20000	377
170	118	850	265	30000	379
180	123	900	269	40000	380
190	127	950	274	50000	381
200	132	1000	278	75000	382
210	136	1100	285	1000000	384

Figures 3.2: Sample Size for Different Sizes and Population

(Source: Krejcie & Morgan, 1970)

3.9 Reliability

According to Mark Saunders, et al., (2016), reliability is defined as the ability to provide the same results as earlier research, and the research is regarded reliable if it does this. The researcher went on to define dependability as the consistency with which the same result could be attained using the same data. The researcher will calculate dependability using Cronbach's Alpha.

Cronbach's Alpha is a statistic that determines whether or not the test and scales used in a study are acceptable. Cronbach's Alpha is composed of an alpha coefficient that ranges from 0 to 1. The Coefficient Range and Strength of Association will be displayed using Cronbach's Alpha. It is acceptable if the Cronbach's Alpha is greater than 0.7. It is deemed good if the Cronbach's Alpha is greater than 0.8, and exceptional if it is 0.9 or higher. Cronbach's Alpha less than 0.6 is deemed poor, but less than 0.5 is considered intolerable.

Table 3.3: Cronbach's Alpha Coefficient Range and Strength of Association

(Source: Saunders, Lewis & Thornhill, 2016)

Cronbach's Alpha Coefficient Range	Strength of Association
$\alpha \geq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

3.10 Validity

In research, questionnaire design is critical because it has an impact on the validity and reliability of the data collected. To avoid eliciting erroneous responses or obtaining data later, the questionnaire design must be abstract. To improve the quality of the information obtained, exploration can use a variety of tactics. By debating the solution in numerous areas, the legitimacy or validity of data could be improved (Mark Saunders, et al., 2016). Inside legitimacy, outward legitimacy, and develop legitimacy are the three types of legitimacy.

3.11 Data Analysis Method

Data analysis is a method of focusing on raw data collection methods and procedures, mining for insights related to primary business objectives, and digging into this information to translate measurements, statistics, and figures into improvement initiatives (Sandra Durcevic, 2020). The researcher will evaluate the data after collecting it using the Statistical Package for Social Sciences (SPSS) software version 20.0 as a statistical tool. SPSS is used by the researcher to analyze and explain many types of data.

This program can handle enormous volumes of data effectively, allowing for the evaluation of data collection and inquiry for quantitative research. SPSS can also grasp a large amount of data and make data collecting and organization easier with a variety of internal administration impacts. SPSS, for example, will use its regular relapse to guarantee that the data collected is consistent, correct, and genuine. When conducting the survey, it will also put supposition to the test. Descriptive analysis, Pearson's correlation coefficient, and multiple regression analysis are among the analysis approaches used.

3.11.1 Descriptive Analysis

The purpose of descriptive analysis is to determine the core trend and dispersion by numerically describing and analyzing variables (Saunders, et al., 2016). The demographics of targeted respondents in both frequency and percentage terms were determined using descriptive analysis tools in this study. To put it another way, descriptive analysis is also used to classify and split people into groups. Every descriptive statistic makes a large amount of data easier to comprehend. The researcher will utilize descriptive analysis to distinguish between respondents who work in SME businesses based on ownership, job tittle, department, and working experiences. The most well-known types of descriptive statistics are center measures such as mode, mean and median, which are used at practically all levels of mathematics and statistics. This could be expressed using terminology like mode, mean, median, and standard deviation to describe independent and dependent variables.

3.11.2 Pearson's Correlation Coefficient

In SME Malaysia, Pearson's Correlation Coefficient (r) is used to assess the strength of the link between the independent and dependent variables. In this study, Pearson's Correlation Coefficient will be utilized to examine whether the relationship between the dependent variables and independent variable of smart supply chain performance is significant. Pearson's correlation coefficient has a value between -1 and +1, indicating perfect negative and perfect positive correlations, respectively, according to Saunders, et al., (2016), however a value of 0 shows no relationship correlation. If the Pearson's correlation coefficient is negative, there is a negative relationship between the independent and dependent variables, which means that when one variable rises, the result of the other declines. If the Pearson correlation coefficient is positive, there is a positive

relationship between the independent and dependent variables, implying that as one rises, the other rises as well.

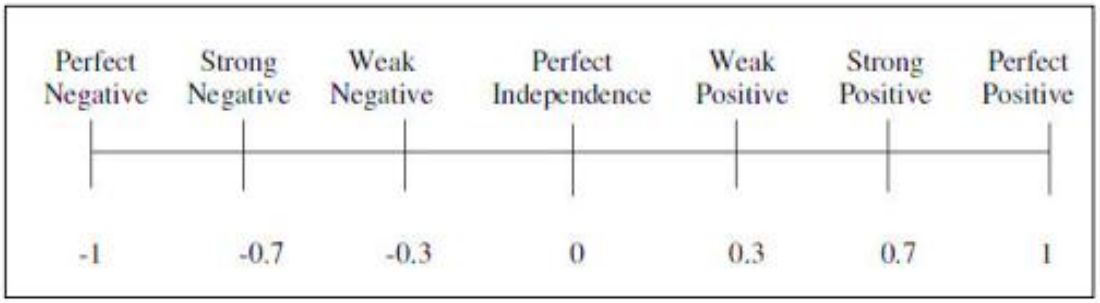


Figure 3.3: Pearson's Correlation Coefficients

Sources: (Saunders, Lewis & Thornill, 2016)

3.11.3 Multiple Regression Analysis

Multiple Regression Analysis is a useful tool for statisticians and researchers. The impact intensity and cause will be investigated in this study, as well as two or more linkages between an independent and an independent variable (Saunders, et al., 2016). Using multiple regression analysis in this study, it will be feasible to establish which independent variables, such as the impact of big data analytics that have the greatest impact on smart supply chain performance. The following is an example of a multiple regression formula:

Equation: $Y = \alpha + \beta 1\ (X1) + \beta 2(X2) + \beta 3(X3)$

Y stands for the dependent variable, which is the acceptance of big data analytics factors in the smart chain supply chain performance in Malaysian SMEs, is the constant value/other effects, and is the coefficient. The independent variables represented by the letters X1, X2, and X3. R is the coefficient of correlation and the square root of R-squared in the multiple regression analysis model. The variance in the dependent variable that can be explained later by independent variables is represented by R square.

3.12 Time Horizon

The time horizon, according to Saunders, et al. (2016), is the time required by researcher to complete the investigation. The cross-sectional time horizon and the longitudinal time horizon are two different methods. Due to the limited time available for data analysis and the requirement needed to complete this research as soon as possible, the researcher will perform this study as a cross-sectional study. According to Saunders, et al., (2016), most research projects in academic courses are essentially time-constrained. A cross-sectional study is one in which data is examined at a single point in time. Then, the type of data collected and the hypothesis to be investigated are used to classify this inquiry. In this case, the researcher used short-term research and respondents will receive the questionnaire between July until September 2022. Then, the investigation will be finished in October 2022, and the results of the collected data will be presented in November 2022.

3.13 Chapter Summary

In this chapter, the researcher demonstrated the methodology for gathering data and information about the variables. It also takes a look at the methods that were employed to answer the research questions. The researcher will use an explanatory research design and a quantitative technique for this study assignment. Both primary and secondary data sources were used in this investigation. To collect responses for this study, the survey approach and questionnaire design will be used as the research strategy. Responses from respondents who work in manufacturing firms will be collected via a digital questionnaire that called as Google Form. The researcher chose Malaysia as the site of the investigation because of the large number of SMEs in these areas. In this study, the researcher will use cross-sectional sample design and pilot testing. The researcher will examine the data by utilizing the Descriptive Analysis, Multiple Regression Analysis, and Pearson's Correlation in the data analysis phase using the Statistical Package for Social Science (SPSS). In the data analysis part, the coefficient will also be described. The numerous procedures that will be used to verify the research study's dependability can be trusted.

CHAPTER 4

DATA ANALYSIS AND DISCUSSION

4.1 Introduction

This chapter will discuss the results of questionnaire from respondent to the titled which is the acceptance of big data analytics factors in the smart supply chain performance among Malaysian Small and Medium-Sized Enterprises (SMEs) had found out by the researcher. Then, SPSS software will use to coded and key in all the result that received from the questionnaires. The data will be analyzed and interpreted. In this case, the pilot test will begin followed by descriptive analysis, Pearson's correlation coefficient, and multiple regression analysis. All the question of the questionnaire had been ensured to responded by all the respondents without any blanks to the questionnaire. All the data collection will be analyzed in the table form by Windows software version SPSS 27.0.

4.2 Pilot Test

Before beginning the study of distributing questionnaires to a large group, a pilot test with a small sample of respondents is conducted to validate the research topic. Pilot testing is a type of software testing that verifies a system component or the entire system in real-time. A pilot test encourages decision-making and thus serves as a small-scale experiment or collection of observations conducted to determine how and when a full-scale project should be launched (Collins English Dictionary, 2014). The pilot test's purpose is to demonstrate the questionnaire's dependability (Saunders et al., 2016).

It is necessary to verify that the respondents understand and are not confused by the questions asked in the questionnaire. To conduct the pilot test, 20 respondents were recruited using a survey questionnaire. The researcher used SPSS 27.0 to test the reliability of the data collected, and the Cronbach's Alpha technique was applied to calculate the reliability. According to Saunders et al. (2016), a Cronbach's Alpha score of 0.7 or above is considered acceptable. While it is good if the Cronbach's Alpha is more than 0.8, values of 0.9 and higher are considered excellent.

Table 4.1: Reliability Statistics

(Sources: SPSS Output)

Case Processing Summary

		N	%
Cases	**Valid**	20	100.0
	Excluded[a]	0	.0
	Total	20	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
0.883	25

According to Table 4.1 above, Cronbach's Alpha was 0.883 which was determined by reliability statistics. Saunders et al. (2016) stated that the values of 0.70 or above show that the questions are being measured on the same scale. The result of 0.883>0.70 proved that the questionnaire was valid.

4.3 Descriptive Statistics of Demographic Background

In this research, descriptive statistics was used by the researcher to analyze the demographic background for the total of 120 respondents. In this section, the background of respondent's is analyzed include ownership, job title, department and working experiences.

4.3.1 Ownership

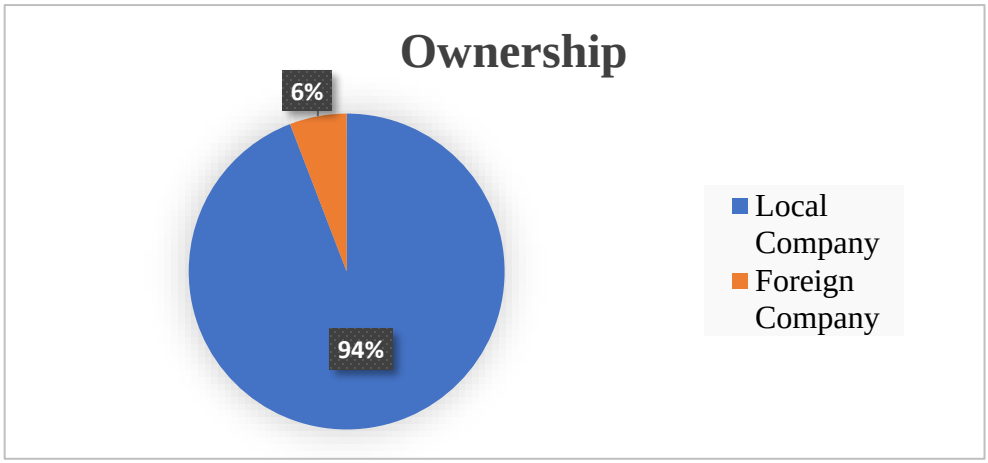


Figure 4.1: Ownership of Respondent

Figure 4.1 shows that the ownership of all 120 respondents who were answering the questionnaires. It shows that the total for local company was 113 company which were 97% from the total, while the total for foreign company was 7 company which were 3% from the total. So, the total of local company was more than foreign company.

4.3.2 Job Title

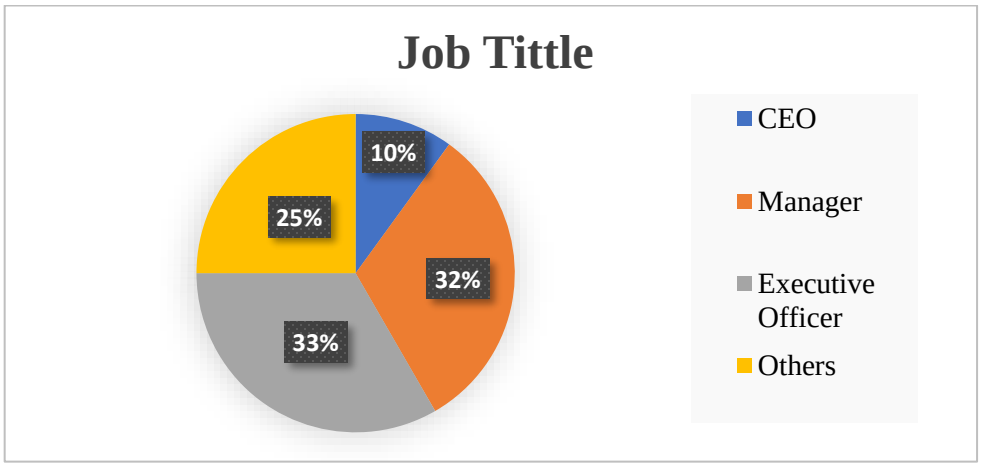


Figure 4.2: Job Tittle of Respondent

Figure 4.2 indicated the job title of all 120 respondents in their company. The highest total of 40 respondents with the percentage of 33% was from the Executive Officer. Then followed by 38 respondents were from manager with the percentage of 32%. The second lowest is from others with 30 respondent and percentage at 25% from the total. Lastly, the lowest total with only 12 respondents with the percentage of 10% was from the Chief Executive Officer (CEO).

4.3.3 Department

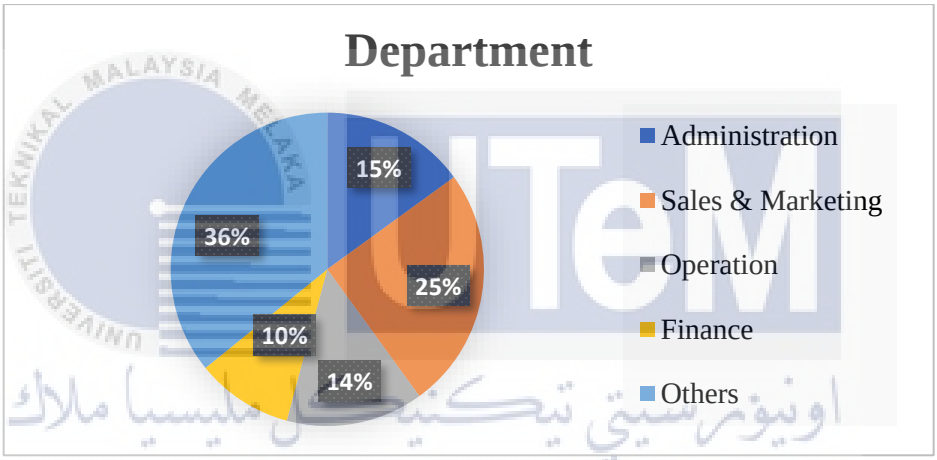


Figure 4.3: Department of Respondent

Figure 4.3 indicated the department of all 120 respondents in their company. The highest total of 43 respondents with the percentage of 36% was from the others department. Then, it followed by 30 respondents were from sales and marketing department with the percentage of 25%. Next, 18 respondents with the percentage of 15% from administration department. Apart from that, the second lowest of respondent is from operation department with only 17 respondents with the percentage of 14%. Lastly, the lowest department with only 12 respondents with the percentage of 10% was from the finance department.

4.3.4 Working Experiences

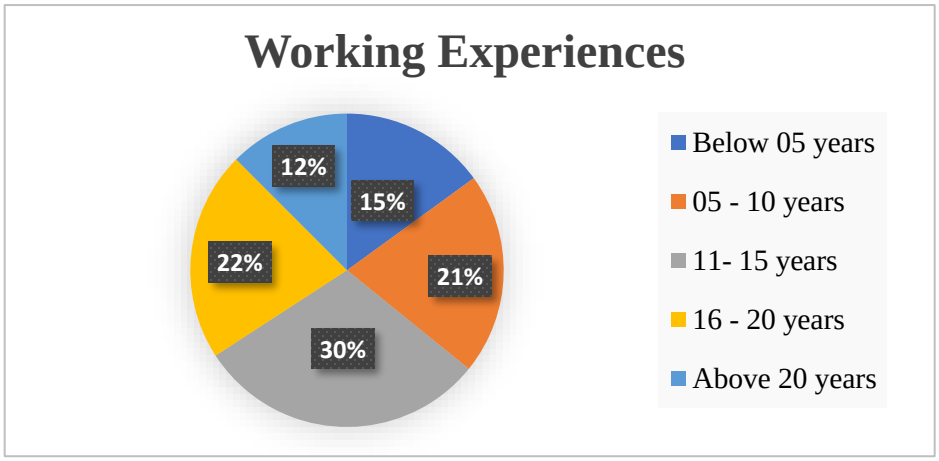


Figure 4.4: Working Experiences of Respondent

Figure 4.4 above show that the duration of work experiences of 120 respondents who answered the questionnaire. According to the data, the highest duration is from11 to 15 years experiences with 36 respondents with the percentage of 30%. Then, it followed by 26 respondents with the percentage of 22% which has between 16 to 20 years of working experiences. Apart from that, the duration between 05 to 10 years came in third with 25 respondents and 21%. Then, the below 05 years represent the second-lowest duration of their work experiences which is only 18 respondents and 15%. Lastly, the lowest year is 20 years and above with only 15 respondents and 12%. From the result above, mostly their experiences are at 11 to 15 years in respondents working experiences.

4.4 Descriptive Statistics

Descriptive statistics are used in research to characterize the fundamental characteristics of data. They provide concise summaries of the sample and measurements. They are the foundation of almost any quantitative data analysis, as well as simple graphical analysis.

In this case, the researcher employed a seven-point Likert Scale to identify the acceptance of big data analytics in the smart supply chain performance among SME. The Linkert Scale will be a five-point rating scale, with 1 signifying as “Strongly disagree”, 2: “Disagree”, 3: “Somewhat disagree”, 4: “Neutral”, 5: “Somewhat agree”, 6: “Agree” and 7: “Strongly agree”.

Table 4.2: Descriptive Statistics for Independent Variables

(Source: SPSS Output)

Descriptive Statistics

Independent Variables	Mean	Standard Deviation
Personalization	6.0867	0.66344
Information Governance	6.2567	0.56222
Supply chain Warning	6.1533	0.58366
Innovation and Learning	6.2233	0.57697

Table 4.2 above shows the descriptive statistics analysis for the four independent variables that were significant in personalization, information governance, supply chain warning, and innovation and learning. According to the table above, the highest mean value is 6.2567, which represents information governance. The second highest mean was 6.2233, which was followed by innovation and learning. The second-lowest mean value is 6.1533 which is representing the supply chain warning. Apart from that, the lowest mean is the last place from all the means is 6.0867 represented by personalization.

Furthermore, standard deviation reflects how accurate the interpretation of the data is and how the answer collects. As a result, the standard deviation for personalization is 0.66344. This means that this independent variable comes first out of all the independent variables listed above. Supply chain warning also pushes it to second place for standard deviation, which is 0.58366. The third spot of standard deviation is 0.57697, which represents innovation and learning. The standard deviation representing information governance has the lowest value of 0.56222.

Table 4.3: Descriptive Statistics for Dependent Variables

(Source: SPSS Output)

Descriptive Statistics

Dependent Variables	Mean	Standard Deviation
Smart Supply Chain Performance	6.2817	0.50576

T able 4.3 above shows the descriptive statistics of the dependent variable which is the smart supply chain performance. According to the table above, the mean value for the dependent variable is 6.2817and the standard deviation value is 0.50576.

4.4.1 Descriptive Statistic of Independent Variable 1 (IV1)

Table 4.4: Descriptive Statistics of Personalization (P)

(Source: SPSS Output)

Statistics

Personalization (IV1)	Mean	Standard Deviation
Your company intends to continue Big Data Analytics in the future	6.18	0.722
Your company will always use Big Data Analytics in operations	6.09	0.810
Your company plan to continue Big Data Analytics frequently	6.02	0.799
Your company have the resources necessary to use Big Data Analytics	6.12	0.900
Availability of technical knowledge required with the connection of both domestic and international business partners	6.02	0.912

The table 4.4 shows that the characteristics of personalization acting as acceptance of big data analytics in the smart supply chain performance among Malaysian Small and Medium-Sized Enterprises (SMEs). Based on the table 4.4, it shows that the value of mean of every item is quite nearest to each other.

The highest value of mean was scored by question 1 with the value of 6.18, most of the respondents are believed that their company intends to continue Big Data Analytics in the future. The second highest values of mean were scored by question 4 with the value of 6.12. The third highest value of mean was scored by question 2 with the value of 6.09.

However, the lowest value of mean was scored by both question 3 and question 5 with the value of 6.02 as respondents were less agreed that their company plan to continue Big Data Analytics frequently and the availability of technical knowledge required with the connection of both domestic and international business partners.

The highest standard deviation value was score by question 5 with the value of 0.912. Thus, even though the question 5 has the highest standard deviation, but it got the lowest mean. The second highest standard value was score by question 4with the value of 0.900. While, the third highest of standard value was score by question 2 with the value of 0.810. Then followed by question 3 as the fourth highest with the value of 0.799. Lastly, the lowest standard deviation value was score by question 1 with the value of 0.722.

4.4.2 Descriptive Statistic of Independent Variable 2 (IV2)

Table 4.5: Descriptive Statistics of Information Governance

(Source: SPSS Output)

Statistics

Information Governance (IV2)	Mean	Standard. Deviation
Useful to carry out the tasks of your company	6.09	0.810
Offers faster delivery of tasks	6.18	0.816
Helps improve productivity	6.41	0.783
Offers the use of quality information for company's growth	6.43	0.657
Offers valuable information on clients	6.18	0.820

The table 4.5 shows that the characteristics of information governance acting as acceptance of big data analytics in the smart supply chain performance among Malaysian Small and Medium-Sized Enterprises (SMEs). Based on the table 4.5, it shows that the value of mean of every item is quite nearest to each other.

The highest value of mean was scored by question 4 with the value of 6.43, it shows that most of the respondents agreed that big data analytics offers the use of quality information for company's growth. The second highest value of mean was scored by question 3 which was 6.41. The third highest value of mean were scored by question 2 and question 5 with the value of 6.18. However, the lowest value mean was scored by question 1 with the value of 6.09, it has the lowest mean value as respondents were less agreed that the big data analytics is useful to carry out the tasks of their company.

Next, the highest standard deviation value was score by question 5 with the value of 0.820. The second highest standard value was score by question 2 with the value of 0.816. While, the third highest standard value was score by question 1with the value of 0.810. Then, followed by question 3 with the value of 0.783. Lastly, the lowest standard deviation value was score by question 4 with the value of 0.657. The question 4 has the lowest value indicates that the data points are spread out over a wider range.

4.4.3 Descriptive Statistic of Independent Variable 3 (IV3)

Table 4.6: Descriptive Statistics of Supply Cain Warning (SCW)

(Source: SPSS Output)

Statistics

Supply Chain Warning (IV3)	Mean	Standard Deviation
The probability of something going wrong with the performance of Big Data Analytics implementation is high	6.11	0.896
Considering the expected level of performance of Big Data Analytics, using it would be very risky for company	6.03	0.912
Provide company with erroneous data	6.09	0.810
The chances of company losing money using Big Data Analytics are very high	6.43	0.657
Generate inconveniences since a lot of time would have to be spent solving errors	6.12	0.812

The table 4.6 shows that the characteristics of supply chain warning acting as acceptance of big data analytics in the smart supply chain performance among Malaysian Small and Medium-Sized Enterprises (SMEs). Based on the table 4.6, it shows that the value of mean of every item is quite nearest to each other.

The highest value of mean was scored by question 4 with the value of 6.43, most of the respondents were agreed that their respondents has supported that the probability of something going wrong with the performance of Big Data Analytics implementation is high. The second highest value of mean was scored by question 5 with the value of 6.12,

followed by the value of mean for question 1 with 6.11 mean as the third highest value. The fourth highest value of mean was scored by question 3 with the value of 6.09. However, the lowest value mean was scored by question 2 with the value of 6.03. It has the lowest mean value as respondents were less agreed that considering the expected level of performance of Big Data Analytics would be very risky for their company.

Next, the highest standard deviation value was score by question 2 with the value of 0.912. The question 2 has the highest value showed that the data points close to the mean of the data set. The second highest standard value was score by question 1 with the value of 0.896. While, the third and fourth highest standard value was score by question 5 then followed by question 3 with the value of 0.812 and 0.810. Lastly, the lowest standard deviation value was score by question 4 with the value of 0.657. The question 4 has the lowest value indicates that the data points are spread out over a wider range.

4.4.4 Descriptive Statistic of Independent Variable 4 (IV4)

Table 4.7: Descriptive Statistics of Innovation and Learning (IL)

(Source: SPSS Output)

Statistics

Innovation and Learning (IV4)	Mean	Standard Deviation
Easy access the clients' need	6.21	0.709
Easy to understand	6.25	0.759
Easy to use	6.16	0.698
Easy to learn	6.32	0.673
Helps generating valuable data easily	6.18	0.733

The table 4.7 shows that the characteristics of innovation and learning acting as acceptance of big data analytics in the smart supply chain performance among Malaysian Small and Medium-Sized Enterprises (SMEs). Based on the table 4.7, it shows that the value of mean of every item is quite nearest to each other.

The highest value of mean was scored by question 4 with the value of 6.32, it shows that most of the respondents agreed that the big data analytics is easy to learn. The second highest value of mean was scored by question 2 which was 6.25. The third highest value of mean was scored by question 1 with the value of 6.21. Then, followed by the fourth highest value of mean was scored by question 5 with the value of 6.18 mean. However, the lowest value mean was scored by question 3 with the value of 6.16. So, it has the lowest mean value as respondents were less agreed that the big data analytics is easy to use.

Next, the highest standard deviation value was score by question 2 with the value of 0.759. The second highest standard value was score by question 5 with the value of 0.733. While, the third highest standard value was score by question 1with the value of 0.709. Then, followed by question 3 with the value of 0.698. Lastly, the lowest standard deviation value was score by question 4 with the value of 0.673. The question 4 has the lowest value indicates that the data points are spread out over a wider range.

4.4.5 Descriptive Statistic of Dependent Variable (DV)

Table 4.8: Descriptive Statistics of Smart Supply Chain Performance (SSCP)

(Source: SPSS Output)

Statistics

Smart Supply Chain Performance (DV)	Mean	Standard Deviation
Inventory levels are visible throughout the supply chain	6.23	0.716
Demand levels are visible throughout the supply chain	6.33	0.663
The use of smart processes facilitates planning, sourcing, making and delivering goods	6.43	0.657
The use of devices gives the activation of monitoring the proper handling conditions of goods	6.31	0.731
Smart processes provide more accurate information for effective decision making	6.12	0.762

The table 4.8 shows the impact of Smart Supply Chain Performance (SSCP) among Malaysian SMEs. Based on the table 4.8, it shows that the value of mean and standard deviation of every question is near to each other.

The highest value of mean was scored by question 3 with the value of 6.43, majority of the respondents agreed that the use of smart processes in facilitates planning, sourcing, making and delivering are the impact of smart supply chain performance. The second highest value of mean was scored by question 2 with the value of 6.33. Then, the third second highest value of mean was scored by question 4 with the value of 6.31,

followed by the fourth highest value by question 1, with the value of 6.23 mean. However, the lowest value mean was scored by question 5 with the value of 6.12.

Next, the highest standard deviation value was score by question 5 with the value of 0.762. The question 5 has the highest value showed that the data points close to the mean of the data set. The second highest standard value was score by question 4 with the value of 0.731. While, the third highest standard value was score by question 1 with the value of 0.716. Then, followed by question 2 with the value of 0.663. The lowest standard deviation value was score by question 3 with the value of 0.657. The question 3 has the lowest value indicates that the data points are spread out over a wider range.

4.5 Result of Measurement

In this section, the researchers will observe the relationship between the dependent variable and the independent variables used in this study in this part. The validity and reliability tests will be performed on all variables that were employed.

4.5.1 Validity Test

The Pearson Correlation test was used to describe the relationship between independent and dependent variables. According to Saunders et al. (2016), the correlation coefficient may be used to determine the strength of the relationship between independent and dependent variables. Table 4.3 shows that the Pearson's Correlation Coefficients for the interpreting correlation range of the R-Values. Table 4.4 below shows Pearson's Correlation Coefficients between the dependent variables and independent variables.

Table 4.9: Range of Pearson's Correlation Coefficients and the Interpretation

(Source: Saunders et. al., 2016)

Pearson's Correlation Coefficient (R-values)	Interpretation
±0.70 to ±1.0	Very strong relationship
±0.40 to ±0.69	Strong relationship
±0.30 to ± 0.39	Moderate relationship
±0.20 to ±0.29	Weak relationship
±0.01 to ±0.19	No relationship

Table 4.10: Correlations between Variables

(Source: SPSS Output)

Correlation

		IV1	IV2	IV3	IV4	DV
IV1 (P)	Pearson Correlation	1	.825**	.696**	.524**	.635**
	Sig. (2-tailed)		.000	.000	.000	.000
	N	120	120	120	120	120
IV2 (IG)	Pearson Correlation	.825**	1	.763**	.531**	.690**
	Sig. (2-tailed)	.000		.000	.000	.000
	N	120	120	120	120	120
IV3 (SCW)	Pearson Correlation	.696**	.763**	1	.526**	.675**
	Sig. (2-tailed)	.000	.000		.000	.000
	N	120	120	120	120	120
IV4 (IL)	Pearson Correlation	.524**	.531**	.526**	1	.807**
	Sig. (2-tailed)	.000	.000	.000		.000
	N	120	120	120	120	120
DV (SSCP)	Pearson Correlation	.635**	.690**	.675**	.807**	1
	Sig. (2-tailed)	.000	.000	.000	.000	
	N	120	120	120	120	120

**. Correlation is significant at the 0.01 level (2-tailed).

Remark

Independent Variables 1 **(IV1)**: Personalization **(P)**

Independent Variables 2 **(IV2)**: Information Governance **(IG)**

Independent Variables 3 **(IV3)**: Supply Chain Warning, **(SCW)**

Independent Variables 4 **(IV4)**: Innovation and Learning **(IL)**

Dependent Variables **(DV)**: Smart Supply Chain Performance **(SSCP)**

Table 4.10 has shown the correlations between the independent variable and dependent variables. All the independent variables and dependent variables above have a unique relationship, and it was defined using Pearson's Correlation Coefficients. According to Saunders et. al., (2015), the Pearson's Correlation Coefficients may describe the strength of the relationship between independent variables and dependent variables.

According to the table above, the correlation of personalization, information governance, supply chain warning, and innovation and learning were categorized as positive relation towards smart supply chain performance as correlation values are 0.635, 0.690, 0.675 and 0.807 respectively.

As for the first independent variable above, it was personalization with a 0.635 correlation coefficient (r) value. The second value of correlation for information governance is 0.690. Next, the correlation value of supply chain warning, and innovation and learning are 0.675 and 0.807 respectively. According to the result of the correlation value, all the independent variables had a very strong positive relationship with the dependent variable. This is because the results showed the correlation coefficient (r) value was higher than 0.5 and the significant level was 0.000 which was ($p<0.05$).

According to the table above, the relationship between all four independent variables and dependent variables is positive and considered to a strong relationship as the correlation value is within 0.60 to 0.80. In conclusion, it revealed that all of the independent variables were related to the dependent variable SSCP.

Table 4.11: Relationship Between Independent Variables

Independent Variables	Pearson's Correlation	Strength of Relationship
Personalization	0.635	Strong Relationship
Information Governance	0.690	Strong Relationship
Supply Chain Warning	0.675	Strong Relationship
Innovation and Learning	0.807	Very Strong Relationship

4.5.2 Reliability Test

According to Saunders et. al., (2016), reliability is defined as replication and consistency. Besides, the reliability is also the data collected is determined by the test of reliability, Heffiner (2014). Furthermore, reliability is the accuracy of the sample, which the survey questionnaire may classify. The Cronbach's Alpha result is used in the reliability test to determine whether the items in the questionnaire are positively connected. The level of reliability applied in this research was measured by a set of numbers in the Cronbach's Alpha Coefficient. Table 4.12 below shows the range of Cronbach's Alpha coefficients and the strength of correlation.

Table 4.12: Cronbach's Alpha Coefficient Range and Strength of Association

(Sources: Saunders et. al., 2016)

Cronbach's Alpha Coefficient Range	Strength of Association
$\alpha \geq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

This research contained 25 questions using Linkert Scales to determine the level of agreement. The scale ranged from 1 to 7, with 1 = Strongly Disagree, 2 = Disagree, 3 = Somewhat Disagree, 4 = Neutral, 5 = Somewhat Agree, 6 = Agree and 7 = Strongly Agree. For all questions, the reliability test was completed, and the reliability results are provided below.

Table 4.13: Case Processing Summary

(Sources: Saunders et. al., 2016)

Case Processing Summary

		N	%
Cases	**Valid**	120	100.0
	Excluded[a]	0	.0
	Total	120	100.0

a. Listwise deletion based on all variables in the procedure.

Table 4.14: Reliability Test for Independent Variables and Dependent Variables

(Sources: Saunders et. al., 2016)

Reliability Statistics

Cronbach's Alpha	N of Items
.940	25

The reliability tests for the dependent variable and independent variables for this research was shown in Tables 4.13 and 4.14 above. The total number of questions was 25 questions belonging to independent variables and dependent variables. Thus, to conduct the reliability test, 120 respondents were recruited using a survey questionnaire and the Cronbach Alpha rating is 0.940 based on the answers to all the questions above. According to the table of Cronbach's Alpha coefficient range and strength of association above, all these questions were excellent and highly reliable.

4.6 Hypothesis Testing

The research requires hypothesis testing in this section to evaluate whether or not the developed hypothesis may be accepted or rejected. The researcher uses Multiple Regression Analysis to test the study hypothesis. Multiple regression analysis was required to investigate the relationship between a dependent variable and independent variables. The significant level was determined and presented as a range of values as a result of the multiple regression analysis. This states that if the level is greater than 0.05, the level is irrelevant because the maximum significant level of the variable was 0.00. This study, it is also consisting of three sections in the Multiple Regression Analysis, which are Model Summary, ANOVA, and coefficient.

4.6.1 Multiple Regression Analysis (Model Summary)

Table 4.15: Multiple Regression Analysis (Model Summary)

(Sources: Saunders et. al., 2016)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.872[a]	.760	.752	.25197

a. Predictors: (Constant), Innovation and Learning (IV4), Personalization (IV1), Supply Chain Warning (IV3), Information Governance (IV2)

b. Dependent Variable: Smart Supply Chain Performance (DV)

Table 4.15 above shows the result of Multiple Regression Analysis for Model Summary is related in this research. It is demonstrated the relationship between the independent variables and dependent variables. The value of the correlation coefficient (R) was 0.872 and the value of the coefficient of the determinant (R Square) was 0.760. According to the result above, both values mean there was a strong relationship between the variables. They suggested that the smart supply chain performance got 76.0% that influence by personalization, information governance, supply chain warning, and innovation and learning. Another (100%-76.0% = 24.0%) was influenced by the other factors that are not been done in this research.

4.6.2 Multiple Regression Analysis (ANOVA)

Table 4.16: Multiple Regression Analysis (ANOVA)

(Sources: Saunders et. al., 2016)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	23.138	4	5.785	91.112	.000[b]
	Residual	7.301	115	.063		
	Total	30.440	119			

a. Dependent Variable: Smart Supply Chain Performance (DV)

b. Predictors: (Constant), Innovation and Learning (IV4), Personalization (IV1), Supply Chain Warning (IV3), Information Governance (IV2)

Table 4.16 above shows the result of Multiple Regression Analysis for ANOVA is related to this research. Since Multiple Regression Analysis is a good fit model of data and results from the output, it can help the researcher get a predicted value of a variable based on two or more variables. According to the result above, the result F-test value was 91.112 with a significant level of p = 0.000 which was lower than 0.05. However, the F-Test result value above is a higher value that means it is a good fit for the data in this research. In this case, Multiple Regression Analysis may use to estimate positive effects when using the big data analytics on the smart supply chain performance. The factor of independent variables is personalization, information governance, supply chain warning, and innovation and learning.

4.6.3 Multiple Regression Analysis (Coefficients)

Table 4.17: Multiple Regression Analysis (Coefficients)

(Sources: Saunders et. Al., 2016)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.771	.295		2.610	.010
	Personalization	.007	.063	.009	.106	.916
	Information Governance	.212	.082	.235	2.566	.012
	Supply Chain Warning	.159	.064	.183	2.502	.014
	Innovation and Learning	.509	.049	.581	10.398	.000

a. Dependent Variable: Smart Supply Chain Performance (DV)

Table 4.17 above indicates that the result of the Coefficient for multiple regression analysis. The beta value of personalization was 0.009 with the significant value of 0.916, while the beta value of information governance was 0.235 with significant value of 0.012. Next, the beta value of supply chain warning is 0.183 with the significant value of 0.14 and lastly the beta value of innovation and learning was 0.581 with the significant value of 0.000. The innovation and learning have the highest beta value compare with other three variables, so it shows that innovation and learning has the greatest impact on big data analytics in the smart supply chain performance.

The linear equation was developed as below:

$$Y = 0.771 + 0.007X_1 + 0.212X_2 + 0.159X_3 + 0.509X_4$$

Where:

Y = Big Data Analytics in The Smart Supply Chain Performance

X1 = Personalization

X2 = Information Governance

X3 = Supply Chain Warning

X4 = Innovation and Learning

Based on the linear equation above, there was a strong relation between personalization, information governance, supply chain warning, and innovation and learning on big data analytics in the smart supply chain performance.

4.6.4 Summary of Hypothesis

Hypothesis 1: Personalization (P)

H_0: There is a significant relationship between personalization and smart supply chain performance.

H_1: There is no significant relationship between personalization and smart supply chain performance.

From the table 4.10, the result of regression for personalization in the smart supply chain performance was shown. The significant value of personalization is 0.916>0.05. In this case, it can be assumed that the personalization had no significant relationship with the smart supply chain performance. Therefore, the researcher had to accept the null hypotheses (H_0) and reject the alternative hypotheses (H_1).

Hypothesis 2: Information Governance (IG)

H_0: There is no significant relationship between information governance and smart supply chain performance.

H_2: There is a significant relationship between information governance and smart supply chain performance.

As from the table above, the result of regression for information governance in the smart supply chain performance was shown. The significant value of information governance is 0.012<0.05. In this case, it can be assumed that information governance had a significant relationship with the smart supply chain performance. Therefore, the researcher had to accept the alternative hypotheses (H_2) and reject the null hypotheses (H_0).

Hypothesis 3: Supply Chain Warning (SCW)

H_0: There is no significant relationship between supply chain warning and smart supply chain performance.

H_3: There is a significant relationship between supply chain warning and smart supply chain performance.

As from the table above, the result of regression for supply chain warning in the smart supply chain performance was shown. The significant value of supply chain warning is 0.014<0.05. In this case, it can be assumed that supply chain warning had a significant relationship with the smart supply chain performance. Therefore, the researcher had to accept the alternative hypotheses (H_3) and reject the null hypotheses (H_0).

Hypothesis 4: Innovation and Learning (IL)

H_0: There is no significant relationship between innovation and learning and smart supply chain performance.

H_4: There is a significant relationship between innovation and learning and smart supply chain performance.

As from the table above, the result of regression for innovation and learning in the smart supply chain performance was shown. The significant value of innovation and learning is 0.000<0.05. In this case, it can be assumed that innovation and learning had a significant relationship with the smart supply chain performance. Therefore, the researcher had to accept the alternative hypotheses (H_4) and reject the null hypotheses (H_0).

Table 4.18: Summary for Hypothesis

Hypothesis	Result
H_1: There is no significant relationship between personalization and smart supply chain performance.	Rejected
H_2: There is a significant relationship between information governance and smart supply chain performance.	Accepted
H_3: There is a significant relationship between supply chain warning and smart supply chain performance.	Accepted
H_4: There is a significant relationship between innovation and learning and smart supply chain performance.	Accepted

4.7 Conclusion

In this chapter, all the data that had been collected was done analyzed by the researcher by using the SPSS software version 27.0 and it was been presented the data by using table and figures. Then, the descriptive statistics, validity test, reliability testing and hypotheses testing had been done to analyze the data collected in this chapter. In this case, the researcher discovered that three hypotheses were acceptable, and one hypothesis was rejected.

CHAPTER 5

DISCUSSION, RECOMMENDATION AND CONCLUSION

5.1 Introduction

The result from the data analysis in Chapter 4 was discussed in this chapter. The researcher will explain the data and the result of the research study that had been analyzed. In this chapter, the part of demographic, research objectives, implication of study, limitation of study and recommendations of future study will be discussed in this chapter.

5.2 Summary of the Study

The purpose of this researcher was to examine the acceptance of big data analytics factors in the smart supply chain performance among Malaysian Small and Medium-Sized Enterprises (SMEs). In this research, there were four independent variables which are personalization, information governance, supply chain warning, and innovation and learning.

5.3 Discussion on the Demographic Background

There are 120 respondents who were answering these questionnaires. Then, it shows that from 120 respondents, only 7 respondents that answering these questionnaires are from foreign company which were only 3% from the total. Then, respondents from a local company stated the highest with 113 respondent which were 97% from the total of ownership demographic. So, the total of local company was more than foreign company.

Next, the highest job title total of 40 respondents with the percentage of 33% was from the Executive Officer. Then followed by 38 respondents were from manager with the percentage of 32%. The second lowest coming from others with 30 respondent and percentage at 25% from the total. Lastly, the lowest total with only 12 respondents with the percentage of 10% was from the Chief Executive Officer (CEO).

Besides, the department of all 120 respondents worked in their company. The highest total was from the others department with the percentage of 36% and 43 respondents. Then, it followed by 30 respondents were from sales and marketing department with the percentage of 25%. Next, 18 respondents with the percentage of 15% from administration department. Apart from that, the second lowest of respondent is from operation department with only 17 respondents with the percentage of 14%. Lastly, the lowest department with only 12 respondents with the percentage of 10% was from the finance department.

As for the duration of work experiences of 120 respondents who answered the questionnaire. The highest duration is from11 to 15 years experiences with 36 respondents with the percentage of 30%, and the least working experiences is 20 years and above with only 15 respondents and percentage at 12%. Then, it followed by 26 respondents with the percentage of 22% which has between 16 to 20 years of working experiences as a second highest. Apart from that, the duration between 05 to 10 years came in third with 25

respondents and 21%. Then, the below 05 years represent the second-lowest duration of their work experiences which is only 18 respondents and 15%. Lastly, from the result above, mostly their experiences are at 11 to 15 years in respondents working experiences.

5.4 Discussion on Research Objectives

The research objectives were stated as below:

i. To identify the acceptance of big data analytics factors that influence the smart supply chain performance among manufacturing firms.
ii. To measure the relationship between big data analytics factors with smart supply chain performance among manufacturing firms.
iii. To determine the most significant factors of big data analytics in the smart supply chain performance among manufacturing firms.

Research Objective 1: To identify the acceptance of big data analytics factors that influence the smart supply chain performance among manufacturing firms.

For the first research objective, the researcher has investigated the acceptance of big data analytics factors that influence the smart supply chain performance from the literature review. The researcher has used the resource-based view (RBV) model in this research. The researcher explained the relationship between the independent variables which are the acceptance of big data analytics (BDA) and the dependent variable is smart supply chain performance (SSCP) among Malaysian SMEs. All the independent variables which are personalization, information governance, supply chain warning, and innovation and learning. are the determinants in the RBV model that had seen as the acceptance of big data analytics factors in Malaysian manufacturer from the previous study. According

to Chen, et al., (2019), the information sharing of BDA in the supply chain benefits both large companies and small businesses, as well as manufacturer performance. Therefore, the objective 1 had been achieving.

Research Objective 2: To measure the relationship between big data analytics factors with smart supply chain performance among manufacturing firms.

In the second research objective, the researcher had used SPSS software to prove the results of the explanatory factor with the Multiple Regression Analysis (MRA). There were four independent variables that influence the smart supply chain performance among Malaysian Small and Medium-Sized Enterprises (SME), which are personalization, information governance, supply chain warning, and innovation and learning.

Through the hypothesis testing in chapter 4, there were three factors of big data analytics that were significant relationship with the smart supply chain performance among Malaysian Small and Medium-Sized Enterprises (SME). However, there was one factor of big data analytics in the smart supply chain performance was rejected and it was known as a no significant relationship with the smart supply chain performance. The factors of big data analytics in the smart supply chain performance that has been accepted is information governance, supply chain warning, and innovation and learning. Then, the factor of big data analytics factors in the smart supply chain performance that has been rejected is personalization.

Moreover, a strong supply chain may help a firm gain a competitive advantage (Widyanesti & Masyithah,2018). In additional, BDA has been found to help increase supply chain adaptation, operational efficiency and resilience. However, the degree of environmental dynamism in logistical systems determines the magnitude of the effect (Wamba et al., 2019). Furthermore, Amineh & Hani (2020), performed research on the direct influence of competitive priorities on institutional performance as well as the

indirect impact of supply chain performance. Therefore, research objective 3 has been achieved.

Hypothesis	Sig.	Result
Hypothesis 1: Personalization (P) H_0: There is a significant relationship between personalization and smart supply chain performance. H_1: There is no significant relationship between personalization and smart supply chain performance.	0.916>0.05	H_1 is rejected (Yun et al., 2021, Morimoto, 2021; Pfiffelmann et al., 2020)
Hypothesis 2: Information Governance (IG) H_0: There is no significant relationship between information governance and smart supply chain performance. H_2: There is a significant relationship between information governance and smart supply chain performance.	0.012<0.05	H_2 is accepted (Joonhwan In et al., 2018)

Hypothesis 3: Supply Chain Warning (SCW) H_0: There is no significant relationship between supply chain warning and smart supply chain performance. H_3: There is a significant relationship between supply chain warning and smart supply chain performance.	0.014<0.05	H_3 is Accepted (Buckley, 2019)
Hypothesis 4: Innovation and Learning (IL) H_0: There is no significant relationship between innovation and learning and smart supply chain performance. H_4: There is a significant relationship between innovation and learning and smart supply chain performance.	0.000<0.05	H_4 is Accepted (Ayub et al., 2022)

Table 5.1 Summary of Hypothesis Testing

Based on Table 5.1, the significant value of information governance, supply chain warning, and innovation and learning were 0.012<0.05, 0.014<0.05and 0.000<0.05 respectively. From the result of multiple regression analysis, it can be assumed that the information governance, supply chain warning, and innovation and learning had a significant relationship with the smart supply chain performance. However, the significant value for personalization was 0.916>0.05, so the multiple regression analysis can be assumed that it had no significant relationship with the smart supply chain performance.

Independent Variables 1: Personalization

Hypothesis 1: There is no significant relationship between personalization and smart supply chain performance.

The result above shows that personalization of big data analytics does not help the smart supply chain performance. Based on the Multiple Regression Analysis results before in chapter four, the p-value for personalization was 0.916. It means that the p-value of these independent variables is more than the suitable p-value of 0.05. In this case, there was no significant relationship between personalization with the smart supply chain performance.

According to the previous research, personalization has become a very important aspect in big data analytics in the smart supply chain performance. However, most of the respondents were not agree with the adoption of big data analytics in personalization of smart supply chain performance. This is means, the respondents think that there is no significant relationship in the big data analytics methodology between personalization and smart supply chain performance.

Moreover, according to (Kumar et al., 2019) the need for personalized interactions and products has increased due to recent technical developments (such as the Internet of Things (IoT) and Artificial Intelligence (AI)) and access to new data types such as data biometrics. However, initiatives to personalize content also face a number of difficulties, including managing big data and algorithms, addressing privacy issues, integrating and making data accessible, and complying with legal requirements like the General Data Privacy Regulation (GDPR) in Europe (Yun et al., 2021). Moreover, despite its potential to foster close, meaningful relationships with businesses and its positive effects on the customer experience and perceived value, consumers may not always embrace personalization due to privacy concerns and perceived intrusiveness (Morimoto, 2021; Pfiffelmann et al., 2020). Because of this, managers must deal with considerable uncertainty when creating, implementing, and carrying out their customization initiatives (Kumar et al., 2019).

In conclusion, the significant value for personalization was more than 0.05. So, the null hypothesis (H_0) was accepted, and the alternative hypothesis (H_1) was rejected. There is no significant relationship between personalization and smart supply chain performance.

Independent Variables 2: Information Governance

Hypothesis 2: There is a significant relationship between information governance and smart supply chain performance.

According to the result above, information governance of big data analytics was helping the smart supply chain in performance. Based on the Multiple Regression Analysis results before in chapter four, the p-value for information governance was 0.012 and it is way less than the p-value of 0.05. In this case, there was a significant relationship between information governance and smart supply chain performance.

Thus, the information governance can maintain the quality of Big Data throughout its life cycle with the right collaboration and procedures. Additionally, researchers have discovered that a strong basis for supply chain integration can come from effective information flow. Such companies can codify freshly acquired or developed information in a similar way towards how information is frequently shared both within and across the supply chain. Generally, the poor coordination of information flows results in weak performance for upstream supply chain participants is supported by these anecdotes. Particularly, poor supply chain information governance frequently results in manufacturers and merchants failing to fulfil their obligations to serve customers farther downstream (Joonhwan In et al., 2018).

In conclusion, the significant value for reduced unnecessary laboratory testing was less than 0.05. So, the null hypothesis (H_0) was rejected, and the alternative hypothesis (H_1) was accepted. In this case, there is a significant relationship between information governance smart supply chain performance.

Independent Variables 3: Supply Chain Warning

Hypothesis 3: There is a significant relationship between supply chain warning and smart supply chain performance.

Based on the result above, supply chain warning of big data analytics was helping the smart supply chain in performance. Based on the Multiple Regression Analysis results before in chapter four, the p-value for supply chain warning was 0.014 and it is way less than the p-value of 0.05. In this case, there was a significant relationship between supply chain warning and smart supply chain performance.

According to (Buckley, 2019), numerous businesses that had previously dominated the home market have expanded internationally through smart supply chain. These businesses provide goods and services in accordance with various market demands while integrating resources from all over the globe. Thus, going global businesses have more possible obstacles to overcome than domestic businesses in terms of organizational management, technical advancement, and individualized demand service. The smart supply chain system, which is based on enterprises that are growing global has exemplary relevance for other companies. As a typical example, Haier has established numerous smart factories and R&D facilities throughout the world that are managed by big data platforms in connecting and utilizing global innovation resources and expertise. Moreover, the supply chain warning approach guarantees in robust supply chain operations and supports intelligent manufacturing. (Yongping Xie, et al., 2020).

In conclusion, the significant value for improve diagnostic imaging was less than 0.05. So, the null hypothesis (H_0) was rejected, and the alternative hypothesis (H_1) was accepted. In this case, there was a significant relationship between supply chain warning and smart supply chain performance.

Independent Variables 4: Innovation and Learning

Hypothesis 4: There is a significant relationship between innovation and learning and smart supply chain performance.

According to the result above innovation and learning of big data analytics was helping the smart supply chain in performance. Based on the Multiple Regression Analysis results before in chapter four, the p-value for reduced contaminated needle sticks was 0.000 and it is way less than the p-value of 0.05. In this case, there was a significant relationship between innovation and learning and smart supply chain performance.

According to Ayub et al., (2022), learning is defined as an organization's capacity to update its operational and processing capabilities with fresh information and insights. It is a procedure made up of three fundamental learning-related processes, namely exploration, adaptation, and exploitation. It is widely acknowledged that learning and innovation are related, and this view characteristic of learning capability as the innovativeness that enables a business to develop, enlarge, or change its resources. Moreover, learning and innovation that improve the quality of the goods or services can provide them a competitive edge. As a result, it consists of three secondary indicators the members' capacity for innovation, the rate at which new technologies are adopted, and the intensity of service development. This capacity for innovation and learning will improve information exchange efficiency and cut down on the amount of time required for each supply chain link (Yongping Xie, et al., 2020).

In conclusion, the significant value for reduced contaminated needle sticks was less than 0.05. So, the null hypothesis (H_0) was rejected, and the alternative hypothesis (H_1) was accepted. In this case, there was a significant relationship between innovation and learning and smart supply chain performance.

Research Objective 3: To determine the most significant factors of big data analytics in the smart supply chain performance among manufacturing firms.

For the third research objective, the researcher has found out the most significant factors of big data analytics in the smart supply chain performance among manufacturing firms from the literature review. Based on Shabbir, Asad, Faisal, and Salman (2019), supply chain strategy will affect any organization's business level strategy since it clearly differentiates a company's primary point of competition and position, such as competing on quality, service, innovation, or low cost. According to Boiko et al. (2019), a strategy of supply chain helps to develop the preparation structure, make timely distributions, enhance warehouse inventory, check offer to request conformance, reduce expenses, and as a consequence, boost the business's market competitiveness. Thus, BDA applications in supply chain could significantly improve a company's logistical effectiveness as well as the system's sustainability and adaptability (Wamba et al., 2019). By fostering better relationships among supply chain stakeholders, and optimizing speed and visibility, BDA may improve supply chain execution and increase efficiency and profitability. Therefore, the objective 3 had been achieving.

5.5 Implication of the Study

In terms of practical contribution, this research provides organizations in better understanding about the benefits of the adoption of big data analytics on smart supply chain. According to Syamsul et al., (2020) in West Sulawesi Province of Indonesia, improved supply chain strategy execution on SMEs can create a greater competitive advantage. In general, it is claimed that this theoretical model will offer practitioners with a clear guidance to continue implementing the correct implementation.

Furthermore, in terms of theoretical contribution, utilizing these big data analytics on supply chain approach can teaches firms on how to work well with their goods' supply

and market to increase operational efficiency and lower production costs in order for the companies to become successful. The advantages of adopting this platform from here is that it may increase competitive advantage.

In conclusion, the adoption of big data analytics on smart supply chain strategy is critical for SMEs since the Industry Revolution 4.0 will be leveraged in decision making to produce value for the SMEs. As a result, it is critical for the employer to understand the plan for implementing the supply chain in their organization so that it may be used for successfully and contribute to increased their work efficiency.

5.6 Limitation of the Study

There are some limitations to this research. The first limitation faced when doing this research was a time constraint; the researcher had a restricted time period of three months to collect data from the respondents, thus the researcher was unable to obtain further replies from the respondents. Due to the time limitation, the researcher only can distribute the survey questionnaire by using Google Form. The researcher had sent the survey questionnaire by using e-mail and WhatsApp's to different work fields of respondent. This is because different work field will have different experience and evaluations.

From September 2022 until November 2022, the researcher gathered data by delivering a questionnaire via email. The method of conducting the survey was the second constraint that the research faced while doing this research. Thus, the researcher's survey method was more for the online platform. There were some difficulties for the respondents when they wanted to distribute the questionnaire to some companies, such as not having the exact email address of the company or the company not responding to the email. The final constraint was the quantity of responses. In this study, only 120 respondents' data was obtained by the researcher.

5.7 Recommendations for Future Research

In this research, the acceptance of big data analytics in the smart supply chain performance among Malaysian Small and Medium-Sized Enterprises (SMEs) was investigated by the researcher. There are a number of recommendations that the researcher can provide to the next researcher.

The first suggestion is that future researchers perform future studies using the qualitative technique to gain better knowledge of the user's perspective. For data gathering the researcher may interview the respondents. This approach may improve respondent engagement and allowing the researcher to obtain additional opinions from the respondent from various viewpoints. This will assist the company in determining the employees' attitude and behavior about the Business Intelligence system's installation.

Besides that, the researcher also can do a research about these big data analytics at a big company or international company. Then, the researcher might get a different result than a research at SMEs company only. All the company in Malaysia including SMEs Company need to improve knowledge about smart supply chain management and to adopt the big data analytics to their company operation. Lastly, funding from the government for implementing the concept and improve the knowledge on the concept is necessary. As a result, more study in these fields is possible.

5.8 Conclusion

In conclusion, the impact of big data analytics on smart supply chain performance is critical for SMEs in order to maintain a competitive advantage. As a result, it is critical for the employer to understand the best method to implement the supply chain process in their organization. So that it may be used successfully and contribute to increased their work productivity. Thus, the resource-based view (RBV) theory will advise SMEs on how to get a better performance by concentrating on sustainable supply chain practices. It is beneficial for the employer to adopt big data analytics in their organization. Thus, from a strategic standpoint, big data can help with knowledge co-creation, which results in knowledge goods that are founded on evidence for improved business rivalry (Acharya et al., 2018).

5.9 Summary

The researcher achieved three research objectives, which are to investigate the acceptance of big data analytics that influence the smart supply chain performance, to measure the relationship between big data analytics with smart supply chain performance among SMEs and to determine the most significant impact of big data analytics in the smart supply chain performance. In this chapter, the implications of the study, limitations of the study, and recommendations for future research were done to advise future researchers regarding to the similar research. The general findings of the study were described in the final section of Chapter 5.

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APPENDIX 1

GANTT CHART FYP 1

PROCEDURE FOR FYP 1	WEEK														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
FYP Briefing Session															
Topic and Supervisor and confirmation															
1st Meeting with Supervisor															
Modify Research Topic															
Briefing on the Content of Chapter 1															
Discussing about LR and Research Framework															
Finding Research Problem Statement															
Completion of Chapter 1															
Chapter 1 Checking and Correction by SV															
Chapter 2 Briefing															
Completion of Chapter 2															
Chapter 3 Briefing															
Completion of Chapter 3															
Submission of FYP 1															

APPENDIX 2

GANTT CHART FYP 2

PROCEDURE FOR FYP 2	WEEK														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Create Questionnaire															
Distribute Questionnaire															
Data Gathering															
Data Analyzing															
Complete Chapter 4															
Complete Chapter 5															
FYP 2 Submission															
FYP 2 Presentation															

APPENDIX 3

QUESTIONNAIRE

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

ADOPTION OF BIG DATA ANALYTICS USING UTAUT2 MODEL APPROACH TOWARDS SMART SUPPLY CHAIN MANAGEMENT IN MANUFACTURING FIRMS

A process used to extract meaningful insights, such as hidden patterns, unknown correlations, market trends, and customer preferences for example While smart supply chain is supply chain that integrates the partners can self-organize and automatically adapt to environmental changes and makes an intelligent decision that best achieves business goals

By looking at the impact of big data analytics adopting on smart supply chain performance, a research work on the adoption of Big data analytics using UTAUT2 model is being carried out by the Faculty of Manufacturing Engineering, Universiti Teknikal Malaysia Melaka (UTeM).

Your cooperation is solicited in filling the questionnaire on behalf of your company. Please pass this questionnaire to the appropriate member (s) of your organization (at least 2-year experience in supply chain operations and use big data analytics (such as Management Information System (MIS), ERP, SAP, BAAN, cloud computing, etc.) in your daily work. If you do not feel comfortable to complete it.

You have been asked to take part in this study because you are an expert which has at least 2 years working experience in

The information given is **STRICTLY CONFIDENTIAL** and will be used only as a material for academic research.

A high response rate is vital for the success of this study. We would be delighted to answer any query regarding the questionnaire. Please return the completed questionnaire using the enclosed envelope.

Thank you for your time and kindness.

NOR RATNA BINTI MASROM
Faculty of Manufacturing Engineering,
University Teknikal Malaysia Melaka (UTeM),
76100 Hang Tuah Jaya, Melaka,
Malaysia.

QUESTIONNAIRE
[SOAL SELIDIK]

INSTRUCTION:
To complete this questionnaire, you are just required to TICK (√) boxes and write in the space of the required information provided, if necessary.

[ARAHAN:
Untuk menjawab soal selidik ini, anda dikehendaki untuk menanda (√) pada kotak jawapan dan menulis maklumat yang dikehendaki pada ruangan yang telah disediakan , jika perlu.]

SECTION A: INFORMATION ON THE SMART MANUFACTURING PRACTICE
[BAHAGIAN A: MAKLUMAT BERKAITAN AMALAN PENGILANGAN PINTAR]

What are your company's current smart manufacturing practices from the past two (2) years? Tick (√) one answer for each statement as follows.
[Apakah amalan pengilangan pintar semasa di syarikat anda bagi tempoh dua (2) tahun yang lalu? Tandakan (√) satu jawapan bagi setiap penrnyataan berikut.]

Strongly Disagree *(Sangat Tidak Setuju)* — Strongly Agree *(Sangat Setuju)*

1 — 7

	Statement *[Pernyataan]*	*Scale [Skala]*						
		1	**2**	**3**	**4**	**5**	**6**	**7**
SSP1	You company have Machines/systems can be controlled through IT *[Mesin/sistem boleh dikawal melalui IT]*	□	□	□	□	□	□	□
SSP2	You company uses Machine to Machine communication where transmission of machine data between mechanical or electronic devices can be done automatically without human intervention	□	□	□	□	□	□	□

	[Syarikat anda menggunakan komunikasi Mesin ke Mesin di mana penghantaran data mesin antara peranti mekanikal atau elektronik boleh dilakukan secara automatik tanpa campur tangan manusia]							
SSP3	Your company is implementing Interoperability technology where it is able to connect and communicate in a coordinated way, without effort from the end user. *[Syarikat anda melaksanakan teknologi saling kendali di mana ia dapat menyambung dan berkomunikasi dengan cara yang diselaraskan, tanpa usaha dari pengguna akhir.]*	□	□	□	□	□	□	□
SSP4	Your company collects inventory data automatically *[Syarikat anda mengumpul data inventori secara automatik]*	□	□	□	□	□	□	□
SSP5	Your company collects Manufacturing throughout times automatically *[Syarikat anda mengumpul Pembuatan sepanjang masa secara automatik]*	□	□	□	□	□	□	□
SSP6	Your company collects equipment capacity utilization automatically *[Syarikat anda mengumpul penggunaan kapasiti peralatan secara automatik]*	□	□	□	□	□	□	□
SSP7	Your company collects Production residues/waste/WIP automatically *[Syarikat anda mengumpul sisa pengeluaran / sisa / WIP secara automatik]*	□	□	□	□	□	□	□
SSP8	Your company collects Employee utilization automatically *[Syarikat anda mengumpul penggunaan Pekerja secara automatik]*	□	□	□	□	□	□	□
SSP9	Your company collects Data about processing, process condition automatically *[Syarikat anda mengumpul Data tentang pemprosesan, keadaan proses secara automatik]*	□	□	□	□	□	□	□

SSP10	Your company collects Production times automatically *[Syarikat anda mengumpul masa Pengeluaran secara automatik]*	□	□	□	□	□	□	□
SSP11	Your company collects Overall equipment effectiveness (OEE) automatically [Syarikat anda mengumpul keberkesanan peralatan keseluruhan (OEE) secara automatik]	□	□	□	□	□	□	□
SSP12	Data you collect used for Predictive maintenance [Data yang anda kumpulkan digunakan untuk penyelenggaraan Ramalan]	□	□	□	□	□	□	□
SSP13	Data you collect used for Optimization of logistics and production processes [Data yang anda kumpulkan digunakan untuk Pengoptimuman proses logistik dan pengeluaran]	□	□	□	□	□	□	□
SSP14	Data you collect used for Creation of transparency across production process [Data yang anda kumpulkan digunakan untuk Penciptaan ketelusan merentasi proses pengeluaran]	□	□	□	□	□	□	□
SSP15	Data you collect used for Quality management [Data yang anda kumpulkan digunakan untuk pengurusan kualiti]	□	□	□	□	□	□	□
SSP16	Data you collect used for Optimization of resource consumption (material, energy) [Data yang anda kumpulkan digunakan untuk Pengoptimuman penggunaan sumber (bahan, tenaga)]	□	□	□	□	□	□	□
SSP17	Data you collect used for Automatic production control through use of real-time data [Data yang anda kumpulkan digunakan untuk kawalan pengeluaran automatik melalui penggunaan data masa nyata]	□	□	□	□	□	□	□
SSP18	Your company currently uses Manufacturing Execution System (MES) [Syarikat anda kini menggunakan sistem pelaksanaan pembuatan (MES)]	□	□	□	□	□	□	□
SSP19	Your company currently uses Enterprise Resource Planning (ERP)	□	□	□	□	□	□	□

	[Syarikat anda kini menggunakan perancangan sumber perusahaan (ERP)]							
SSP20	Your company currently uses Product Lifecycle Management (PLM) [Syarikat anda kini menggunakan pengurusan kitaran hayat produk (PLM)]	□	□	□	□	□	□	□
SSP21	Your company currently uses Product Data Management (PDM) [Syarikat anda kini menggunakan pengurusan data produk (PDM)]	□	□	□	□	□	□	□
SSP22	Your company currently uses Production Planning System (PPS) [Syarikat anda kini menggunakan sistem perancangan pengeluaran (PPS)]	□	□	□	□	□	□	□
SSP23	Your company currently uses Production Data Acquisition (PDA) [Syarikat anda kini menggunakan pemerolehan data pengeluaran (PDA)]	□	□	□	□	□	□	□
SSP24	Your company currently uses Machine Data Collection (MDC) [Syarikat anda kini menggunakan pengumpulan data mesin (MDC)]	□	□	□	□	□	□	□
SSP25	Your company currently uses Computer-Aided Design (CAD) [Syarikat anda kini menggunakan reka bentuk bantuan komputer (CAD)]	□	□	□	□	□	□	□
SSP26	Your company currently uses Supply Chain Management (SCM) [Syarikat anda kini menggunakan pengurusan rantaian bekalan (SCM)]	□	□	□	□	□	□	□

SECTION B: INFORMATION ON THE BIG DATA ANALYTICS ADOPTION
[BAHAGIAN B: MAKLUMAT BERKAITAN PENGGUNAAN ANALITIK DATARAYA]

What are your company current in big data analytics adoption from the past two (2) years? Tick (√) one answer for each statement as follows.
[Apakah penggunaan analitik dataraya di syarikat anda bagi tempoh dua (2) tahun yang lalu? Tandakan (√) satu jawapan bagi setiap penrnyataan berikut.]

Strongly Disagree *(Sangat Tidak Setuju)* — Strongly Agree *(Sangat Setuju)*

1 — **7**

	Statement *[Pernyataan]*	*Scale [Skala]*						
		1	**2**	**3**	**4**	**5**	**6**	**7**
BDA1	Useful to carry out the tasks of your company *Berguna untuk menjalankan tugas syarikat anda*	□	□	□	□	□	□	□
BDA2	Offers faster delivery of tasks *Menawarkan penghantaran tugas yang lebih cepat*	□	□	□	□	□	□	□
BDA3	Helps improve productivity *Membantu meningkatkan produktiviti*	□	□	□	□	□	□	□
BDA5	Offers the use of quality information for company's growth *Menawarkan penggunaan maklumat berkualiti untuk pertumbuhan syarikat*	□	□	□	□	□	□	□
BDA6	Offers valuable information on clients *Menawarkan maklumat berharga kepada pelanggan*	□	□	□	□	□	□	□
BDA7	Easy access the clients' need. *Akses mudah keperluan pelanggan*	□	□	□	□	□	□	□
BDA8	Easy to understand *Mudah difahami*	□	□	□	□	□	□	□
BDA9	Easy to use *Mudah digunakan*	□	□	□	□	□	□	□
BDA10	Easy to learn *Mudah dipelajari*	□	□	□	□	□	□	□

BDA11	Helps generating valuable data easily *Membantu menjana data berharga dengan mudah*	□	□	□	□	□	□	□
BDA12	Trustworthy *Boleh dipercayai*	□	□	□	□	□	□	□
BDA13	All operational data are confidential *Semua data operasi adalah sulit*	□	□	□	□	□	□	□
BDA14	Get an immediate notification when the operational data is completed. *Pemberitahuan segera apabila data operasi selesai*	□	□	□	□	□	□	□
BDA15	Reliable *Boleh dipercayai*	□	□	□	□	□	□	□
BDA16	Your company intends to continue Big Data Analytics in the future *Syarikat anda berhasrat untuk meneruskan Analitik Dataraya pada masa akan datang*	□	□	□	□	□	□	□
BDA17	Your company will always use Big Data Analytics in operations *Syarikat anda akan sentiasa menggunakan Analitik Dataraya dalam operasi*	□	□	□	□	□	□	□
BDA18	Your company plan to continue Big Data Analytics frequently *Syarikat anda merancang untuk meneruskan Analitik Dataraya dengan kerap*	□	□	□	□	□	□	□
BDA19	Your company have the resources necessary to use Big Data Analytics *Syarikat anda mempunyai sumber yang diperlukan untuk menggunakan Analitik Dataraya*	□	□	□	□	□	□	□
BDA20	Availability of technical knowledge required with the connection of both domestic and international business partners. *Ketersediaan pengetahuan teknikal yang diperlukan dengan sambungan kedua-dua rakan kongsi perniagaan domestik dan antarabangsa.*	□	□	□	□	□	□	□

BDA21	Compatible with other organisations' activities for easy to access Big Data Analytics. *Sesuai dengan aktiviti organisasi lain untuk mengakses Dataraya dengan mudah.*	□	□	□	□	□	□	□
BDA22	Availability of trained staff to handle Big Data Analytics to complete tasks faster. *Ketersediaan kakitangan terlatih untuk mengendalikan Analitik Dataraya untuk menyelesaikan tugas dengan lebih cepat.*	□	□	□	□	□	□	□
BDA23	Using Big Data Analytics is entirely within your company's control. *Menggunakan Analitik Dataraya sepenuhnya dalam kawalan syarikat anda.*	□	□	□	□	□	□	□
BDA24	Your company have the knowledge necessary to use *Syarikat anda mempunyai pengetahuan yang diperlukan untuk digunakan*	□	□	□	□	□	□	□

SECTION C: INFORMATION ON THE BIG DATA ANALYTICS PERCEIVED RISK

[BAHAGIAN C: MAKLUMAT BERKAITAN RISIKO ANALITIK DATARAYA YANG DIRASAKAN]

What are your current perceived risk in big data analytics in your company from the past two (2) years? Tick (√) one answer for each statement as follows.
[Apakah risiko yang dirasakan di dalam analitik dataraya di syarikat anda bagi tempoh dua (2) tahun yang lalu? Tandakan (√) satu jawapan bagi setiap penrnyataan berikut.]

Strongly Disagree *(Sangat Tidak Setuju)* — Strongly Agree *(Sangat Setuju)*

1 — 7

PR1	Could be malfunctioning and by obtaining wrong data could lead the company to make wrong decisions *Mungkin tidak berfungsi dan dengan mendapatkan data yang salah boleh menyebabkan syarikat membuat keputusan yang salah*	□	□	□	□	□	□	□
PR2	Unsafe to protect company's data *Tidak selamat untuk melindungi data syarikat*	□	□	□	□	□	□	□
PR3	The probability of something going wrong with the performance of Big Data Analytics implementation is high *Kebarangkalian sesuatu yang tidak kena dengan prestasi pelaksanaan Analitik Dataraya adalah tinggi*	□	□	□	□	□	□	□
PR4	Considering the expected level of performance of Big Data Analytics, using it would be very risky for company *Memandangkan tahap prestasi Analitik Dataraya yang dijangkakan, menggunakannya akan menjadi sangat berisiko bagi syarikat*	□	□	□	□	□	□	□
PR5	Provide company with erroneous data *Menyediakan syarikat dengan data yang salah*	□	□	□	□	□	□	□
PR6	The chances of company losing money using Big Data Analytics are very high	□	□	□	□	□	□	□

	Peluang syarikat kehilangan wang menggunakan Analitik Dataraya adalah sangat tinggi							
PR7	Waste time by having to install new type of software *Buang masa dengan perlu memasang jenis perisian baru*	□	□	□	□	□	□	□
PR8	Generate inconveniences since a lot of time would have to be spent solving errors *Menjana kesulitan kerana banyak masa perlu dibelanjakan untuk menyelesaikan kesilapan*	□	□	□	□	□	□	□
PR9	Considering the investment in time and start-up of the System, such investment would be risk *Memandangkan pelaburan dalam masa dan permulaan Sistem, pelaburan tersebut akan menjadi risiko*	□	□	□	□	□	□	□
PR10	The probability of wasting time with system start-up and learning is very high *Kebarangkalian membuang masa dengan permulaan sistem dan pembelajaran sangat tinggi*	□	□	□	□	□	□	□
PR11	Conflict with company's concept *Konflik di dalam Kesesuaian dengan konsep syarikat*	□	□	□	□	□	□	□
PR12	Company's business concept will get worse and suffer a loss of reputation *Konsep perniagaan syarikat akan menjadi lebih teruk dan mengalami kehilangan reputasi*	□	□	□	□	□	□	□
PR13	The probability of using Big Data Analytics and losing control of data privacy is high *Kebarangkalian menggunakan Analitik Dataraya dan kehilangan kawalan privasi data adalah tinggi*	□	□	□	□	□	□	□
PR14	Using Big Data Analytics will lead to loss of privacy *Menggunakan Analitik Dataraya akan menyebabkan kehilangan privasi*	□	□	□	□	□	□	□
PR15	Using Big Data Analytics is globally risky *Menggunakan Analitik Dataraya adalah berisiko di seluruh dunia*	□	□	□	□	□	□	□

PR16	It is dangerous to use Big Data Analytics *Adalah berbahaya untuk menggunakan Analitik Dataraya*	□	□	□	□	□	□	□
PR17	Using *Analitik Dataraya* exposes our company to risk *Menggunakan Analitik Dataraya mendedahkan syarikat kami kepada risiko*	□	□	□	□	□	□	□

SECTION D: INFORMATION ON THE TECHNOLOGY READINESS
[BAHAGIAN D: MAKLUMAT BERKAITAN KESEDIAAN TEKNOLOGI]

What is your company's current in technology readiness from the past two (2) years? Tick (√) one answer for each statement as follows.
[Apakah kesediaan teknologi syarikat anda bagi tempoh dua (2) tahun yang lalu? Tandakan (√) satu jawapan bagi setiap penrnyataan berikut.]

Strongly Disagree *(Sangat Tidak Setuju)* — Strongly Agree *(Sangat Setuju)*

1 — **7**

	Statement *[Pernyataan]*	*Scale [Skala]*						
		1	**2**	**3**	**4**	**5**	**6**	**7**
TR1	New technologies contribute to a better quality of life *Teknologi baru menyumbang kepada kualiti hidup yang lebih baik*	□	□	□	□	□	□	□
TR2	Technology gives more freedom of mobility *Teknologi memberikan lebih banyak kebebasan mobility*	□	□	□	□	□	□	□
TR3	Technology gives more control over daily lives *Teknologi memberi lebih banyak kawalan ke atas kehidupan seharian*	□	□	□	□	□	□	□
TR4	Technology makes more productive *Teknologi menjadikan lebih produktif*	□	□	□	□	□	□	□
TR5	Other people come to you for advice on new technologies *Orang lain datang kepada anda untuk mendapatkan nasihat mengenai teknologi baru*	□	□	□	□	□	□	□

TR6	In general, you are the first in your circle of friends to acquire new technology when it appears *Secara umum, anda adalah yang pertama dalam kalangan rakan anda untuk memperoleh teknologi baru apabila ia muncul*	□	□	□	□	□	□	□
TR7	You can usually figure out new high-tech products and services without help from others *Anda biasanya boleh memikirkan produk dan perkhidmatan berteknologi tinggi baru tanpa bantuan daripada orang lain*	□	□	□	□	□	□	□
TR8	You keep up with the latest technological developments *Anda mengikuti perkembangan teknologi terkini*	□	□	□	□	□	□	□
TR9	When you get technical support from a provider of a high-tech product or service, you sometimes feel as if you are being taken advantage of by someone who knows more than you do *Apabila anda mendapat sokongan teknikal daripada pembekal produk atau perkhidmatan berteknologi tinggi, kadang-kadang anda merasa seolah-olah anda diambil kesempatan oleh seseorang yang tahu lebih banyak daripada yang anda lakukan*	□	□	□	□	□	□	□
TR10	Technical support lines are helpful because they explain things in understandable terms *Talian sokongan teknikal membantu kerana mereka menerangkan perkara dalam istilah yang dapat difahami*	□	□	□	□	□	□	□
TR11	Sometimes, you think that technology systems are NOT designed for use by ordinary people *Kadang-kadang, anda fikir bahawa sistem teknologi TIDAK direka untuk digunakan oleh orang biasa*	□	□	□	□	□	□	□

TR12	There is no such thing as a manual for a high-tech product or service that's written in plain language *Tidak ada manual untuk produk atau perkhidmatan berteknologi tinggi yang ditulis dalam bahasa biasa*	□	□	□	□	□	□	□
TR13	Too much technology distracts people to a point that is harmful *Terlalu banyak teknologi mengalihkan perhatian orang ke titik yang berbahaya*	□	□	□	□	□	□	□
TR14	Technology lowers the quality of relationships by reducing personal interaction *Teknologi merendahkan kualiti hubungan dengan mengurangkan interaksi peribadi*	□	□	□	□	□	□	□
TR15	You do not feel confident doing business with a place that can only be reached online *Anda tidak yakin menjalankan perniagaan dengan tempat yang hanya dapat dicapai dalam talian*	□	□	□	□	□	□	□

SECTION E: INFORMATION ON THE CURRENT ON SMART SUPPLY CHAIN PERFORMANCES
[BAHAGIAN E: MAKLUMAT BERKAITAN PRESTASI RANGKAIAN BEKALAN PINTAR SEMASA]

What are your company's current smart supply chain performances from the past two (2) years? Tick (√) one answer for each statement as follows.
[Apakah prestasi rangkaian bekalan pintar syarikat anda bagi tempoh dua (2) tahun yang lalu? Tandakan (√) satu jawapan bagi setiap penrnyataan berikut.]

	Statement *[Pernyataan]*	*Scale [Skala]*						
		1	**2**	**3**	**4**	**5**	**6**	**7**
SSM1	The exchange of information will give better quality relationships with supply chain partners. *[Pertukaran maklumat akan memberikan hubungan yang lebih berkualiti dengan rakan kongsi rantaian bekalan.]*	□	□	□	□	□	□	□
SSM2	The involvement of stakeholders will give better decisions to produce new products. *[Penglibatan pihak berkepentingan akan memberikan keputusan yang lebih baik untuk menghasilkan produk baharu.]*	□	□	□	□	□	□	□
SSM3	The use of value stream mapping will identify and eliminate waste throughout the supply chain. *[Penggunaan pemetaan aliran nilai akan mengenal pasti dan menghapuskan sisa sepanjang rantaian bekalan]*	□	□	□	□	□	□	□
SSM4	Your supply chain will generate high stock turnover and minimizes inventory *[Rantaian bekalan anda akan menjana pusing ganti stok yang tinggi dan meminimumkan inventori]*	□	□	□	□	□	□	□

SSM5	Your supply chain can forecast customer demands. *[Rantaian bekalan anda boleh meramalkan permintaan pelanggan.]*	□	□	□	□	□	□	□
SSM6	Adequate information systems linkages exist with partners in the supply chain network. *[Hubungan sistem maklumat yang mencukupi wujud dengan rakan kongsi dalam rangkaian rantaian bekalan.]*	□	□	□	□	□	□	□
SSM7	The information exchange will help the establishment of business planning with the supply chain partners. *[Pertukaran maklumat akan membantu penubuhan perancangan perniagaan dengan rakan kongsi rantaian bekalan*.]	□	□	□	□	□	□	□
SSM8	Your company will have enough information to understand the skills and competencies of the supplier. *[Syarikat anda akan mempunyai maklumat yang mencukupi untuk memahami kemahiran dan kecekapan pembekal.]*	□	□	□	□	□	□	□
SSM9	Your company can replace one supply source with another at a low cost. *[Syarikat anda boleh menggantikan satu sumber bekalan dengan yang lain pada kos yang rendah.]*	□	□	□	□	□	□	□
SSM10	Integrated technology improved your supply chain management. *[Teknologi bersepadu meningkatkan pengurusan rantaian bekalan anda.]*	□	□	□	□	□	□	□
SSM11	Real-time enterprise improved your monitoring capabilities *[Operasi masa nyata meningkatkan keupayaan pemantauan anda]*	□	□	□	□	□	□	□

SSM12	Inventory levels are visible throughout the supply chain. *[Tahap inventori boleh dilihat di seluruh rantaian bekalan.]*	□	□	□	□	□	□	□
SSM13	Demand levels are visible throughout the supply chain. *[Tahap permintaan boleh dilihat di seluruh rantaian bekalan.]*	□	□	□	□	□	□	□
SSM14	The use of smart processes facilitates planning, sourcing, making and delivering goods. *[Penggunaan proses pintar memudahkan perancangan, penyumberan, pembuatan dan penghantaran barangan.]*	□	□	□	□	□	□	□
SSM15	The use of devices gives the activation of monitoring the proper handling conditions of goods *[Penggunaan peranti memberikan pengaktifan pemantauan keadaan pengendalian barang yang betul]*	□	□	□	□	□	□	□
SSM16	Smart processes provide more accurate information for effective decision making *[Proses pintar menyediakan maklumat yang lebih tepat untuk membuat keputusan yang berkesan]*	□	□	□	□	□	□	□

GENERAL INFORMATION
[MAKLUMAT AM]

1. Company Name:
   _____
   [Nama Syarikat:]

2. Ownership: □ Local (Malaysia) □ Foreign, please specify :_____
   [Pemilikan :] *[Syarikat tempatan]* *[Syarikat asing, sila nyatakan:]*

Respondents Information:
[Maklumat Responden:]

Name *:*
_____
[Nama]

Job title *:*
_____
[Jawatan]

Department *:*
_____
[Jabatan]

Working experience (years) *:*
_____
[Pengalaman kerja (tahun)]

Contact number *:*
_____
[Number untuk dihubungi]

E-mail *:*
_____
[Emel]

Would you like to receive a concise summary of the results from the survey?
[Adakah anda berminat untuk mendapatkan keputusan kajian tinjauan ?

□ Yes □ Tidak
[Ya] [No]

Would you like to take part in the next phase of this study?
[Adakah anda ingin mengambil bahagian untuk fasa seterusnya dalam kajian ini ?

□ Yes □ Tidak
[Ya] [No]

Thank you very much for your time and kind-co-operation. Please ensure that you answer as many questions as possible. For analysis purpose, please return the questionnaire even if your company is not engaged in cleaner production and lean production practice in your production activities.

[Terima kasih untuk masa dan kerjasama anda. Sila pastikan bahawa anda menjawab sebanyak soalan yang mungkin. Bagi tujuan analisis, sila kembalikan borang tinjuan ini walaupun syarikat anda tidak melibarkan diri dalam amalan pengeluaran bersih dan pengeluaran lean dalam aktiviti pengeluaran anda.]

---------- **END OF SURVEY**----------
(Kaji selidik Tamat)

GLOSSARY

	Statement	*Definition*
1.	**Supply chain** ***Rantaian bekalan***	A systematic approach to managing flows of assets from sourcing raw materials, and product manufacturing, to delivering to end customers significantly affects the business goals of the partners in supply networks. *Pendekatan sistematik untuk menguruskan aliran aset dari sumber bahan mentah, dan pembuatan produk, untuk menyampaikan kepada pelanggan akhir memberi kesan ketara kepada matlamat perniagaan rakan kongsi dalam rangkaian bekalan.*
2.	**Smart supply chain** ***Rantaian bekalan pintar***	A supply chain that integrates the partners can self-organize and automatically adapt to environmental changes and makes an intelligent decision that best achieves business goals *Rantaian bekalan yang mengintegrasikan rakan kongsi boleh mengatur sendiri dan secara automatik menyesuaikan diri dengan perubahan alam sekitar dan membuat keputusan pintar yang terbaik mencapai matlamat perniagaan*
3	**Supply chain partner** ***Rakan kongsi rantaian bekalan***	Successful long-term relationships amongst trading partners in the supply chain that are enabled by mutual trust, organizational compatibility, top management support, and information sharing *Hubungan jangka panjang yang berjaya di kalangan rakan perdagangan dalam rantaian bekalan yang diaktifkan oleh kepercayaan bersama, keserasian organisasi, sokongan pengurusan atasan, dan perkongsian maklumat*

4	**Supply chain performance** **Prestasi rantaian bekalan**	The ability of a supply chain to cost-effectively carry out its activities while minimizing costs, for the main purpose of meeting the ultimate customer's needs *Keupayaan rantaian bekalan untuk menjalankan aktivitinya dengan kos efektif sambil meminimumkan kos, untuk tujuan utama memenuhi keperluan pelanggan utama*
5.	**Big Data Analytics** ***Big Data Analytics***	A process used to extract meaningful insights, such as hidden patterns, unknown correlations, market trends, and customer preferences *Proses yang digunakan untuk mengekstrak pandangan yang bermakna, seperti corak tersembunyi, korelasi yang tidak diketahui, trend pasaran, dan pilihan pelanggan*
6.	**Big data analytics application in Supply chain management.** ***Aplikasi Big data analytics dalam Pengurusan rantaian bekalan.***	Predictive analytics define and forecast all aspects of the supply chain, including inventory, procurement, delivery, and returns for example ERP, Cloud Computing, RFID, or IoT, etc. Analisis ramalan menentukan dan meramalkan semua aspek rantaian bekalan, termasuk inventori, perolehan, penghantaran, dan pulangan contohnya ERP, Pengkomputeran Awan, RFID atau IoT