BIG DATA ANALYTICS CAPABILITY FOR COMPETITIVE ADVANTAGE AND FIRM PERFORMANCE IN MALAYSIAN MANUFACTURING FIRMS

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DEDICATION

This thesis is dedicated to my father, who taught me that the best kind of knowledge to have is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

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ABSTRACT

Some recent studies claim that Data Analytics Capability (BDAC) is largely focused on developed countries such as the United States and the current adoption level of big data analytics in business is still very low. In the context of Malaysia, BDAC has not yet reached the optimal level and it was also found that previous studies did not evaluate the impact of BDAC on competitive advantage in the manufacturing industry. A lacking study on BDAC, competitive advantage, and firm performance coupled with inconsistent findings between competitive advantage and firm performance has raised many questions, leading to an unclear direction for business decision-makers. Hence, this phenomenon has been investigated and the study was underpinned by the Resourced-Based View (RBV) and the entanglement view of sociomaterialism (EVS) theories in examining the relationships among higher order of BDAC, cost advantage, differentiation advantage, market, and operational performance. The study adopted a quantitative and cross-sectional research method by distributing the survey to the companies listed in the Federation of Malaysian Manufacturers (FMM) directory 2018 (49th edition). The sampling frame consisted of 3,828 companies. Employing a systematic sampling method, a sample size of 1,000 companies was determined for the study. A total of 689 companies agreed to participate in the research. 191 responses were usable and resulted in an effective response rate of 27.72 percent. IBM SPSS version 23 and Smart PLS version 3 were used to analyze the data. This study discovered that BDAC is a bundle of resources that consists of data, technology, data-driven culture, the intensity of organizational learning, and technical and managerial skills. Empirical findings provided adequate evidence that BDAC positively influences cost advantage and differentiation advantage and subsequently leads to superior firm performance. Additionally, the differentiation advantage was found to be a key factor in predicting market performance, however, failed to influence operational performance. Theoretically, both RBV and EVS could be used to link higher order of BDAC, differentiation advantage, and market performance to explain superior firm performance. This research outlined some limitations of the study and offered some recommendations for future research directions.

ABSTRAK

Beberapa kajian baru-baru ini mendakwa bahawa Keupayaan Analitis Data (BDAC) banyak memberi tumpuan kepada negara maju seperti Amerika Syarikat dan tahap penerimaan semasa analitik data dalam perniagaan adalah masih sangat rendah. Dalam konteks Malaysia, BDAC masih belum mencapai tahap optimum dan juga didapati kajian lepas tidak menilai kesan BDAC terhadap kelebihan daya saing dalam industri pembuatan. Kajian yang kurang tentang BDAC, kelebihan daya saing dan prestasi firma ditambah pula dengan penemuan yang tidak konsisten antara kelebihan daya saing dan prestasi firma telah menimbulkan banyak persoalan, yang membawa kepada hala tuju yang tidak jelas bagi pembuat keputusan perniagaan. Oleh itu, fenomena ini telah disiasat menggunakan Pandangan Berasaskan Sumber (RBV) dan keterjalinan teori-teori sosiomaterialisme (EVS) dalam mengkaji hubungan antara BDAC, kelebihan kos, kelebihan pembezaan, pasaran, dan prestasi operasi. Kajian ini menggunakan kaedah penyelidikan kuantitatif dan keratan rentas dengan mengedarkan tinjauan kepada syarikat yang tersenarai dalam direktori Persekutuan Pekilang Malaysia (FMM) 2018 (edisi ke-49). Kerangka persampelan terdiri daripada 3,828 syarikat. Menggunakan kaedah persampelan sistematik, saiz sampel sebanyak 1,000 syarikat telah ditentukan untuk kajian ini. Sebanyak 689 syarikat bersetuju untuk mengambil bahagian dalam penyelidikan ini. 191 respons yang boleh digunapakai telah diterima menghasilkan kadar maklum balas yang berkesan sebanyak 27.72 peratus. IBM SPSS versi 23 dan Smart PLS versi 3 digunakan untuk menganalisis data. Kajian ini mendapati bahawa BDAC ialah himpunan sumber yang terdiri daripada data, teknologi, budaya berasaskan data, intensiti pembelajaran organisasi dan kemahiran teknikal dan pengurusan. Penemuan empirikal memberikan bukti yang mencukupi bahawa BDAC secara positif mempengaruhi kelebihan kos dan kelebihan pembezaan dan seterusnya mempengaruhi prestasi firma yang unggul. Selain itu, kelebihan pembezaan didapati sebagai faktor utama yang meramalkan prestasi pasaran, tetapi gagal mempengaruhi prestasi operasi. Secara teorinya, kedua-dua RBV dan EVS boleh digunakan untuk menghubungkan BDAC, kelebihan pembezaan dan prestasi pasaran untuk menerangkan prestasi firma yang unggul. Penyelidikan ini juga menggariskan beberapa batasan kajian dan menawarkan beberapa cadangan untuk hala tuju penyelidikan masa hadapan.

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LIST OF ABBREVIATIONS

AMOS	-	Analysis of Moment Structures
AVE	-	Average Variance Extracted
APeJ	-	Asia-Pacific excluding Japan
BDA		Big Data Analytics
BDAC	-	Big Data Analytics Capability
CMV	-	Common Method Variance
CA	-	Cronbach Alpha
CBSEM	-	Covariance-Based Structural Equation Modelling
CR	-	Composite Reliability
DC	-	Data-driven Culture
DCV	-	Dynamic-Capability View
DIFF	-	Differentiation
EQS	-	Equations
FMM	-	Federation of Malaysian Manufacturers
HTMT	-	Heterotrait-Heteromethod
IDC		International Data Corporation
LC	-	Low Cost
LISREL	-	Linear Structural Relation
ML	-	Maximum Likelihood
MP	-	Market Performance
MS	-	Managerial Skills
OL	-	The Intensity of Organisational Learning
OP	-	Operational Performance
PLS	-	Partial Least Square
RAMONA	-	Reticular Action Model or Near Approximation
SEPATH	-	Structural Equations and Path Analysis
TS	-	Technical Skills
VBSEM	-	Variance-Based Structural Equation Modelling
VIF	-	Variance Inflation Factor
VRIN	-	Valuable, Rare, Inimitability and non-substitutability

LIST OF SYMBOLS

β	-	Path coefficient
n^{th}	-	Value estimated from the population number divided by the sample size
N	-	Number of items assigned to the factor
f^2	-	Effect size on the changes of R^2
q^2	-	Effect size on the changes of Q^2
Q^2	-	Predictive relevance
R^2	-	Path coefficient of determination
$\sigma^2 i$	-	Variance of item *i*
$\sigma^2 t$	-	Variance of the sum of all assigned items' scores

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CHAPTER 1

INTRODUCTION

1.1 Introduction

This research presents the effect of big data analytics capability (BDAC) on competitive advantage and firm performance by offering a resource-based view and the entanglement view of sociomaterialism of BDAC in the manufacturing sector. Section 1.2 illustrates the background of the study, and Section 1.3 presents the existing issues faced by manufacturers in adopting big data analytics for achieving a competitive advantage and better firm performance in Malaysia. Section 1.4 specifies the research questions to accomplish the research objectives stipulated in Section 1.5 of this thesis. Section 1.6 explains the scope of this research and Section 1.7 outlines the significance of this research. Definitions of the key terms are described in section 1.8 and followed by outlining the organisation of this thesis.

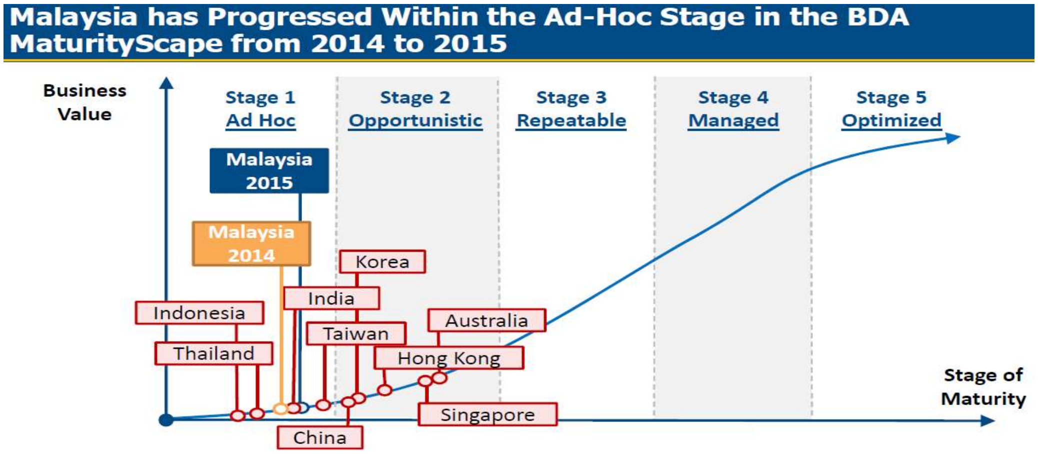
1.2 Background of the Study

Industry 4.0 (the fourth industrial revolution) is revolutionising manufacturing by providing manufacturers with the opportunity to utilise advanced information technology (IT) capabilities for the sake of gaining competitiveness in the market (Boggess, 2019; Subramaniam, 2020). This is critical for firms to achieve a competitive advantage in enhancing firm performance through the domain of IT (Hardaker, Trick and Sabki, 1994; Kettinger *et al.*, 1994; Daugherty, Germain and Droge, 1995; Ravichandran and Lertwongsatien, 2005; Wong, Soh and Chong, 2016; Boggess, 2019; Daniels, 2019; Hitch, 2019; Subramaniam, 2020; Shah, 2021). The IT domain is found to facilitate the achievement of low-cost or differentiation advantage (Porter and Millar, 1985; Feraud, 1998; Chiu and Yang, 2019; Subramaniam, 2020). One of the major IT trends that will dominate manufacturing in the year 2021 is having greater visibility into big data analytics that helps manufacturers understand more of their business processes (Boggess, 2019; Feyen *et al.*, 2021). This is because big data analytics enables manufacturers to improve production, optimise operations, and address issues before they arise (Tan, 2018; Azeem *et al.*, 2021).

The fundamental concept of big data analytics indicates two prospects which are big data (BD) and business analytics (BA) (Duan and Xiong, 2015; Boldosova and Luoto, 2020). Big data refers to data sets that have been accumulated over time to meet the 3Vs which are volume, velocity, and variety, whereby volume concerns the size of data, velocity relates to the quickness of getting the information on a real-time basis, and variety refers to the type of data (Panimalar, Shree and Kathrine, 2017; Azeem *et al.*, 2021). This is consistent with Chen and Zhang (2014); Garmaki, Boughzala and Wamba (2016); and Taylor (2021), who claimed that big data is huge, real-time, and a variety of data sets that go beyond the traditional computation ability to apprehend, analyse, and convert big data into an idea. Business analytics provides specialised assistance in accessing, exploring, visualizing, and integrating large amounts of data (Chen and Zhang, 2014; Morris, 2021). In Malaysia, big data analytics has provided numerous possibilities to improve their operations, and thus, big data analytics has become one of the critical elements to develop a knowledge economy for the country (Kumar, 2014; Economic Planning Unit, 2020). Therefore, the Ministry of Communication and Multimedia Commission (MCMC) and Malaysia Digital Economy Corporation (MDEC) aimed to make Malaysia one of the regional big data analytics hubs by driving the National Big Data Initiatives to produce earnings of RM53.2 trillion in the year 2030 (MDEC, 2021).

Big data analytics investments in Malaysia have continued to rise and could reach RM595 million in the year 2021, increasing by 10.9 percent from the year 2016 (Chellam, 2018). Big data analytics in the manufacturing industry is anticipated to record a compound annual growth rate (CAGR) of above 30.9 percent throughout the projection phase in the years 2019 to 2024 (Mordorintelligence, 2019). Thus, it is worth studying the effect of big data analytics capability in the manufacturing sector, which is comprised of many successful manufacturers like Top Glove (the world's biggest rubber glove producer) that collaborated with a Malaysia-based big data firm on getting some big data analytics resolution that applied detectors to control the compound of rubber substances to enhance productivity (Chellam, 2018; Top Glove Corporation Bhd, 2020). UMW Holdings Bhd (automotive, equipment, manufacturing, and engineering company) has digitised its business processes to accumulate data in the interest of applying data analytics and predictive support (Zainul, 2017). Intel also applied big data analytics to speed up the testing of its microprocessors and enhance its company performance by saving up to $3 million in the first year of implementation (Protiviti, 2017; Intel, 2020).

To increase the productivity of manufacturers, the government is motivating them to apply big data analytics to gain competitiveness in the marketplace (Govinsider, 2015; Subramaniam, 2020). Malaysian organisations have moved slightly across the ad-hoc phase in terms of big data strategy and sponsorship projects in the International Data Corporation (IDC)'s Big Data analytics MaturityScape from the year 2014 to 2015 (IDC, 2015). The ad-hoc stage has been defined as a pilot project, an undefined process, and a lack of resources (IDC, 2015). This inferred that many Malaysian organisations are still new to big data analytics and only conduct small-scale big data analytics projects due to inadequate big data analytics capability (BDAC). According to Schwab (2019), the ranking of Malaysia is rated as 33rd place in terms of using technology to support its business operations worldwide. Nevertheless, Malaysia is still slow compared to the dominant countries like Korea, Singapore, Australia, Hong Kong, etc. (refer to Figure 1.1). The aforementioned literature shows the development of the BDAC in Malaysia. As such, it is worth strengthening the achievement of competitive advantage and better firm performance by studying the contribution of BDAC in the context of the manufacturing sector within Malaysia.



Source: IDC Malaysia Big Data Analytics Maturity Benchmark, 2015 (n=100)

Figure 1.1 IDC APeJ Big Data Analytics Maturity Assessment and Benchmark

According to research conducted by Dell EMC (Electromagnetic Compatibility) Corporation, around 40 percent of Malaysian businesses have already achieved a competitive advantage as a result of adopting big data analytics, while 69 percent believe that big data will define the winners and losers of their industry since the year 2013 (Tan, 2013). In the study conducted by International Data Corporation (IDC) (2015), 26 percent of the respondents came from Thailand, the Philippines, Malaysia, and Hong Kong have reached a modest standard of maturity and capability to reap the value from the adoption of big data analytics, while another 28 percent of the respondents have started their big data analytics journey but the outcomes of big data analytics adoption have not met their presumptions.

Wong, Chuah, and Ong (2015), who found that around 52 percent of those who are ready for change management and adaptability related to big data analytics have obtained more business opportunities from the outcomes of big data analytics. They further explained that most Malaysian companies have started to change their culture to make the right decisions based on the outputs produced by big data analytics. However, none of the organisations reached the optimising level by using big data analytics to identify business opportunities for creating business value (Wong, Chuah, and Ong, 2015). The finding is somehow consistent with Goh (2015) and Protiviti (2017), who have found some factors that caused the nascent level of using big data analytics, such as lack of awareness of the benefits of big data analytics, the unwillingness of certain organisations to open up their data, insufficient human capital, the lack of success stories, etc. Along with this line of thought, Goh (2014), Yap (2019) and Chuah and Thurusamry (2021) have stated the prerequisite for successful firms to exchange their experience in adopting big data analytics to stimulate more firms to accept these up-to-date technologies.

Big data analytics may provide firms with more opportunities to gain a competitive advantage (Mcafee and Brynjolfsson, 2012; Singh and Del Giudice, 2019), as the output generated by the big data analytics software can provide unexpected inspiration for firms to make the right decision and, as a result, improve their business performance (Akter et al., 2016; Gupta and George, 2016; Mikalef et al., 2020). Big data analytics software like cloud-based, parallel computing approaches, open-source software, data visualisation tools, and databases are the main choices for handling and processing big data (Akter et al., 2016; Gupta and George, 2016; Mikalef et al., 2020). Cloud-based services can be described as a network that is provided by a remote host via a network connection to communicate the computing tasks of multiple computers (Chen, Chang and Lin, 2015).

To apply parallel computing approaches, many companies have purchased the pre-written software called Enterprise Resource Planning (ERP) (Mocean, 2011) to make integrated operations that come from manufacturing, marketing, human resources, accounting, customer relationship management, and others in a firm (Tarigan, Siagian and Jie, 2021). To motivate a company to use big data analytics, there is a lot of open-source software that can be used freely to process the data. Open-source software is now a trend and has witnessed a rampant evolution due to fewer start-up costs, user-friendliness, and many other benefits (Chong, Siti Zaleha and Haliyana, 2021). Some examples of open-source software, such as Apache Hadoop, Project Storm, and Apache Drill, are just to list some popular big data solutions that have been used frequently in the market (Taylor, 2022). Among these, extensive spending has been made on big data analytics software like Hadoop, NoSQL, HBase, MongoDB, and Cassandra to process the big data to gain some useful statistical information about the current market that they are serving (Mikalef et al., 2017).

1.3 Problem Statement

Manufacturers are under heavy pressure to improve their capability and performance in managing big data analytics (Protiviti, 2017; Subramaniam, 2020) because the race is to explore this enormous number of data sets to collect some unknown configuration, industry direction, and more helpful statistics about the current market (Chong, 2017; Feyen et al., 2021). The trend toward adopting data analytics is unavoidable as many multinational firms are embracing these new technologies to outperform each other (Gupta and George, 2016; Jha, Agi and Ngai, 2020; Mikalef et al., 2020). International companies, as well as small and medium enterprises (SMEs), are also struggling to learn this new technology to survive in the exponentially growing data-centric economy (Zainul, 2017; Menon, 2018; Chuah and Thurusamry, 2021). If the local companies do not follow the trend, they could fail to retain their customers (Tan, 2018; Tien et al., 2020). However, Baharuden, Isaac and Ameen (2019) and Tien et al. (2020) cite that the current acceptance level of big data analytics in business is still very low and Malaysia is yet to reach an optimum level. As such, it is important to study the current stage of their capability to use big data analytics in the context of Malaysian manufacturing firms.

In the domain of IT, the adoption rate of big data analytics continues its upward trend, and currently, the writing about big data analytics is nevertheless at a premature level (Cosic, Shanks and Maynard, 2012; Mikalef *et al.*, 2017, 2020; Mandal, 2018; Baharuden, Isaac and Ameen, 2019; Jha, Agi and Ngai, 2020). The lack of literature contribution related to big data analytics in Malaysia has attracted the attention of researchers and the Malaysian government (Mishra *et al.*, 2018; Chuah and Thurusamry, 2021). This is consistent with the Ministry of International Trade and Industry (MITI, 2018) by urging more researchers to examine the evolution movement of big data analytics and its key performance indicators for firms to stay competitive through the National Fourth Industrial Revolution (4IR) Policy. This is reflected in this research by having cost and differentiation advantages as the efficiency indicators for manufacturing firms to achieve better firm performance through enhancing their big data analytics capability.

The literature has shown that big data analytics could establish benefits for firms by enabling the improvement of business processes (Wong *et al.*, 2015; Akter *et al.*, 2016; Wamba *et al.*, 2017; Mandal, 2018; Subramaniam, 2020) and firm performance (Cosic, Shanks and Maynard, 2012; Gupta and George, 2016; Gunasekaran *et al.*, 2017; Baharuden, Isaac and Ameen, 2019; Jha, Agi and Ngai, 2020). Despite empirical evidence that big data analytics has provided benefits to an organisation, few studies provide a sound theoretical basis for understanding how to qualify a resource or capability in terms of its value, rareness, inimitability, and non-substitutability (VRIN) that could create BDAC and subsequently achieve competitive advantage over time (Gupta and George, 2016; Mikalef *et al.*, 2020). Furthermore, not all firms have gained substantial returns after making a large investment in big data analytics (Cosic, Shanks and Maynard, 2012; Mcafee and Brynjolfsson, 2012; Ross, Beath and Quaadgras, 2013; Davenport, 2014; Maritz, Eybers and Hattingh, 2020; Mikalef *et al.*, 2020). The benefits of using big data analytics are yet to be clear, although the adoption of big data analytics has increased gradually (Shaheera, 2017; Chuah and Thurusamry, 2021). This is because of unclear direction to the firms on how to use their BDAC to gain competitive advantage and greater firm performance (Akter et al., 2016; Dubey et al., 2016; Gupta and George, 2016; Mikalef et al., 2020; Papadopoulos et al., 2021). Therefore, this research is important to provide a direction to ensure a company can attain a high level of firm performance through examining its extent of BDAC in achieving a competitive advantage against the backdrop of uncertain global trade.

1.4 Research Questions

This research examined the extent of BDAC in manufacturing firms in Malaysia and explained the linkage between BDAC, competitive advantage, and firm performance. There are five research questions as follows:

1. What is the current stage of BDAC in manufacturing firms?
2. Does the BDAC positively influence competitive advantage?
3. Does the BDAC positively influence firm performance?
4. Does the competitive advantage positively influence firm performance?
5. Does the competitive advantage positively mediate the relationship between BDAC and firm performance?

1.5 Research Objectives

Five research objectives were stipulated to answer the research questions for this research.

1. To identify the current stage of BDAC in manufacturing firms.
2. To examine the relationships between BDAC and competitive advantage.
3. To examine the relationships between BDAC and firm performance.
4. To examine the relationships between competitive advantage and firm performance.
5. To examine the mediating role of competitive advantage between BDAC and firm performance.

1.6 Research Scope

Due to time and financial constraints, the scope of the research was focused on the following areas only. First, this research assessed the extent of BDAC among manufacturing firms in Malaysia. Second, the distributed questionnaire has been limited to the manufacturing firms registered in the Federation of Malaysian Manufacturers (FMM) 2018 in the 49th edition. Third, this research examined the linkage between BDAC, competitive advantage, and firm performance in the Malaysian manufacturing industry.

1.7 Significance of the Study

1.7.1 Theoretical Significance

The first theoretical significance is using the Resource-Based View (RBV) and the entanglement view of sociomaterialism theories to support the research model. RBV provides reasoning to identify and qualify whether a resource or capability of the firm may be significant with the criterion of valuable, rare, imitability, and non-substitutability (VRIN) to gain competitive advantage and better firm performance. According to the entanglement view of sociomaterialism, BDAC has been regarded as a bundle of resources that consists of data, technology, data-driven culture, the intensity of organisational learning, technical and managerial skills. The second theoretical significance is to fill in the missing empirical evidence between BDAC and competitive advantage. BDAC has been found to be a critical variable to achieve differentiation advantage and success with better market performance. The third theoretical significance is to provide a sliver of evidence on the mediating role of differentiation advantage between BDAC and market performance. The fourth theoretical significance is to reply to the call for more research echoed by Govinsider (2015); IDC (2015); Baharuden, Isaac and Ameen (2019); Jha, Agi and Ngai (2020); Mikalef *et al.* (2020). This research aims to fill in the literature about BDAC by examining the current stage of BDAC and its extent in achieving competitive advantage for greater firm performance among the manufacturing firms in Malaysia.

1.7.2 Managerial Significance

The first managerial significance is to present the current stage of BDAC in manufacturing firms. The results show that the current stage of BDAC in manufacturing is experiencing positive growth compared to the previous literature. Although the rate of adoption is progressing well, only 33.5 percent of the respondents have reached a professional level of capability to use big data analytics. The second managerial significance is to prove BDAC as a valuable, rare, inimitable, and non-substitutable resource for manufacturers to enhance their firm performance. The research findings indicate that BDAC is significant to achieve a better market and operational performance. The third managerial significance is to determine the linkage between the BDAC and competitive advantage among the manufacturing firms in Malaysia. The results show that BDAC is one of the key resources for manufacturers to achieve a differentiation advantage. The fourth practical significance is to examine the relationship between competitive advantage and firm performance in the context of the manufacturing sector. The research findings show that a cost advantage is less likely to help manufacturers achieve greater market and operational performance. A differentiation advantage is positively leading to greater market performance.

1.8 Definition of Key Terms

This research has identified five variables, which are BDAC, cost advantage, differentiation advantage, operational performance, and market performance. The section presents the operational definitions of those terms.

i. Big Data Analytics Capability (BDAC) – means a firm's competencies to collect, incorporate, and organise its big data-specific resources like tangible resources, intangible resources, and human skills (Gupta and George, 2016; Mikalef *et al.*, 2020).

ii. Cost advantage – refers to a strategy to operate at the lowest cost relative to its competitors (Best, 2000; Wang *et al.*, 2006; Wong, Soh and Chong, 2016; Kankam-Kwarteng, Osman and Donkor, 2019).

iii. Differentiation advantage – refers to a strategy for differentiating a company's product or service offering from its key competitors in terms of attributes, speed, and adaptability, where cost is not a significant factor (Hambrick, 1983; Wong, Soh and Chong, 2016; Semuel, Siagian and Octavia, 2017).

iv. Operational performance - is a measurement perspective of the achievement, namely consistency, quality of service, speed of delivery, productivity, profitability, inventory turnover rate, and manufacturing cycle time of a business operation (Wang *et al.*, 2012; Gupta and George, 2016).

v. Market performance - is a measurement perspective of the firm's achievement namely the speed and success of the firm in entering a new market and introducing new products or services to the marketplace (Wang *et al.*, 2012; Gupta and George, 2016).

1.9 Organisation of the Thesis

This thesis is divided into five chapters. Chapter 1 provides the background of the study, justifies the reasons for doing this research with accompanying problem statements, research questions, research objectives, research scope, the significance of the study, and definition of key terms. Chapter 2 contains literature relating to the RBV and the entanglement view of sociomaterialism theories that forms the hypothesised relationship of this study as well as the research model. Chapter 3 presents the research design and sources of the measurement items, sampling technique, questionnaire design, and pilot test. The procedure of assessing measurement and structural models through Structural Equation Modelling has been detailed throughout Chapter 3. Chapter 4 presents the results, respondents' characteristics, the findings of the hypothesised relationships and concludes with a summary of the results. Chapter 5 discussed the results, implications of the outcomes, and limitations of this research. This research ends by offering future research directions and concluding remarks.

REFERENCES

Abba, M.T. (2021) 'Analysing competitor and creating a competitive advantage', *Interdisciplinary Journal of Applied and Basic Subjects*, 1(8), pp. 31-42.

Acquaah, M. and Agyapong, A. (2015) 'The Relationship between Competitive Strategy and Firm Performance in Micro and Small Businesses in Ghana: The Moderating Role of Managerial and Marketing Capabilities', *Africa Journal of Management*, 1(2), pp. 172–193.

Adam, E.E. and Swamidass, P.M. (1989) 'Assessing operations management from a strategic perspective.', *Journal of Management*, 15(2), pp. 181–203.

Ajah, I.A. and Nweke, H.F. (2019) 'Big Data and Business Analytics: Trends, Platforms, Success Factors and Applications', *Big Data and Cognitive Computing*, 3(32), pp. 1–30.

Akter, S., D'Ambra, J. and Ray, P. (2011) 'Trustworthiness in mHealth Information Services: An Assessment of a Hierarchical Model with Mediating and Moderating Effects Using Partial Least Squares (PLS)', *Journal of The American Society For Information Science And Technology*, 62(1), pp. 100–116.

Akter, S., Gunasekaran, A., Wamba, S.F., Babu, M.M. and Hani, U. (2020) 'Reshaping competitive advantages with analytics capabilities in service systems', *Technological Forecasting and Social Change*, 159(October), pp. 120–180.

Akter, S., McCarthy, G., Sajib, S., Michael, K., Dwivedi, Y., A'Ambra, J. and Shen, K.N. (2021) 'Algorithmic bias in data-driven innovation in the age of AI', *International Journal of Information Management*, 60(October), pp. 102–387.

Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R. and Childe, S. (2016) 'How to improve firm performance using big data analytics capability and business performance?', *International Journal of Production Economics*, 182, pp. 113-131.

Alshawi, S. (2001) 'Logistics in the Internet age: Towards a holistic information and processes picture.', *Logistics Information Management*, 14(4), pp. 235–241.

Alshurideh, M., Alsharari, N.M. and Kurdi, B.A. (2019) ‘Supply Chain Integration and Customer Relationship Management in the Airline Logistics’, *Theoretical Economics Letters*, 9(2), pp. 1–23.

Amit, R. and Schoemaker, P.J.H. (1993) ‘Strategic assets and organizational rent’, *Strategic Management Journal*, 14(1), pp. 33–46.

Anthey, S. (2017) ‘Beyond prediction: Using big data for policy problems’, *Science*, 355(6324), pp. 1–3.

Arias-Pérez, J., Coronado-Medina, A. and Perdomo-Charry, G. (2021) ‘Big data analytics capability as a mediator in the impact of open innovation on firm performance’, *Journal of Strategy and Management*, 15(1), pp. 1–15.

Armstrong, J.S. (1982) ‘The value of formal planning for strategic decisions: Review of empirical research.’, *Strategic Management Journal*, 3(3), pp. 197–211.

Armstrong, J.S. and Overton, T.S. (1977) ‘Estimating Nonresponse Bias in Mail Surveys.’, *Journal of Marketing Research*, 14(3), pp. 396–402.

Ashaari, M.A., Singh, K.S.D., Abbasi, G.A., Amran, A. and Liebana-Cabanillas, F.J. (2021) ‘Big data analytics capability for improved performance of higher education institutions in the Era of IR 4.0: A multi-analytical SEM & ANN perspective.’, *Technological Forecasting and Social Change*, 173, pp. 1–16.

Aulakh, P.S., Kotabe, M. and Teegen, H. (2000) ‘Export Strategies and Performance of Firms from Emerging Economies.’, *Academy of Management Journal*, 43(3), pp. 342–361.

Awan, U., Shamim, S., Khan, Z., Ul Zia, N., Muhammad Shariq, S. and Naveed Khan, M. (2021) ‘Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance’, *Technological Forecasting and Social Change*, 168, pp. 1–12.

Azeem, M., Haleem, A., Bahl, S., Javaid, M., Suman, R. and Nandan, D. (2021) ‘Big data applications to take up major challenges across manufacturing industries: A brief review’, *Materials Today*, pp. 1–10.

Babu, M.M., Rahman, M., Alam, A. and Dey, B.L. (2021) 'Exploring big data-driven innovation in the manufacturing sector: evidence from UK firms', *Annals of Operations Research*, pp. 1–28.

Bagozzi, R.P., Dholakia, U.M. and Basuroy, S. (2003) 'How effortful decisions get enacted: The motivating role of decision processes, desires, and anticipated emotions.', *Journal of Behavioral Decision Making*, 16, pp. 273–295.

Bagozzi, R.P. and Yi, Y. (2012) 'Specification, evaluation, and interpretation of structural equation models', *Journal of the Academy of Marketing Science*, 40, pp. 8–34.

Baharuden, A.F., Isaac, O. and Ameen, A. (2019) 'Factors Influencing Big Data and Analytics (BDandA) Learning Intentions with Transformational Leadership as Moderator Variable: Malaysian SME Perspective.', *International Journal of Management and Human Science (IJMHS)*, 3(1), pp. 10-20.

Bain, J.S. (1956) *Barriers to New Competition*. Cambridge, MA: Harvard University Press.

Banker, R.D., Mashruwala, R. and Tripathy, A. (2014) 'Does a differentiation strategy lead to more sustainable financial performance than a cost leadership strategy?', *Management Decision*, 52(5), pp. 872–896.

Barney, J. (1991) 'Firm Resources and Sustained Competitive Advantage', *Journal of Management*, pp. 99–121.

Barney, J., Wright, M. and Ketchen, D.J. (2001) 'The resource-based view of the firm Ten years after 1991', *Journal of Management*, 27, pp. 625–641.

Barney, J.B. (1986) 'Strategic Factor Markets: Expectations, Luck, and Business Strategy', *Management Science*, 32(10), pp. 1231–1241.

Barney, J.B. (1995) 'Looking inside for competitive advantage.', *Academy of Management Perspectives*, 9(4), pp. 49–61.

Barney, J.B. (2001) 'Resource-based theories of competitive advantage: A tenyear retrospective on the resource-based view', *Journal of Management*, 27, pp. 643–650.

Barney, J.B. and Clark, D.N. (2007) *Resource-based theory: creating and sustaining competitive advantage.* New York: Oxford University Press.

Basbeth, F., Ramli, A., Ashlyzan, M.B.R.N., Zain, R.M. and Noorshella, B.C.N. (2019) 'The Role of Multi Dimensional EO in the Competitive Strategy - Performance Link.', *Research in World Economy*, 10(2), pp. 20–25.

Becker, J.-M., Klein, K. and Wetzels, M. (2012) 'Hierarchical Latent Variable Models in PLS-SEM: Guidelines for Using Reflective-Formative Type Models', *Long Range Planning*, 45, pp. 359–394.

Belhadi, A., Kamble, S., Jabbour, C.J.C., Gunasekaran, A., Ndubisi, N.O. and Venkatesh, M. (2021) 'Manufacturing and service supply chain resilience to the COVID-19 outbreak: Lessons learned from the automobile and airline industries.', *Technological Forecasting and Social Change*, 163, pp. 1–19.

Bername (2021) *FMM clears misconception on Covid-19 cases from factory cluster*. Available at: https://www.theedgemarkets.com/article/fmm-clears-misconception-covid19-cases-factory-clusters (Accessed: 8 August 2021).

Bernerth, J.B. and Aguinis, H. (2016) 'A critical review and best-practice recommendations for control variable usage', *Personnel Psychology*, 69, pp. 229–283.

Bernerth, J.B., Cole, M.S., Taylor, E.C. and Walker, H.J. (2018) 'Control Variables in Leadership Research: A Qualitative and Quantitative Review', *Journal of Management*, 44(1), pp. 131–160.

Best, R.J. (2000) *Market-based management: Strategies for growing customer value and profitability*. 2nd edn. Prentice Hall, Upper Saddle River, New Jersey 07458.

Bharadwaj, A.S. (2000) 'A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation', *Management Information Systems*, 24(1), pp. 169–196.

Bhatt, G. and Grover, V. (2005) 'Types of Information Technology Capabilities and their roles in Competitive Advantage: an empirical study', *Journal of Management Information Systems*, 22(2), pp. 253–277.

Bhattacharyya, S.S. and Thakre, S. (2021) 'Coronavirus pandemic and economic lockdown; study of strategic initiatives and tactical responses of firms', *International Journal of Organisational Analysis*, 29(5), pp. 1–29.

Bhattacherjee, A. (2012) *Social Science Research: Principles, Methods, and Practices*. 3rd edn. Scholar Commons: University of South Florida. Available at: http://scholarcommons.usf.edu/oa_textbooks/3. (Accessed: 8 August 2021).

Bhunia, P. (2017) *Malaysia digital economy corporation launches ASEAN data analytics exchange to build talent pool*. Available at: https://www.opengovasia.com/malaysia-digital-economy-corporation-launches-asean-data-analytics-exchange-to-build-talent-pool/ (Accessed: 12 September 2019).

Black, J.A. and Boal, K.B. (1994) 'Strategic resources: Traits, configurations and paths to sustainable competitive advantage', *Strategic Management Journal*, 15(2), pp. 131–148.

Bloom, N., Bunn, P., Mizen, P., Smietanka, P. and Thwaites, G. (2020) *The Impact of Covid-19 on Productivity*. No. 28233. Available at: https://www.nber.org/system/files/working_papers/w28233/revisions/w28233.rev0.pdf. (Accessed: 8 August 2021).

Boggess, M. (2019) *10 Trends That Will Dominate Manufacturing in 2019*. Available at: https://us.hitachi-solutions.com/blog/top-manufacturing-trends/ (Accessed: 28 December 2019).

Boldosova, V. and Luoto, S. (2020) 'Storytelling, business analytics and big data interpretation: Literature review and theoretical propositions.', *Management Research Review*, 43(2), pp. 204–222.

Bollen, K.A. (2011) 'Evaluating effect, composite and causal indicators in structural equation models', *MIS Quarterly*, 35(2), pp. 359–372.

Bougie, R. and Sekaran, U. (2020) *Research method for business: A skill building approach*. 8th edn. New York: John Wiley and Sons.

Bowden, A., Fox-Rushby, J.A., Nyandieka, L. and Wanjau, J. (2002) 'Methods for pre-testing and piloting survey questions: illustrations from the KENQOL survey of health-related quality of life', *Health Policy and Planning*, 17(3), pp. 322–330.

Bowersox, D.J. and Daugherty, P.J. (1995) 'Logistics paradigms: The impact of information technology.', *Journal of Business Logistics*, 16(1), pp. 65–80.

Brown, S., Squire, B. and Blackmon, K. (2007) 'The contribution of manufacturing strategy involvement and alignment to world-class manufacturing performance.', *International Journal of Operations & Production Management*, 27(3), pp. 282–302.

Cain, M.K., Zhang, Z. and Yuan, K.H. (2016) 'Univariate and multivariate skewness and kurtosis for measuring nonnormality: Prevalence, influence and estimation', *Behavior Research Methods*, 49(5), pp. 1716–1735.

Calicchio, A.C. and Marcondes, R.C. (2016) 'Relevant factors for competitiveness in information technology consulting business', *Gestão & Produção*, 23(3), pp. 625–637.

Castanias, R.P. and Helfat, C.E. (1991) 'Managerial resources and rents.', *Journal of Management*, 17(1), pp. 155–171.

Caves, R.E. and Porter, M.E. (1978) 'Market structure, oligopoly, and stability of market shares', *Journal of Industrial Economics*, 26(4), pp. 289–313.

Chadwick, C. and Flinchbaugh, C. (2021) 'Searching for competitive advantage in the HRM-firm performance relationship', *Academy of Management Perspectives*, 35(2), pp. 181–207.

Chae, B. and Olson, D.L. (2013) 'Business Analytics for Supply Chain: A Dynamic-Capabilities Framework', *International Journal of Information Technology & Decision Making*, 12(1), pp. 9–26.

Chellam, R. (2018) *Econ 4.0: How big is big data?*, *The Edge Market*. Available at: https://www.theedgemarkets.com/article/econ-40-how-big-big-data (Accessed: 29 December 2019).

Chen, C.L. and Zhang, C.Y. (2014) 'Data-intensive applications, challenges, techniques and technologies: a survey on Big Data', *Information Science*, 275, pp. 314–347.

Chen, H.-M., Chang, K.-C. and Lin, T.-H. (2015) 'A cloud-based system framework for performing online viewing, storage, and analysis on big data of massive BIMs', *Automation in Construction*, 71(1), pp. 34-48.

Cheng, L.C. and Grimm, C.M. (2006) 'The application of empirical strategic management research to supply chain management.', *Journal of Business Logistics*, 27(1), pp. 1–57.

Chin, C.F. (2020) 'The impact of food supply chain disruptions amidst COVID-19 in Malaysia.', *Journal of Agriculture, Food Systems, and Community Development*, 9(4), pp. 161–163.

Chin, W.W. (1998) *The partial least squares approach for structural equation modeling: Modern Methods for Business Research*. G.A. Marco. Lawrence Erlbaum Associates Inc., Mahway, NJ.

Chin, W.W. (2010) *How to write up and report PLS analyses: Handbook of partial least squares*. Springer, Heidelberg, Dordrecht, London, New York.

Chiu, C.-N. and Yang, C.-L. (2019) 'Competitive advantage and simultaneous mutual influences between information technology adoption and service innovation: Moderating effects of environmental factors', *Structural Change and Economic Dynamics*, 49, pp. 192–205.

Chong, C.L., Siti Zaleha, A.S. and Haliyana, K. (2021) 'Open-source software is now a trend and has witnessed a rampant evolution due to less start-up cost, user-friendliness and many other benefits', in *2021 7th International Conference on Research and Innovation in Information Systems (ICRIIS)*, pp. 1–6.

Chong, J.X. (2017) *MDEC to spearhead bigger push for big data adoption in Malaysia*. Available at: https://www.digitalnewsasia.com/digital-economy/mdec-spearhead-bigger-push-big-data-adoption-malaysia (Accessed: 16 October 2018).

Chowdhury, M.T., Sarkar, A., Paul, S.K. and Moktadir, M.A. (2020) ‘A case study on strategies to deal with the impacts of Covid-19 pandemic in the food and beverage industry’, *Operations Management Research*, pp. 1–13.

Chuah, M.H. and Thurusamry, R. (2021) ‘Challenges of big data adoption in Malaysia SMEs based on Lessig’s modalities: A systematic review’, *Cogent Business & Management*, 8(1), pp. 1–8.

Chukwunonso, F., Omoju, J.O., Ikani, D. and Ribadu, M.B. (2011) ‘Management of information technology for competitive advantage: a savvy case study’, *Journal of Scientific Research*, 1(2), pp. 121–129.

Closs, D.J., Goldsby, T.J. and Clinton, S.R. (1997) ‘Information technology influences on world class logistics capability.’, *International Journal of Physical Distribution & Logistics Management*, 27(1), pp. 4–17.

Coff, R.W. (1997) ‘Human assets and management dilemmas: Coping with hazards on the road to resource-based theory’, *Academy of Management Review*, 22(2), pp. 374–402.

Cohen, J. (1988) *Statistical power analysis for the behavioral sciences*. Hillsdale, NJ: Lawrence Erlbaum.

Cohen, J. (1992) ‘A Power Primer’, *Psychological Bulletin*, 112(1), pp. 155–159.

Collier, J.E. and Bienstock, C.C. (2007) ‘An analysis of how nonresponse error is assessed in academic marketing research’, *Marketing Theory*, 7(2), pp. 163–183.

Columbus, L. (2017) *53% of companies are adopting Big Data Analytics.*, *Forbes*. Available at: https://www.forbes.com/sites/louiscolumbus/2017/12/24/53-of-companies-are-adopting-big-data-analytics/#60aa2b7d39a1 (Accessed: 3 September 2019).

Conway, J.M. and Lance, C.E. (2010) ‘What Reviewers Should Expect from Authors Regarding Common Method Bias in Organizational Research’, *Journal of Business and Psychology*, 25, pp. 325–334.

Côrte-Real, N., Oliveira, T. and Ruivo, P. (2017) ‘Assessing business value of Big Data Analytics in European firms’, *Journal of Business Research*, 70, pp. 379–390.

Cosic, R., Shanks, G. and Maynard, S. (2012) 'Towards a business analytics capability maturity model.', in. In Proceeding of the 23rd Australasian Conference on Information Systems, Geelong, 3-5 Dec 2012, pp. 1-11.

Cukier, K. and Mayer-Schoenberger, V. (2013) *The rise of big data: How it's changing the way we think about the world. Foreign Affairs*. Available at: http://cs.brown.edu/courses/cs100/lectures/readings/riseOfBigData.pdf (Accessed: 20 August 2021).

Curran, P.J., West, S.G. and Finch, J.F. (1996) 'The Robustness of Test Statistics to Nonnormality and Specification Error in Confirmatory Factor Analysis', *Psychological Methods*, 1(1), pp. 16–29.

Dan, B., Zhang, S. and Zhou, M. (2018) 'Strategies for warranty service in a dual-channel supply chain with value-added service competition', *International Journal of Production Research*, 56(17), pp. 5677–5699.

Daniels, J. (2019) *5 manufacturing trends for 2020*. Available at: https://industrytoday.com/article/5-manufacturing-trends-for-2020/ (Accessed: 28 December 2019).

Daugherty, P.J., Germain, R. and Droge, C. (1995) 'Predicting EDI technology adoption in logistics management: The influence of context and structure.', *Logistics & Transportation Review*, 31(4), pp. 309–324.

Davenport, T. (2014) 'How strategists use "big data" to support internal business decisions, discovery and production', *Strategy and Leadership*, 42(4), pp. 45–50.

Day, G.S. (1994) 'The Capabilities of Market-Driven Organizations', *Journal of Marketing*, 58(4), pp. 37-53.

Dean JR, J.W. and Sharfman, M.P. (1996) 'Does decision process matter? A study of strategic decision-making effectiveness.', *Academy of Management Journal*, 39(2), pp. 368–396.

Dess, G.G. and Davis, P.S. (1984) 'Porter's (1980) generic strategies as determinants of strategic group membership and organizational performance.', *Academy of Management Journal*, 27(3), pp. 467–488.

Diamantopoulos, A. (2008) ‘Formative indicators: Introduction to the special issue.’, *Journal of Business Research*, 61(12), pp. 1201–1202.

Diamantopoulos, A. and Siguaw, J.A. (2006) ‘Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration.’, *British Journal of Management*, 17(4), pp. 263–282.

Dierickx, I. and Cool, K. (1989) ‘Asset stock accumulation an sustainability of competitive advantage’, *Management Science*, 35(12), pp. 1504-1511.

Doyle, P. and Wong, V. (1998) ‘Marketing and competitive performance: An empirical study.’, *European Journal of Marketing*, 32(5/6), pp. 514–535.

Duan, L. and Xiong, Y. (2015) ‘Big data analytics and business analytics’, *Journal of Management Analytics*, 2(1), pp. 1–21.

Dubey, R., Gunasekaran, A., Childe, S.J. and Fosso Wamba, S. Papadopoulos, T. (2016) ‘The impact of big data on world-class sustainable manufacturing’, *The International Journal of Advanced Manufacturing Technology*, 84, pp. 631–645.

Economic Planning Unit, P.M.D. (2020) *Malaysia Digital Economy Blueprint*. Available at: https://www.epu.gov.my/sites/default/files/2021-02/malaysia-digital-economy-blueprint.pdf. (Accessed: 8 August 2021).

Edwards, J.R. (2001) ‘Multidimensional constructs in organizational behavior research: An integrative analytical framework.’, *Organizational Research Methods*, 4(2), pp. 144–192.

Ehie, I. and Muogboh, O. (2016) ‘Analysis of manufacturing strategy in developing countries: A sample survey of Nigerian manufacturers’, *Journal of Manufacturing Technology Management*, 27(2), pp. 234–260.

Eisenhardt, K.M. and Martin, J.A. (2000) ‘Dynamic capabilities: What are they?’, *Strategic Management Journal*, 21(Special Issue: The Evolution of Firm Capabilities), pp. 1105–1121.

Elgendy, N. and Elragal, A. (2014) ‘Big Data Analytics: A Literature Review Paper’, *Springer International Publishing Switzerland*, pp. 214–227.

Ernest, C.R. (2011) ‘Big Data, Analytics and the Path From Insights to Value’, *MIT Sloan: Management Review*, 52(2), pp. 21–31.

Fahy, J. (2000) ‘The resource-based view of the firm: some stumblingblocks on the road to understanding sustainable competitive advantage’, *Journal of European Industrial Training*, 24/2(3/4), pp. 94–104.

Fan, W. and Yan, Z. (2010) ‘Factors affecting response rates of the web survey: A systematic review.’, *Computers in Human Behavior*, 26(2), pp. 132–139.

Feraud, G.J.S. (1998) ‘Improving strategic decision making in logistics information management - A framework.’, *Logistics Information Management*, 11(4), pp. 232–243.

Fernando, Y. (2012) ‘Impact of internal marketing on operational performance: An empirical study in low cost carrier industry’, *Procedia - Social and Behavioral Sciences*, 65, pp. 913–918.

Fernando, Y., Chidambaram, R.R.M. and Wahyuni, I.S.T.D. (2018) ‘Fernando, Y., Chidambaram, R. R. M., & Wahyuni, I. S. T. D’, *Benchmarking: An International Journal*, 25(9), pp. 4009–4034.

Feyen, E., Frost, J., Gambacorta, L., Natarajan, H. and Saal, M. (2021) *Fintech and the digital transformation of financial services: implications for market structure and public policy*. Available at: https://www.bis.org/publ/bppdf/bispap117.pdf. (Accessed: 8 August 2021).

Fitzsimmons, J.A. and Fitzsimmons, M.J. (1998) *Service management: Operations, strategy, and information technology*. 2nd edn. New York: McGraw-Hil.

Floortje, B.D., Dalen, J. V. and Ende, J.V.D. (2010) ‘Subjective performance assessment of innovation projects.’, *Journal of Production Innovation Management*, 27, pp. 572–592.

FMM 49th Edition & Advertisement in FMM 50th Edition Directory (JB/08/2019) (2021) *Federation of Malaysian Manufacturers*. Available at: https://www.fmm.org.my/Johor-@-Branch_Circulars-@-FMM_49th_Edition_-◘-_Advertisiment_in_FMM_50th_Edition_Directory_(JB-s-08-s-2019).aspx (Accessed: 12 December 2021).

Foong, A. (2021) *Finally Answered: How much does a data scientist earn in Malaysia?*, *UCAN Technologies*. Available at: https://thelead.io/data-science/how-much-does-a-data-scientist-earn-in-malaysia (Accessed: 3 December 2021).

Franke, G. and Sarstedt, M. (2019) 'Heuristics versus statistics in discriminant validity testing: a comparison of four procedures', *Internet Research*, pp. 1066–2243. Available at: https://doi.org/10.1108/IntR-12-2017-0515. (Accessed: 8 August 2021).

Frankfort-Nachmias, C. and Nachmias, D. (1992) *Research methods in the social sciences*. 4th edn. New York: St. Martin's Press.

Galbraith, J.R. (2014) 'Organisation design challenges resulting from big data', *Journal of Organisation Design*, 3(1), pp. 2–13.

Galbreath, J., Lucianetti, L., Thomas, B. and Tisch, D. (2020) 'Entrepreneurial orientation and firm performance in Italian firms: The moderating role of competitive strategy.', *International Journal of Entrepreneurial Behavior & Research*, 26(4), pp. 629–646.

Garmaki, M., Boughzala, I. and Wamba, S.F. (2016) 'The effect of big data analytics capability on firm performance', in *Pacific Asia Conference on Information Systems (PACIS)*, pp. 1–10. Available at: http://aisel.aisnet.org/pacis2016/301. (Accessed: 8 August 2021).

Gatignon, H. and Xuereb, J.-M. (1997) 'Strategic Orientation of the Firm and New Product Performance', *Journal of Marketing Research*, 34(1), pp. 77–90.

Gefen, D., Rigdon, E.E. and Straub, D. (2011) 'An Update and Extension to SEM Guidelines for Administrative and Social Science Research', *MIS Quarterly*, 35(2), pp. 1–7.

Gehani, R.R. (2013) ‘Innovative Strategic Leader Transforming From a Low-Cost Strategy to Product Differentiation Strategy’, *Journal of Technology Management & Innovation*, 8(2), pp. 144–155.

Geisser, S. (1974) ‘A predictive approach to the random effects model.’, *Biometrika*, 61, pp. 101–107.

Geoffrion, M. and Powers, F. (1995) ‘Twenty years of strategic distribution system design: An evolutionary perspective.’, *Interfaces*, 25, pp. 105–127.

Ghasemaghaei, M. and Calic, G. (2019) ‘Does big data enhance firm innovation competency? The mediating role of data-driven insights’, *Journal of Business Research*, 104, pp. 69–84.

Gibson, C.B., Gibson, S.C. and Webster, Q. (2021) ‘Expanding Our Resources: Including Community in the Resource-Based View of the Firm’, *Journal of Management*, 47(7), pp. 1878–1898.

Goh, E.A., Suhaiza, Z. and Nabsiah, A.W. (2006) ‘A study on the impact of environmental management system (EMS) certification towards firms’ performance in Malaysia.’, *Management of Environmental Quality: An Internal Journal*, 17(1), pp. 73–93.

Goh, T.E. (2014) *Big data analytics: Companies still struggling with the basic*. Available at: https://www.digitalnewsasia.com/enterprise/big-data-analytics-companies-still-struggling-with-the-basics (Accessed: 28 August 2021).

Goh, T.E. (2015) *Big data: Malaysia takes ‘small but significant’ first step*. Available at: http://www.digitalnewsasia.com/digital-economy/big-data-malaysia-tak (Accessed: 10 October 2018).

Gökalp, M.O., Gökalp, E., Kayabay, K., Koçyiğit, A. and Eren, P.A. (2021) ‘Data-driven manufacturing: An assessment model for data science maturity’, *Journal of Manufacturing Systems*, 60, pp. 527–546.

Gold, A.H., Malhotra, A. and Segars, A.H. (2001) ‘Knowledge management: an organizational capabilities perspective’, *Journal of Management Information Systems*, 18(1), pp. 185–214.

Goodboy, A.K. and Kline, R.B. (2017) ‘Statistical and Practical Concerns With Published Communication Research Featuring Structural Equation Modeling’, *Communication Research Reports*, 34(1), pp. 68–77.

Goodhue, D., Lewis, W. and Thompson, R. (2007) ‘Statistical Power in Analyzing Interaction Effects: Questioning the Advantage of PLS with Product Indicators’, *Information Systems Research*, 18(2), pp. 211–227.

Govinsider (2015) *Inside Malaysia’s national big data plan*. Available at: https://govinsider.asia/innovation/inside-malaysias-national-big-data-plan/ (Accessed: 10 September 2019).

Grant, R.M. (1991) ‘The resource-based theory of competitive advantage: Implications for strategy formulation’, *California Management Review*, 33(3), pp. 114–135.

Grant, R.M. (2010) *Contemporary Strategy Analysis and Cases: Text and Cases*. 7th edn. United Kingdom: John Wiley and Sons.

Greco, L., Maresca, P. and Caja, J. (2019) ‘Big data and advanced analytics in industry 4.0: a comparative analysis across the European Union.’, *Procedia Manufacturing*, pp. 383–390.

Grover, V. and Malhotra, M.K. (1999) ‘A framework for examining the interface between operations and information systems: Implications for research in the new millennium.’, *Decision Sciences*, 30(4), pp. 901–920.

Gu, V.C., Zhou, B., Cao, Q. and Adams, J. (2021) ‘Exploring the relationship between supplier development, big data analytics capability, and firm performance’, *Annals of Operations Research*, 302, pp. 151–172.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S.F., Childe, S.J., Hazen, B. and Akter, S. (2017) ‘Big data and predictive analytics for supply chain and organisational performance.’, *Journal of Business Research*, 70, pp. 308-317.

Gupta, M. and George, J.F. (2016) ‘Towards the development of a big data analytics capability.’, *Information and Management*, 53(8), pp. 1049–1064.

Gupta, S., Drave, V.A., Dwivedi, Y.K., Baabdullah, A.M. and Ismagilova, E. (2020) ‘Achieving superior organizational performance via big data predictive analytics: A dynamic capability view’, *Industrial Marketing Management*, 90(October), pp. 581–592.

Hahn, E.D. and Ang, S.H. (2017) ‘From the editors: New directions in the reporting of statistical results in the Journal of World Business’, *Journal of World Business*, 52(2), pp. 125–126.

Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2017) *A Primer on Partial Least Squares Structural Equation Modeling*. 2nd edn. Thousand Oaks, California: Sage Publications Inc.

Hair, J.F., Page, M. and Brunsveld, N. (2020) *Essentials of business research methods*. Fourth. New York and London: Routledge Taylor Francis Group.

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2011) ‘PLS-SEM: Indeed a silver bullet.’, *The Journal of Marketing Theory and Practice*, 19(2), pp. 139–152.

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2013) ‘Editorial Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance’, *Long Range Planning*, pp. 1–12.

Hair, J.J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2014) *Multivariate data analysis*. 7th edn. Upper Saddle River, N.J.: Pearson Prentice Hall.

Hair, J.J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2019) *Multivariate data analysis.* 8th editio. United Kingdom: Cengage Learning.

Hall, W.K. (1980) ‘Survival strategies in a hostile environment.’, *Harvard Business Review*, 58, pp. 75–85.

Hallberg, N.L. and Brattström, A. (2019) ‘Concealing or revealing? Alternative paths to profiting from innovation’, *European Management Journal*, 37(2), pp. 165–174.

Hallikainen, H., Savimäki, E. and Laukkanen, T. (2020) ‘Fostering B2B sales with customer big data analytics’, *Industrial Marketing Management*, 86, pp. 90–98.

Hambrick, D.C. (1983) ‘High profit strategies in mature capital goods industries: A contingency approach.’, *Academy of Management Journal*, 26, pp. 687–707.

Hamilton, R.H. and Sodeman, W.A. (2020) ‘The questions we ask: Opportunities and challenges for using big data analytics to strategically manage human capital resources’, *Business Horizons*, 63(1), pp. 85–95.

Hammant, J. (1995) ‘Information technology trends in logistics.’, *Logistics of Information Management*, 8(6), pp. 32–37.

Hannon, J. (2013) ‘Incommensurate practices: sociomaterial entanglements of learning technology implementation’, *Journal of Computer Assisted Learning*, 29, pp. 168–178.

Hao, S., Zhang, H. and Song, M. (2019) ‘Big Data, Big Data Analytics Capability, and Sustainable Innovation Performance’, *Sustainability*, 11(7145), pp. 1–15.

Hardaker, G., Trick, R.R. and Sabki, A.A. (1994) ‘The use of IT in freight forwarding in the UK.’, *Logistics Information Management*, 7(4), pp. 19–22.

Hartmann, P.M., Zaki, M., Feldmann, N. and Neely, A. (2016) ‘Capturing value from big data - a taxonomy of data-driven business models used by start-up firms’, *International Journal of Operations & Production Management*, 36(10), pp. 1382–1406.

Hassan, H. (2020) *Most Malaysian companies struggling under movement control curbs, unemployment at a 10-year high.*, *The Straits Times*. Available at: https://www.straitstimes.com/asia/se-asia/most-malaysian-companies-struggling-under-movement-control-curbs-unemployment-at-a-10 (Accessed: 8 August 2021).

Hayes, A.F. (2009) ‘Beyond Baron and Kenny: Statistical Mediation Analysis in the New Millennium.’, *Communication Monographs*, 76(4), pp. 408–420.

Helfat, C.E. and Raubitschek, R.S. (2000) ‘Product sequencing: co-evolution of knowledge, capabilities and products’, *Strategic Management Journal*, 21(1011), pp. 961–979.

Helm, S. (2005) ‘Academic Research Designing a formative measure for corporate reputation.’, *Corporate Reputation Review*, 8(2), pp. 95–109.

Henderson, J.C. and Venkatraman, H. (1993) ‘Strategic alignment: leveraging information technology for transforming organisations’, *IBM Systems Journal*, 32(1), pp. 472–484.

Henry, R. and Venkatraman, S. (2015) ‘Big data analytics the next big learning opportunity’, *Journal of Management Information & Decision Sciences*, 18(2), pp. 17–29.

Henseler, J. (2016) ‘Guest editorial’, *Industrial Management & Data Systems*, 16(9), pp. 1842–1848.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015) ‘A new criterion for assessing discriminant validity in variance-based structural equation modeling’, *Journal of the Academy of Marketing Science*, 43, pp. 115–135.

Henseler, J., Ringle, C.M. and Sinkovics, R.R. (2009) ‘The use of partial least squares path modeling in international marketing.’, *Advances in International Marketing*, 20(1), pp. 277–319.

Hill, C.W.L. and Jones, G.R. (2001) *Strategic management theory: An integrated approach*. 5th edn. Boston, New York: Houghton Mifflin Company.

Hitch, J. (2019) *Exposing the top ten manufacturing tech trends of the 2020s*. Available at: https://www.industryweek.com/manufacturing-technology-an-industryweek-event/media-gallery/22027228/exposing-the-top-ten-manufacturing-tech-trends-of-the-2020s/ (Accessed: 28 December 2019).

Hitt, M.A., Ireland, R.D. and Hoskisson, R.E. (2009) *Strategic management: Competitiveness and globalization (concepts)*. 8th edn. Canada: South-Western Cengage Learning.

Holmlund, M., Vaerenbergh, Y.V., Ciuchita, R., Ravald, A., Sarantopoulos, P. Ordenes, F.V. and Zaki, M. (2020) ‘Customer experience management in the age of big data analytics: A strategic framework’, *Journal of Business Research*, 116(August), pp. 356–365.

Hope, C. and Mühlemann, A. (1997) *Service operations management: strategy, design and delivery.* London New York: Prentice Hall.

Huang, F., Gardner, S. and Moayer, S. (2016) ‘Towards a framework for strategic knowledge management practice: Integrating soft and hard systems for competitive advantage’, *VINE Journal of Information and Knowledge Management Systems*, 46(4).

Hudson, L.A. and Ozanne, J.L. (1988) ‘Alternative Ways of Seeking Knowledge in Consumer Research’, *The Journal of Consumer Research*, 14(4), pp. 508–521.

Hulland, J. (1999) ‘Use of Partial Least Squares (PLS) in Strategic Management Research: A Review of Four Recent Studies’, *Strategic Management Journal*, 20 (April), pp. 195–204.

Hunt, S.D. (1991) ‘Positivism and paradigm dominance in consumer research: Toward critical pluralism and rapprochement.’, *Journal of Consumer Research*, 18, pp. 32–44.

Huo, B., Selen, W., Yeung, H.Y. and Zhao, X. (2008) ‘Understanding drivers of performance in the 3PL industry in Hong Kong.’, *International Journal of Operation & Production Management*, 28(8), pp. 772–800.

Hussein, A.A. (2020) ‘How Many Old and New Big Data V’s Characteristics, Processing Technology, And Applications (BD1)’, *International Journal of Application or Innovation in Engineering & Management*, 9(9), pp. 15–27.

IDC (2015) *National Big Data Analytics MaturityScape Assessment: Final Report.* Available at: https://disruptivetechasean.com/big_news/big-data-analytics-bda-maturity-assessment-study-survey/. (Accessed: 28 December 2019).

Intel (2020) *Annual Report 2020*. Available at: https://www.annualreports.com/HostedData/AnnualReports/PDF/NASDAQ_INTC_2020.pdf. (Accessed: 8 August 2021).

Isaac, O., Aldholay, A., Abdullah, Z. and Ramayah, T. (2019) ‘Online learning usage within Yemeni higher education: The role of compatibility and task-technology fit as mediating variables in the IS success model’, *Computers & Education*, 136, pp. 113–129.

Jain, N. and Maitri (2018) ‘Big Data and Predictive Analytics: A Facilitator for Talent Management.’, *Data Science Landscape*, 38, pp. 199–204.

Janssen, M., Van der Voort, H. and Wahyudi, A. (2017) ‘Factors influencing big data decision-making quality’, *Journal of Business Research*, 70, pp. 338–345.

Jarvis, D., MacKenzie, S. and Podsakoff, P. (2003) ‘A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research’, *Journal of Consumer Research*, 30(2), pp. 199–218.

Jha, A.K., Agi, M.A.N. and Ngai, E.W.T. (2020) ‘A note on big data analytics capability development in supply chain.’, *Decision Support Systems*, 138 (November 2020), pp. 1–9.

Jordan, P.J. and Troth, A.C. (2020) ‘Common method bias in applied settings: the dilemma of researching in organizations’, *Australian Journal of Management*, 45(1), pp. 3–14.

Kankam-Kwarteng, C., Osman, B. and Donkor, J. (2019) ‘Innovative low-cost strategy and firm performance of restaurants: The moderation of competitive intensity.’, *Asia Pacific Journal of Innovation and Entrepreneurship*, 13(3), pp. 266–281.

Karim, J. (2009) ‘Emotional Labor and Psychological Distress: Testing the Mediatory Role of Work-Family Conflict’, *European Journal of Social Sciences*, 11(4), pp. 584–598.

Kart, L. and Linden, A. (2014) *Hype cycle for emerging technologies*. Available at: http://docshare01.docshare.tips/files/30318/303180190.pdf (Accessed: 26 August 2021).

Kathuria, R. (2000) ‘Competitive priorities and managerial performance: A taxonomy of small manufacturers.’, *Journal of Operations Management*, 18(6), pp. 627–641.

Kaur, K., Kunasegaran, M., Singh, J., Salome, S. and Sandhu, S.K. (2020) 'Impact of the First Phase of Movement Control Order during the COVID-19 pandemic in Malaysia on purchasing behavior of Malaysian Consumers.', *Journal of Humanities and Social Sciences Research*, 2, pp. 131–144.

Kearns, G.S. and Lederer, A.L. (2003) 'A resource-based view of strategic IT alignment: How knowledge sharing creates competitive advantage.', *Decision Sciences*, 34(1), pp. 1-29.

Kenny, D.A. and Judd, C.M. (2014) 'Power Anomalies in Testing Mediation', *Psychological Science*, 25(2), pp. 334– 339.

Kettinger, W., Grover, V., Guha, S. and Segars, A. (1994) 'Strategic information systems revisited: A study in sustainability and performance', *MIS Quarterly*, 18(1), pp. 31–58.

Khanra, S., Dhir, A. and Mäntymäkia, M. (2020) 'Big data analytics and enterprises: a bibliometric synthesis of the literature', *Enterprise Information Systems*, 14(6), pp. 737–768.

Kharub, M., Mor, R.S. and Sharma, R. (2019) 'The relationship between cost leadership competitive strategy and firm performance: A mediating role of quality management.', *Journal of Manufacturing Technology Management*, 30(6), pp. 920–936.

Kim, G., Shin, B. and Kwon, O. (2012) 'Investigating the Value of Sociomaterialism in Conceptualizing IT Capability of a Firm', *Journal of Management Information Systems*, 29(3), pp. 327–362.

King, W.R., Grover, V. and Hufnagel, E. (1986) 'Seeking competitive advantage using information-intensive strategies: facilitators and inhibitors', in *Proceedings of the New York University Symposium on Strategic Uses of Information Technology, New York,* pp. 11–27.

Klein, R. (2007) 'Customization and real time information access in integrated ebusiness supply chain relationships.', *Journal of Operations Management*, 25(6), pp. 1366–1381.

Kline, R.B. (2016) *Principles and practice of structural equation modeling*. 4th edition. New York and London: The Guilford Press.

Kock, N. (2015) 'Common method bias in PLS-SEM: A full collinearity assessment approach', *International Journal of e-Collaboration*, 11(4), pp. 1–10.

Kock, N. (2017) 'Which is the best way to measure job performance: Self-perceptions or official supervisor evaluations?', *International Journal of e-Collaboration*, 13(2), pp. 1–9.

Kock, N. and Lynn, G.S. (2012) 'Lateral Collinearity and Misleading Results in Variance-Based SEM: An Illustration and Recommendations', *Journal of the Association for Information Systems*, 13(7), pp. 546–580.

Kohli, R. and Grover, V. (2008) 'Business value of IT: An essay on expanding research directions to keep up with the times.', *Journal of the Association for Information Systems*, 9(1), pp. 23–37.

Koo, C.M., Koh, C.E. and Nam, K. (2004) 'An examination of Porter's competitive strategies in electronic virtual markets: A comparison of two on-line business models.', *International Journal of Electronic Commerce*, 9(1), pp. 163–180.

Kraaijenbrink, J., Spender, J.-C. and Groen, A.J. (2010) 'The resource-based view: A review and assessment of its critiques', *Journal of Management*, 36(1), pp. 349–372.

Krishnan, S., Magalingam, P. and Ibrahim, R. (2018) 'Review on data analytics framework in heart disease', *Open International Journal of Informatics (OIJI)*, 6(4), pp. 42–53.

Krohmer, H., Homburg, C. and Workman, J.P. (2002) 'Should marketing be cross-functional? Conceptual development and international empirical evidence.', *Journal of Business Research*, 55(6), pp. 451–465.

Kumar, A. (2014) *The Big Data Ace in Malaysia's digital strategy: MDeC*. Available at: https://computerworld.com.my/resource/applications/the-bg-data-ace-in-malaysias-digital-strategy-mdec/ (Accessed: 10 October 2018).

Kumar, S., Raut, R.D., Narwane, V.S. and Narkhede, B.E. (2020) 'Applications of industry 4.0 to overcome the COVID-19 operational challenges', *Diabetes & Metabolic Syndrome: Clinical Research & Review*, 14, pp. 1283–1289.

Kushwaha, G.S. (2012) 'Operational performance through supply chain management practices', *International Journal of Business and Social Science*, 3(2), pp. 222–232.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M.S. and Kruschwitz, N. (2011) 'Big data, analytics and the path from insights to value', *MIT Sloan: Management Review*, 52(2), pp. 21–31.

Lee, A.S. (1991) 'Integrating positivist and interpretive approaches to organisational research.', *Organisation Science*, 2(4), pp. 342–365.

Lee, H.L. (2004) 'The triple-A supply chain', *Harvard Business Review*, 82(10), pp. 102–112.

Lee, I. (2017) 'Big data: Dimensions, evolution, impacts, and challenges', *Business Horizons*, 60(3), pp. 293–303.

Leung, S.-O. (2011) 'A Comparison of Psychometric Properties and Normality in 4-, 5-, 6-, and 11-Point Likert Scales', *Journal of Social Service Research*, 37(4), pp. 412–421.

Lewis, I. and Talalayevsky, A. (2000) 'Third-party logistics: Leverage information technology.', *Journal of Business Logistics*, 21(2), pp. 173–185.

Li, X., Wang, B., Liu, C., Freiheit, T. and Epureanu, B.I. (2020) 'Intelligent Manufacturing Systems in COVID-19 Pandemic and Beyond: Framework and Impact Assessment.', *Chinese Journal of Mechanical Engineering*, 33(58), pp. 1–5.

Lin, W.L., Law, S.H. and Azman-Saini, W.N.W. (2019) 'Market differentiation threshold and the relationship between corporate social responsibility and corporate financial performance', *Corporate Social Responsivity and Environment Management*, pp. 1–15.

Lincoln, Y.S. and Guba, E.G. (1985) *Naturalistic Inquiry*. London and New Delhi: Sage Publications.

Lind, D.A., Marchal, W.G. and Wathen, S.A. (2012) *Statistical techniques in business and economics*. 15th edn. New York: McGraw-Hill Irwin.

Liu, X., Grant, D.B., Mckinnon, A.C. and Feng, Y. (2010) 'An empirical examination of the contribution of capabilities to the competitiveness of logistics service providers: A perspective from China.', *International Journal of Physical Distribution & Logistics Management*, 40(10), pp. 847–866.

Liu, X., Shin, H. and Burns, A.C. (2021) 'Examining the impact of luxury brand's social media marketing on customer engagement: Using big data analytics and natural language processing', *Journal of Business Research*, 125(March), pp. 815–826.

Loh, C.-H. and Teoh, A.-P. (2020) 'The Adoption of Big Data Analytics Among Manufacturing Small and Medium Enterprises During Covid-19 Crisis in Malaysia.', in *Paper presented at the Proceedings of the Ninth International Conference on Entrepreneurship and Business Management (ICEBM 2020)*.

Lozada, N., Arias-Pérez, J. and Perdomo-Charry, G. (2019) 'Big data analytics capability and co-innovation: An empirical study', *Heliyon*, 5(10), pp. 1–7.

Lynch, D.F., Keller, S.B. and Ozment, J. (2000) 'The effect of logistics capabilities and strategy on firm performance.', *Journal of business logistics*, 21(2), pp. 47–67.

Mageto, J. (2021) 'Big Data Analytics in Sustainable Supply Chain Management: A Focus on Manufacturing Supply Chains', *Sustainability*, 13(13), pp. 1-22.

Makarius, E., Mukherjee, D., Fox, J.D. and Fox, A.K. (2020) 'Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization', *Journal of Business Research*, 120 (November), pp. 262–273.

Makhija, M. (2003) 'Comparing the resource-based and market-based view of the firm: empirical evidence from Czech privatization', *Strategic Management Journal*, 24, pp. 433–451.

Malter, A.J. and Dickson, P.R. (2001) 'The effect of individual learning on competitive decision-making and firm performance.', *International Journal of Research in Marketing*, 18(1), pp. 99–117.

Mandal, S. (2018) ‘An examination of the importance of big data analytics in supply chain agility development: A dynamic capability perspective.’, *Management Research Review*, 41(10), pp. 1201-1219.

Maritz, J., Eybers, S. and Hattingh, M. (2020) ‘Implementation Considerations for Big Data Analytics (BDA): A Benefit Dependency Network Approach’, in *Conference on e-Business, e-Services and e-Society (I3E 2020): Responsible Design, Implementation and Use of Information and Communication Technology*, pp. 481–492.

Marr, B. (2015) *Big data: Using SMART Big Data Analytics and Metrics to Make Better Decisions and Improve Performance*. United Kingdom: John Wiley & Sons Ltd.

Marshall, A., Mueck, S. and Shockley, R. (2015) ‘How leading organizations use big data and analytics to innovate’, *Strategy and Leadership*, 43(5), pp. 32 – 39.

Mata, J.F., Fuerst, W.L. and Barney, J.B. (1995) ‘Information technology and sustained competitive advantage: An organizational resource-based analysis.’, *MIS Quarterly*, 19(4), pp. 487–505.

Mavridis, I. and Karatza, H. (2017) ‘Performance evaluation of cloud-based log file analysis with Apache Hadoop and Apache Spark’, *Journal of Systems and Software*, 125, pp. 133–151.

Mawhinney, L. and Self, R. (2013) ‘Big data for SMEs: Questions of opportunities, challenges, benefits and operations’, in *IT practices for SME success series*. 2nd edition. University of Derby.

Mcafee, A. and Brynjolfsson, E. (2012) ‘Big data: the management revolution.’, *Harvard Business Review*, 90(10), pp. 60–68.

McMaster, M., Nettleton, C., Tom, C., Xu, B., Cao, C. and Qiao, P. (2020) ‘Risk Management: Rethinking Fashion Supply Chain Management for Multinational Corporations in Light of the COVID-19 Outbreak’, *Journal of Risk and Financial Management*, 13(173), pp. 1–16.

McQuitty, S. (2004) ‘Statistical power and structural equation models in business research’, *Journal of Business Research*, 57, pp. 175– 183.

MDEC (2015) *20 years and beyond: Malaysia’s national big data analytics initiatives*, *Malaysia Digital Economy Corporation Sdn Bhd*. Available at: https://calabarzon.neda.gov.ph/wp-content/uploads/2016/10/02-Big-Data-Analytics-MDEC.pdf (Accessed: 3 September 2019).

MDEC (2017) *Big Data analytics (BDA).*, *Malaysia Digital Economy Corporation Sdn Bhd*. Available at: https://www.mdec.my/digital-innovation-ecosystem/big-data-analytics. (Accessed: 30 June 2018).

MDEC (2021) *MDEC targets high value investment flows in data and analytics*, *Malaysia Digital Economy Corporation Sdn Bhd*. Available at: https://mdec.my/news/mdec-targets-high-value-investment-flows-in-data-and-analytics/ (Accessed: 10 May 2021).

Menon, S. (2018) *HELP moving towards data analytics*. Available at: https://www.thestar.com.my/news/education/2018/04/15/help-moving-towards-data-analytics/ (Accessed: 30 June 2018).

Mentzer, J.T. and Kahn, K.B. (1995) ‘A Framework of Logistics Research.’, *Journal of Business Logistics*, 16(1), pp. 231–250.

Michalisin, M.D., Smith, R.D. and Kline, D.M. (1997) ‘In Search of Strategic Assets’, *The International Journal of Organizational Analysis*, 5(4), pp. 360–387.

Mikalef, P., Danielsen, F., Augustin Framnes, V., Krogstie, J. and Håkon Olsen, D. (2017) ‘Big Data Analytics Capability: Antecedents and Business Value’, in *Twenty First Pacific Asia Conference on Information Systems, Langkawi 2017*, pp. 1–13. Available at: https://www.researchgate.net/profile/Patrick-Mikalef/publication/316738305_Big_Data_Analytics_Capability_Antecedents_and_Business_Value/links/60872a0e8ea909241e28bcea/Big-Data-Analytics-Capability-Antecedents-and-Business-Value.pdf. (Accessed: 10 May 2021).

Mikalef, P., Krogstie, J., Pappas, I.O. and Pavlou, P. (2020) 'Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities.', *Information & Management*, 57(2), pp. 1–15.

Mikalef, P., Pappas, I.O., Krogstie, J. and Giannakos, M. (2018) 'Big data analytics capabilities: a systematic literature review and research agenda', *Information Systems and e-Business Management*, 16, pp. 547–578.

Miller, D. (1986) 'Configuring of strategy and structure: Towards a synthesis', *Strategic Management Journal*, 7(3), pp. 233–249.

Miller, D. and Friesen, P.H. (1986) 'Porter's (1980) generic strategies and performance: An empirical examination with American data.', *Part II: Performance implications. Organization Studies*, 7(3), pp. 255–261.

Mishra, D., Gunasekaran, A., Papadopoulos, T. and Childe, S.J. (2018) 'Big data and supply chain management: A review and bibliometric analysis.', *Annals of Operations Research*, 270(1–2), pp. 313–336.

Mithas, S., Ramasubbu, N. and Sambamurthy, V. (2011) 'How information management capability influences firm performance', *MIS Quarterly: Management Information Systems*, 35(1), pp. 237–256.

MITI (2018) *Industry 4WRD: National Policy on Industry 4.0*, *Ministry of International Trade and Industry*. Available at: https://www.miti.gov.my/miti/resources/National Policy on Industry 4.0/Industry4WRD_Final.pdf (Accessed: 15 October 2021).

Mocean, L. (2011) 'The Modeling of the ERP Systems within Parallel Calculus.', *Informatica Economica*, 15(3), pp. 128–135.

Mordorintelligence (2019) *Big data analytics in manufacturing industry - growth, trends, Covid-19 impact, and forecast (2021 - 2026)*, *Mordorintelligence*. Available at: https://www.mordorintelligence.com/industry-reports/big-data-analytics-in-retail-marketing-industry (Accessed: 30 July 2021).

Morris, A. (2021) *23 Case Studies and Real-World Examples of How Business Intelligence Keeps Top Companies Competitive*, *Oracle Netsuite*. Available at: https://www.netsuite.com/portal/resource/articles/business-strategy/business-intelligence-examples.shtml (Accessed: 20 October 2021).

Muhtaroglu, F.C.P., Demir, S., Obali, M. and Girgin, C. (2013) 'Business Model Canvas Perspective on Big Data Applications', in *In: Proceedings of the IEEE International Conference*. IEEE, pp. 32–37.

Narasimhan, R. and Jayaram, J. (1998) 'Causal linkages in supply chain management: An exploratory study of North American manufacturing firms.', *Decision Sciences*, 29(3), pp. 579–606.

Nayyar, P.R. (1993) 'On the measurement of competitive strategy: Evidence from a large multiproduct U.S. firm', *Academy of Management Journal*, 36(6), pp. 1652–1669.

Nevo, S. and Wade, M.R. (2010) 'The formation and value of IT-enabled resource: Antecedents and consequences of synergistic relationships', *MIS Quarterly*, 34(1), pp. 163–183.

Newbert, S.L. (2007) 'Empirical research on the resource-based view of the firm_An assessment and suggestions for future research', *Strategic Management Journal*, 28, pp. 121–146.

Newbert, S.L. (2008) 'Value, rareness, competitive advantage, and performance', *Strategic Management Journal*, 29, pp. 745–768. Available at: https://doi.org/10.1002/smj.

Ng, E. (2021) *Businesses shut as Malaysia enters second virus lockdown*, *Associated Press News*. Available at: https://apnews.com/article/malaysia-coronavirus-pandemic-health-business-5911f6922f4ff17f8bfb98b273281fe6 (Accessed: 6 July 2021).

Nikbin, D., Iranmanesh, M., Ghobakhloo, M. and Behzad, F. (2021) 'Marketing mix strategies during and after COVID-19 pandemic and recession: a systematic review', *Asia-Pacific Journal of Business Administration*, pp. 1–16.

Nolega, K.S., Oloko, M., William, S. and Oteki, E.B. (2015) 'Effects of product differentiation stategies on firm product performance: A case of Kenya Seed Company (KSC), Kitale', *International Journal of Novel Research in Marketing Management and Economics*, 2(3), pp. 100–110.

O' Callaghan, R., Kaufmann, P.J. and Konsynski, R.B. (1992) 'Adoption correlates and share effects of electronic data interchange systems in marketing channels.', *Journal of Marketing*, 56, pp. 45–56.

Obrenovic, B., Du, J., Godinic, D., Tsoy, D., Aamie, M., Khan, S. and Jakhongirov, I. (2020) 'Sustaining enterprise operations and productivity during the COVID-19 pandemic: enterprise effectiveness and sustainability model', *Sustainability*, 12(15), pp. 1–27.

Okorie, O.S., Subramoniam, R. and Charnley, F. (2020) 'Manufacturing in the time of COVID-19: An Assessment of barriers and enablers', *IEEE Engineering Management Review*, 48, pp. 167–175.

Olavarrieta, S. and Ellinger, A.E. (1997) 'Resource-based theory and strategic logistics research', *International Journal of Physical Distribution and Logistics*, 27(9), pp. 559–587.

Omar, A.R.C., Ishak, S. and Jusoh, M.A. (2020) 'The impact of Covid-19 movement control order on SMEs' business and survival strategies', *Geografia - Malaysia Journal of Society and Space*, 16(2), pp. 139–150.

Ong, E. (2020) *10 Businessed in Malaysia that are shutting down due to Covid-19 pressures*. Available at: https://www.klook.com/en-MY/blog/malaysia-business-closures/ (Accessed: 28 August 2021).

Orlikowski, W.J. (2007) 'Sociomaterial Practices: Exploring Technology at Work', *Organization Studies*, 28(9), pp. 1435–1448.

Ortega, M.J.R. (2010) 'Competitive strategies and firm performance: Technological capabilities' moderating roles.', *Journal of Business Research*, 63, pp. 1273–1281.

Oztemel, E. and Gursev, S. (2020) 'Literature review of Industry 4.0 and related technologies', *Journal of Intelligent Manufacturing*, 31, pp. 127–182.

Pandey, D.L. and Risal, N. (2020) ‘Information Technology Spillover and Organizational Performance’, *International Journal of Recent Technology and Engineering (IJRTE)*, 9(4), pp. 30–36.

Panimalar, A.S., Shree, V.S. and Kathrine, V.A. (2017) ‘The 17 V’s of Big Data.’, *International Research Journal of Engineering and Technology (IRJET)*, 4(9), pp. 329–333.

Papadopoulos, T., Singh, S.P., Spanaki, K., Gunasekaran, A. and Dubey, R. (2021) ‘Towards the next generation of manufacturing: implications of big data and digitalization in the context of industry 4.0.’, *Production Planning & Control.* [Preprint]. Available at: https://doi.org/10.1080/09537287.2020.1810767. (Accessed: 10 May 2021).

Park, S., Lee, H. and Chae, S.W. (2017) ‘Rethinking balanced scorecard (BSC) measures: formative versus reflective measurement models.’, *International Journal of Productivity and Performance Management*, 66(1), pp. 92–110.

Pavlou, P.A. and El Sawy, O.A. (2006) ‘From IT leveraging competence to competitive advantage in turbulent environments: The case of new product development’, *Information Systems Research*, 17(3), pp. 198–227.

Pearce II, J.A., Freeman, E.B. and Robinson JR, R.B. (1987) ‘The tenuous link between formal strategic planning and financial performance.’, *Academy of Management Review*, 12(4), pp. 658–675.

Penrose, E.T. (1959) *The Theory of the Growth of the Firm.* New York: John Wiley.

Pereira, J., Braga, V., Correia, A. and Salamzadeh, A. (2021) ‘Unboxing organisational complexity: how does it affect business performance during the COVID-19 pandemic?’, *Journal of Entrepreneurship and Public Policy*, 10(3), pp. 424–444.

Peteraf, M.A. (1993) ‘The cornerstones of competitive advantage: A resource-based view.’, *Strategic Management Journal*, 14(3), pp. 179–191.

Pituch, K.A. and Stevens, J.P. (2016) *Applied Multivariate Statistics for the Social Sciences: Analyses with SAS and IBM's SPSS*. 6th edn. New York and London: Routledge, Taylor & Francis Group.

Podsakoff, P.M., MacKenzie, S.B., Jeong-Yeon, L. and Podsakoff, N.P. (2003) 'Common method biases in behavioural research: A critical review of the literature and recommended remedies', *Journal of Applied Psychology*, 88(5), pp. 879-903.

Porter, M.E. (1979) 'The structure within industries and companies' performance', *Review of Economics and Statistics*, 61(2), pp. 214–227.

Porter, M.E. (1980a) *Competitive Strategy: Techniques for Analyzing Industries and Competitors*. New York: Free Press.

Porter, M.E. (1980b) 'How competitive forces shape strategy?', *The McKinsey Quarterly*, pp. 34-50.

Porter, M.E. (1983) 'Industrial organization and the evolution of concepts for strategic planning: The new learning', *Managerial and Decision Economics*, 4(3), pp. 172–180.

Porter, M.E. and Millar, V.E. (1985) 'How information gives you competitive advantage: The information revolution is transforming the nature of competition.', *Harvard Business Review*, pp. 149–174.

Powell, T.C. and Dent-Micallef, A. (1997) 'Information technology as competitive advantage: The role of human, business and technology resources', *Strategic Management Journal*, 18(5), pp. 375–405.

Prahalad, C.K. and Hamel, G. (1990) 'The core competence of the corporation.', *Harvard Business Review*, 68(3), pp. 79–91.

Protiviti (2017) *Big data adoption in manufacturing: forging an edge in a challenging environment*. Available at: https://www.protiviti.com/sites/default/files/united_states/insights/big-data-adoption-in-manufacturing-protiviti.pdf (Accessed: 31 December 2019).

Queiroz, M.M. and Telles, R. (2018) ‘Big data analytics in supply chain and logistics: an empirical approach’, *The International Journal of Logistics Management*, 29(2), pp. 767–783.

Quimno, V., Imran, A. and Turner, T. (2013) ‘Introducing a Sociomaterial Perspective to Investigate E-learning for Higher Educational Institutions in Developing Countries’, in *24th Australasian Conference on Information Systems, 4-6 Dec 2013, Melbourne*, pp. 1–12.

Rai, A., Patnayakuni, R. and Seth, N. (2006) ‘Firm performance impacts of digitally enabled supply chain integration capabilities.’, *MIS Quarterly*, 30(2), pp. 225-246.

Rai, A. and Tang, X. (2010) ‘Leveraging IT capabilities and competitive process capabilities Portfolios, for the management of interorganizational relationship’, *Information Systems Research*, 21(3), pp. 516–542.

Rajapathirana, R.P.J. and Hui, Y. (2018) ‘Relationship between innovation capability, innovation type, and firm performance’, *Journal of Innovation & Knowledge*, 3(1), pp. 44–55.

Ramayah, T. and Soto-Acosta, P. (2020) ‘Developing process and product innovation through internal and external knowledge sources in manufacturing Malaysian firms: the role of absorptive capacity’, *Business Process Management Journal*, 26(5), pp. 1021–1039.

Ramlawati (2018) ‘Just in time and competitive advantage: understanding their linkages and impact on operational performance’, *Archives of Business Research*, 6(8), pp. 189–204.

Raut, R.D., Mangla, S.K., Narwane, V.S., Gardas, B.B., Priyadarshinee, P. and Narkhede, B.E. (2019) ‘Linking big data analytics and operational sustainability practices for sustainable business management’, *Journal of Cleaner Production*, 224(1), pp. 10–24.

Ravichandran, T. and Lertwongsatien, C. (2005) ‘Effect of information systems resources and capabilities on firm performance: A resource-based perspective.’, *Journal of Management Information Systems*, 21(4), pp. 237–276.

Reed, R. and DeFillippi, R.J. (1990) ‘Causal Ambiguity, Barriers to Imitation, and Sustainable Competitive Advantage.’, *Academy of Management Review*, 15(1), pp. 88–102.

Reio, J.T.G. (2010) ‘The threat of common method variance bias to theory building.’, *Human Resource Development Review*, 9(4), pp. 405–411.

Richardson, H.A., Simmering, M.J. and Sturman, M.C. (2009) ‘A tale of three perspectives examining post hoc statistical techniques for detection and correction of common method variance.’, *Organizational Research Methods*, 12(4), pp. 762–800.

Ringle, C.M., Wende, S. and Becker, J.-M. (2015) *SmartPLS 3. Bönningstedt: SmartPLS*, *SmartPLS*. Available at: https://www.smartpls.com (Accessed: 12 December 2020).

Ross, J.W., Beath, C.M. and Quaadgras, A. (2013) ‘You may not need big data after all’, *Harvard Business Review*, 91, pp. 90–98.

Rungtusanatham, M., Miller, J.W. and Boyer, K.K. (2014) ‘Theorizing, testing, and concluding for mediation in SCM research: Tutorial and procedural recommendations’, *Journal of Operations Management*, 32(3), pp. 99–113.

Rushton, A., Croucher, P. and Baker, P. (2017) *The handbook of logistics & distribution management: Understanding the supply chain*. 6th edn. United Kingdom: Kogan Page.

Russell, D.W. (2002) ‘In search of underlying dimensions: the use (and abuse) of factor analysis in personality and social psychology bulletin.’, *Personality and Social Psychology Bulletin*, 28(12), pp. 1629–1646.

Russom, P. (2013) *Managing Big Data. Available Online at: The Data Warehousing Institute.* Available at: https://tdwi.org/articles/2013/10/01/executive-summary-managing-big-data.asp (Accessed: 5 January 2016).

Sahoo, S. (2021) ‘Aligning operational practices to competitive strategies to enhance the performance of Indian manufacturing firms’, *Benchmarking: An International Journal*, 28(1), pp. 131–165.

Sambamurthy, V., Bharadwaj, A. and Grover, V. (2003) ‘Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms.’, *MIS Quarterly*, 27(2), pp. 237–263.

Sandberg, E. and Abrahamsson, M. (2011) ‘Logistics capabilities for sustainable competitive advantage.’, *International Journal of Logistics: Research and Applications*, 14(1), pp. 61–75.

Sanders, N.R. and Premus, R. (2005) ‘Modeling the relationship between firm IT capability, collaboration and performance.’, *Journal of Business Logistics*, 26(1), pp. 1–23.

Saunders, M.N.K., Lewis, P. and Thornhill, A. (2019) *Research Methods for Business Students*. 8th editio. United Kingdom: Pearson Education Limited.

Sauvage, T. (2003) ‘The relationship between technology and logistics third party provider.’, *International Journal of Physical Distribution and Logistics Management*, 33(3), pp. 236–253.

Schendel, D.E. and Patton, G.R. (1978) ‘A simultaneous equation model of corporate strategy.’, *Management Science*, 24(15), pp. 1611–1621.

Schilke, O., Reimann, M. and Thomas, J.S. (2009) ‘When does international marketing standardization matter to firm performance?’, *Journal of International Marketing*, 17(4), pp. 24-46.

Schlegelmilch, B.B. and Winer, R.S. (2021) *The Routledge Companion to Strategic Marketing*. 1st edn. New York: Routledge.

Schoenherr, T. and Speier-Pero, C. (2015) ‘Data science, Predictive analytics and big data in supply chain management: current state and future potential’, *Journal of Business Logistics*, 36(1), pp. 120–132.

Schwab, K. (2019) *The Global Competitiveness Report 2019*. Available at: https://www3.weforum.org/docs/WEF_TheGlobalCompetitivenessReport2019.pdf. (Accessed: 5 January 2020).

Semuel, H., Siagian, H. and Octavia, S. (2017) ‘The effect of leadership and innovation on differentiation strategy and company performance’, *Procedia - Social and Behavioral Sciences*, 237, pp. 1152–1159.

Sena, V., Bhaumik, S. and Sengupta, A. (2019) ‘Big data and performance: What can management research tell us?’, *British Journal of Management*, 30(2), pp. 219–228.

Sethi, V. and King, W.R. (1994) ‘Development of Measures to Assess the Extent to Which an Information Technology Application Provides Competitive Advantage’, *Management Science*, 40(12), pp. 1601–1627.

Shah, T.R. (2021) ‘Can big data analytics help organisations achieve sustainable competitive advantage? A developmental enquiry’, *Technology in Society*, 68(2022), pp. 1-13

Shaheera, A.S. (2017) *Growing demand for big data expertise.*, *The Malaysian Reserve*. Available at: https://themalaysianreserve.com/2017/09/15/growing-demand-big-data-expertise/ (Accessed: 5 September 2019).

Shamim, S., Zeng, J., Khan, Z. and Ul Zia, N. (2020) ‘Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms’, *Technological Forecasting and Social Change*, 161, pp. 1–10.

Shan, S., Luo, Y., Zhou, Y. and Wei, Y. (2019) ‘Big data analysis adaptation and enterprises’ competitive advantages: the perspective of dynamic capability and resource-based theories’, *Technology Analysis & Strategic Management*, 31(4), pp. 1–16.

Shang, K.C. (2009) ‘Integration and organisational learning capabilities in third-party logistics providers.’, *Service Industries Journal*, 29(3), pp. 331–343.

Shankar, A.C. (2021) ‘MDEC’s commissioned study shows Malaysia’s big data analytics market expected to grow to US$1.9b by 2025’, *The Edge Market*, 17 May. Available at: https://www.theedgemarkets.com/article/mdecs-commissioned-study-shows-malaysias-big-data-analytics-market-expected-grow-us19b-2025. (Accessed: 5 January 2022).

Shmueli, G., Ray, S., Estrada, J.M.V. and Chatla, S.B. (2016) ‘The elephant in the room: Predictive performance of PLS models’, *Journal of Business Research*, 69, pp. 4552–4564.

Shmueli, G., Sarstedt, M., Hair, J.F., Cheah, J.-H., Ting, H., Vaithilingam, S. and Ringle, C.M. (2019) ‘Predictive model assessment in PLS-SEM: guidelines for using PLS predict’, *European Journal of Marketing*, 53(11), pp. 2322–2347.

Singh, S.K. and Del Giudice, M. (2019) ‘Big data analytics, dynamic capabilities and firm performance’, *Management Decision*, 57(8), pp. 1729–1733.

Smith, A.D. (2008) ‘Resource based view of the firm: Measures of reputation among health service-sector businesses.’, *Health Marketing Quarterly*, 25(4), pp. 361–382.

Sobh, R. and Perry, C. (2005) ‘Research design and data analysis in realism research.’, *European Journal of Marketing*, 40(11/12), pp. 1194–1209.

Song, M., Calantone, R.J. and Di Benedetto, C.A. (2002) ‘Competitive forces and strategic choice decisions: An experimental investigation in the United States and Japan.’, *Strategic Management Journal*, 23, pp. 969–978.

Soon, K.W.K., Lee, C.A. and Boursier, P. (2016) ‘A study of the determinants affecting adoption of big data using integrated technology acceptance model (TAM) and diffusion of innovation (DOI) in Malaysia.’, *Indian Journal of Applied Business and Economic Research*, 14(1), pp. 17–47.

Spanos, Y.E. and Lioukas, S. (2001) ‘An examination into the causal logic of rent generation: contrasting Porter’s competitive strategy framework and the resource based perspective.’, *Strategic Management Journal*, 22(10), pp. 907–934.

Spanos, Y.E., Zaralis, G. and Lioukas, S. (2004) ‘Strategy and industry effects on profitability: Evidence from Greece.’, *Strategic Management Journal*, 25(2), pp. 139–165.

Spector, P.E. and Brannick, M.T. (2011) ‘Methodological Urban Legends: The Misuse of Statistical Control Variables’, *Organisational Research Methods*, 14(2), pp. 287–305.

Spulber, D. (2003) ‘The intermediation theory of the firm: integrating economic and management approaches to strategy’, *Managerial and Decision Economics*, 24(4), pp. 253-266.

Stalk Jr., G., Evans, P. and Shulman, L.E. (1992) ‘Competing on capabilities: The new rules of corporate strategy’, *Harvard Business Review*, 70(2), pp. 57–69.

Stone, M. (1974) ‘Cross-validatory choice and assessment of statistical predictions.’, *Journal of the Royal Statistical*, 36, pp. 111–147.

Su, Z., Guo, H. and Sun, W. (2017) ‘Exploration and Firm Performance: The Moderating Impact of Competitive Strategy’, *British Journal of Management*, 28(3), pp. 357–371.

Subramaniam, P. (2020) *4th industrial revolution - Urgency to fast track 4IR*, *The Edge Market*. Available at: https://www.theedgemarkets.com/article/4th-industrial-revolution-urgency-fast-track-4ir (Accessed: 20 October 2021).

Sun, B. and Liu, Y. (2021) ‘Business model designs, big data analytics capabilities and new product development performance: evidence from China’, *European Journal of Innovation Managemen*, 24(4), pp. 1162–1183.

Swamidass, P.M. and Newell, W.T. (1987) ‘Manufacturing strategy, environmental uncertainty and performance: A path-analytic model.’, *Management Science*, 33(4), pp. 509–524.

Tallman, S.B. (1991) ‘Strategic management models and resource-based strategies among MNEs in a host market.’, *Strategic Management Journal*, 12 (Summer Special Issue), pp. 69–82.

Tan, K.C. (2013) *EMC Survey Reveals Big Data Adoption Trends in Malaysia*, *EMC Corporation*. Available at: https://www.it-sideways.com/2013/09/emc-survey-reveals-big-data-adoption.html?m=0 (Accessed: 19 February 2019).

Tan, Z.Y. (2018) *IoT: Stey-by-step approach to automation*, *The Edge Market*. Available at: https://www.theedgemarkets.com/article/IoT-stepbystep-approach-automation (Accessed: 17 April 2018).

Tarigan, Z.J.H., Siagian, H. and Jie, F. (2021) 'Impact of Enhanced Enterprise Resource Planning (ERP) on Firm Performance through Green Supply Chain Management', *Sustainability*, 13(4358), pp. 1–20.

Tavalaei, M.M. and Santalo, J. (2019) 'Pure versus hybrid competitive strategies in the airport industry', *Transportation Research Part A: Policy and Practice*, 124 (June), pp. 444–455.

Tay, S.I., Alipal, J. and Lee, T.C. (2021) 'Industry 4.0: Current practice and challenges in Malaysian manufacturing firms', *Technology in Society*, 67 (November), pp. 1017–1049.

Taylor, D. (2021) *What is BIG DATA? Introduction, Types, Characteristics and Examples*, *Guru99*. Available at: https://www.guru99.com/what-is-big-data.html (Accessed: 20 October 2021).

Taylor, D. (2022) *Top 15 Big Data Tools and Software (Open Source) 2022*, *Guru99*. Available at: https://www.guru99.com/big-data-tools.html (Accessed: 27 June 2022).

Team, B. (2021) *#TECH: MDEC, MDA team up to provide digital insights, offer digital training to Malaysian talents*, *New Straits Times*. Available at: https://www.nst.com.my/lifestyle/bots/2021/10/735821/tech-mdec-mda-team-provide-digital-insights-offer-digital training (Accessed: 20 October 2021).

Teece, D. (2019) 'A capability theory of the firm: an economics and (Strategic) management perspective', *New Zealand Economic Papers*, 53(1), pp. 1–43.

Teece, D.J. (2014) 'The foundations of enterprise performance: dynamic and ordinary capabilities in an (economic) theory of firms', *The Academy of Management Perspectives*, 28(4), pp. 328–352.

Teece, D.J., Pisano, G. and Shuen, A. (1997) 'Dynamic capabilities and strategic management', *Strategic Management Journal*, 18(7), pp. 509–533.

Teeratansirikool, L., Siengthai, S., Badir, Y. and Charoenngam, C. (2013) 'Competitive strategies and firm performance: the mediating role of performance measurement', *International Journal of Productivity and Performance Management*, 62(2), pp. 168–184.

Teng, B.. and Cummings, J.L. (2002) 'Trade-offs in managing resources and capabilities', *Academy of Management Executive*, 16(2), pp. 81–91.

Thomas, A. (2020) 'Convergence and digital fusion lead to competitive differentiation', *Business Process Management Journal*, 26(3), pp. 707–720.

Tien, E.L., Ali, N.M., Miskon, S., Ahmad, N. and Abdullah, N.S. (2020) 'Big Data Analytics Adoption Model for Malaysian SMEs.', in *Paper presented at the International Conference of Reliable Information and Communication Technology.*

Top Glove Corporation Bhd (2020) *The World's Largest Manufacturer of Gloves: Doing Well by Doing Good*. Available at: https://www.topglove.com/App_ClientFile/7ff8cb3f-fbf6-42e7-81da-6db6a0ab2ef4/Assets/anual_report/Integrated Annual Report 2020_Latest.pdf. (Accessed: 5 January 2021).

Troisi, O., Maione, G., Grimaldi, M. and Loia, F. (2020) 'Growth hacking: Insights on data-driven decision-making from three firms', *Industrial Marketing Management*, 90(October), pp. 538–557.

Urbach, N. and Ahlemann, F. (2010) 'Structural equation modeling in information systems research using partial least squares', *Journal of Information Technology Theory and Application*, 11(2), pp. 5–40.

Valášková, K., Ward, P. and Svabova, L. (2021) 'Deep Learning-assisted Smart Process Planning, Cognitive Automation, and Industrial Big Data Analytics in Sustainable Cyber-Physical Production Systems', *Journal of Self-Governance and Management Economics*, 9(2), pp. 9–20.

Vassakis, K., Kopanakis, I. and Petrakis, E. (2018) 'Big Data Analytics: Applications, Prospects and Challenges', *Springer International Publishing AG*, pp. 3–20.

Venkatraman, N. and Henderson, J.C. (1993) 'Continuous strategic alignment: exploiting information technology capabilities for competitive success', *European Management Journal*, 11(2), pp. 139–149.

Venkatraman, N. and Ramanujam, V. (1986) ‘Measurement of business performance in strategy research: A comparison of approaches’, *Academy of Management Review*, 11(4), pp. 801–814.

Vickery, S.K., Droge, C. and Markland, R.R. (1993) ‘Production competence and business strategy: Do they affect business performance.’, *Decision Sciences*, 24(2), pp. 435-456.

Voss, C.A., Ahlstrom, P. and Blackmon, K. (1997) ‘Benchmarking and operational performance: Some empirical results.’, *International Journal of Operations & Production Management*, 17(10), pp. 1046–1058.

Wade, M. and Hulland, J. (2004) ‘Review: The resource-based view and information systems research: Review, extension, and suggestions for future research’, *MIS Quarterly: Management Information Systems*, 28(1), pp. 107–142.

Waller, M.A. and Fawcett, S.E. (2013) ‘Click Here for a Data Scientist: Big Data, Predictive Analytics, and Theory Development in the Era of a Maker Movement Supply Chain.’, *Journal of Business Logistics*, 34(4), pp. 249–252.

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S..-F., Dubey, R. and Childe, S.. (2017) ‘Big data analytics and firm performance: Effects of dynamic capabilities’, *Journal of Business Research*, 70, pp. 356–365.

Wang, C., Zhang, Q. and Zhang, W. (2020) ‘Corporate social responsibility, Green supply chain management and firm performance: The moderating role of big-data analytics capability’, *Research in Transportation Business & Management*, 37, pp. 1–10.

Wang, N., Liang, H., Zhong, W., Xue, Y. and Xiao, J. (2012) ‘Resource structuring or capability building? An empirical study of the business value of information technology.’, *Journal of Management Information Systems*, 29(2), pp. 325–367.

Wang, Q., Zantow, K., Lai, F. and Wang, X. (2006) ‘Strategic postures of third-party logistics providers in mainland China.’, *International Journal of Physical Distribution & Logistics Management*, 36(10), pp. 793–819.

Ward, P.T., Leong, G.K. and Boyer, K.K. (1994) 'Manufacturing proactiveness and performance.', *Decision Sciences*, 25, pp. 337–358.

Warren, K. (2002) *Competitive strategy dynamics.* Chichester: John Willey.

Wernerfelt, B. (1984) 'A Resource-based View of the Firm', *Strategic Management Journal*, 5(1), pp. 171–180.

Wetzels, M., Odekerken-Schroder, G. and Van Oppen, C. (2009) 'Using PLS Path Modeling for Assessing Hierarchical Construct Models: Guidelines and Empirical Illustrations', *MIS Quarterly*, 33(1), pp. 177–195.

Williamson, J. (2016) *Big data analytics is transforming manufacturing*. Available at: https://www.themanufacturer.com/articles/big-data-analytics-is-transforming-manufacturing/ (Accessed: 31 December 2019).

Wixom, B.H., Yen, B. and Relich, M. (2013) 'Maximizing value from business analytics', *MIS Quarterly Executive*, 12(2), pp. 111–123.

Wong, K.L., Chuah, M.H. and Ong, S.F. (2015) 'Are Malaysian companies ready for the big data economy? A business intelligence model approach.', in *In proceeding of the International Conference on Accounting Studies (ICAS) 2015*. Johor, Malaysia., pp. 113–119.

Wong, W.P., Soh, K.L. and Chong, C.L. (2016) 'Differentiated service consumption and low cost production: Striking a balance for a sustainable competitive advantage in Malaysia', *International Journal of Production Economics*, 181, pp. 450-459.

Wong, W.P., Soh, K.L., Chong, C.L. and Karia, N. (2015) 'Logistics firms performance: Efficiency and effectiveness perspectives', *International Journal of Productivity and Performance Management*, 64(5), pp. 686-701.

WTO (2020) *Export prohibitions and restrictions: Information Note*. Available at: https://www.wto.org/english/tratop_e/covid19_e/export_prohibitions_report_e.pdf. (Accessed: 5 January 2022).

Yadegaridehkordi, E., Hourmand, M., Nilashi, M., Shuib, L., Ahani, A. and Ibrahim, O. (2018) ‘Influence of big data adoption on manufacturing companies’ performance: An integrated DEMATEL-ANFIS approach.’, *Technological Forecasting and Social Change*, 137 (December), pp. 199–210.

Yap, C. (2019) *Big data analytics key to business growth.*, *The Star Online*. Available at: https://www.thestar.com.my/metro/metro-news/2019/05/06/big-data-analytics-key-to-business-growth (Accessed: 30 August 2019).

Yau, E.K.B., Pang, N.T.P., Shoesmith, W.D., James, S., Hadi, N.M.N. and Loo, J.L. (2020) ‘The Behaviour Changes in Response to COVID-19 Pandemic within Malaysia.’, *The Malaysian Journal of Medical Science*, 27(2), pp. 45–50.

Yeo, A.C.M. and Carter, S. (2017) ‘Segregate the Wheat from the Chaff Enabler: Will Big Data and Data Analytics Enhance the Perceived Competencies of Accountants/Auditors in Malaysia?’, *Journal of Self-Governance and Management Economics*, 5(3), pp. 28–51.

Yeung, H.Y., Selen, W., Sum, C.C. and Huo, B. (2006) ‘Linking financial performance to strategic orientation and operational priorities: An empirical study of third-party logistics providers.’, *International Journal of Physical Distribution & Logistics Management*, 36(3), pp. 210–230.

Yu, W., Wong, C.Y., Chavez, R. and Jacobs, M.A. (2021) ‘Integrating big data analytics into supply chain finance: The roles of information processing and data-driven culture’, *International Journal of Production Economics*, 236 (June), pp. 108–135.

Zahra, S.A. and Covin, J.G. (1993) ‘Business strategy, technology policy and firm performance.’, *Strategic Management Journal*, 14, pp. 451–478.

Zainul, E. (2017) *Small players slow to adopt big data.*, *The Edge Market*. Available at: https://www.theedgemarkets.com/article/small-players-slow-adopt-big-data (Accessed: 30 August 2019).

Zdravevski, E., Lameski, P., Apanowicz, C. and Ślęzak, D. (2020) ‘From Big Data to business analytics: The case study of churn prediction’, *Applied Soft Computing*, 90, pp. 106–164.

Zhao, J.L., Fan, S. and Hu, D. (2014) 'Business challenges and research directions of management analytics in the big data era', *Journal of Management Analytics*, 1(3), pp. 169–174.

Zhao, X., Lynch Jr., J.G. and Chen, Q. (2010) 'Reconsidering Baron and Kenny: Myths and Trusts about Mediation Analysis.', *The Journal of Consumer Research*, 37(2), pp. 197–206.

Zhao, X., Yeung, J.H.Y. and Zhou, Q. (2002) 'Competitive priorities of enterprises in mainland China.', *Total Quality Management*, 13(3), pp. 285–300.

Appendix A Reliability Analysis (Pilot Test)

Case Processing Summary

		N	%
Cases	Valid	37	100.0
	Excluded[a]	0	.0
	Total	37	100.0

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

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.934	.937	5

Item Statistics

	Mean	Std. Deviation	N
Learning1	6.0270	.89711	37
Learning2	6.0000	.91287	37
Learning3	5.8378	.95782	37
Learning4	5.7297	1.12172	37
Learning5	5.4865	1.04407	37

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	5.816	5.486	6.027	.541	1.099	.049	5

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
29.0811	19.410	4.40567	5

Case Processing Summary

		N	%
Cases	Valid	37	100.0
	Excluded[a]	0	.0
	Total	37	100.0

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

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.753	.758	5

Item Statistics

	Mean	Std. Deviation	N
Culture1	6.3514	.78938	37
Culture2	6.0000	.88192	37
Culture3	5.5946	1.21242	37
Culture4	5.9189	.79507	37
Culture5	5.9730	.86559	37

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	5.968	5.595	6.351	.757	1.135	.072	5

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
29.8378	10.695	3.27035	5

Case Processing Summary

		N	%
Cases	Valid	37	100.0
	Excluded[a]	0	.0
	Total	37	100.0

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

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.877	.880	5

Item Statistics

	Mean	Std. Deviation	N
Managerial1	5.9730	.83288	37
Managerial2	5.7568	.89460	37
Managerial3	5.6216	.82836	37
Managerial4	5.8378	.89795	37
Managerial5	5.6486	1.08567	37

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	5.768	5.622	5.973	.351	1.063	.021	5

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
28.8378	13.973	3.73804	5

Case Processing Summary

		N	%
Cases	Valid	37	100.0
	Excluded[a]	0	.0
	Total	37	100.0

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

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.929	.931	5

Item Statistics

	Mean	Std. Deviation	N
Technical1	4.8378	1.40463	37
Technical2	5.1081	1.36999	37
Technical3	5.2703	1.38742	37
Technical4	5.2703	1.28341	37
Technical5	5.0811	1.47908	37

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	5.114	4.838	5.270	.432	1.089	.032	5

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
25.5676	37.419	6.11710	5

Case Processing Summary

		N	%
Cases	Valid	37	100.0
	Excluded[a]	0	.0
	Total	37	100.0

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

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.893	.892	5

Item Statistics

	Mean	Std. Deviation	N
Technology1	5.4324	1.38525	37
Technology2	4.9730	1.55432	37
Technology3	5.4324	1.44416	37
Technology4	5.0541	1.45193	37
Technology5	4.9730	1.38417	37

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	5.173	4.973	5.432	.459	1.092	.057	5

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
25.8649	36.565	6.04686	5

Case Processing Summary

		N	%
Cases	Valid	37	100.0
	Excluded[a]	0	.0
	Total	37	100.0

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

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.952	.952	3

Item Statistics

	Mean	Std. Deviation	N
Data1	5.2432	1.53488	37
Data2	5.1892	1.68057	37
Data3	5.1081	1.57734	37

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	5.180	5.108	5.243	.135	1.026	.005	3

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
15.5405	20.977	4.58012	3

Case Processing Summary

		N	%
Cases	Valid	37	100.0
	Excluded[a]	0	.0
	Total	37	100.0

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

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.988	.989	4

Item Statistics

	Mean	Std. Deviation	N
Cost1	5.7838	1.10893	37
Cost2	5.7838	1.10893	37
Cost3	6.0270	1.23573	37
Cost4	6.0270	1.23573	37

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	5.905	5.784	6.027	.243	1.042	.020	4

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
23.6216	21.297	4.61490	4

Case Processing Summary

		N	%
Cases	Valid	37	100.0
	Excluded[a]	0	.0
	Total	37	100.0

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

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.978	.985	9

Item Statistics

	Mean	Std. Deviation	N
Diff1	5.7027	1.33052	37
Diff2	5.1622	2.11494	37
Diff3	5.7027	1.12706	37
Diff4	5.9459	1.26811	37
Diff5	4.9189	1.93475	37
Diff6	5.9459	1.26811	37
Diff7	5.7027	1.33052	37
Diff8	5.4595	1.52014	37
Diff9	5.4595	1.52014	37

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	5.556	4.919	5.946	1.027	1.209	.119	9

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
50.0000	159.500	12.62933	9

Case Processing Summary

		N	%
Cases	Valid	37	100.0
	Excluded[a]	0	.0
	Total	37	100.0

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

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.928	.939	4

Item Statistics

	Mean	Std. Deviation	N
MP1	4.2162	1.93125	37
MP2	4.4865	1.80465	37
MP3	5.0000	1.22474	37
MP4	4.4865	1.50225	37

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	4.547	4.216	5.000	.784	1.186	.107	4

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
18.1892	35.324	5.94343	4

Case Processing Summary

		N	%
Cases	Valid	37	100.0
	Excluded[a]	0	.0
	Total	37	100.0

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

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.985	.986	4

Item Statistics

	Mean	Std. Deviation	N
OP1	4.7568	1.47959	37
OP2	4.4865	1.50225	37
OP3	4.4865	1.50225	37
OP4	4.2162	1.65219	37

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	4.486	4.216	4.757	.541	1.128	.049	4

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
17.9459	36.108	6.00900	4

Appendix B Questionnaire

UTM AZMAN HASHIM INTERNATIONAL BUSINESS SCHOOL

UNIVERSITI TEKNOLOGI MALAYSIA

SURVEY QUESTIONNAIRE

RE: BIG DATA ANALYTICS CAPABILITY FOR SUSTAINABLE COMPETITIVE ADVANTAGE AND FIRM PERFORMANCE IN MALAYSIAN MANUFACTURING FIRMS.

We are researchers from Universiti Teknologi Malaysia, presently researching on the extent of the big data analytics (BDA) capabilities contributing to sustainable competitive advantage in improving firm performance. Big data analytics has been defined as a process of collecting, organising, and analysing large sets of data (called big data) to discover patterns and other useful information (Jain and Maitri, 2018) that could be used to formulate competitive strategic decision making to achieve better firm performance.

As part of the research process, we need to collect data from manufacturing firms in order to achieve our research objectives. Enclosed herewith is a questionnaire seeking information from you. I hope that you could spend approximately 15 minutes to answer the questionnaire attached. Kindly return the completed questionnaire to our enumerator.

We can assure you that whatever information you provide will be treated with utmost confidentiality. The data will be aggregated and no sources or persons will be identified.

Your kind cooperation in filling the questionnaire will indeed be very valuable for completion of our research project. Should you have any queries, please do not hesitate to contact me at clchong@tarc.edu.my.

For the purpose of this study, we require individual who is actively using big data analytics to manage the business. If you meet this criterion, please respond to the attached survey. Thank you very much for your time and effort.

Yours sincerely,

____________________	____________________
Ms. Chong Chu Le	Professor Madya Dr Siti
PhD Candidate	Deputy Chair of School of GS
Universiti Teknologi Malaysia	Universiti Teknologi Malaysia

Part A – Profile

11. How knowledgeable are you with regards to the usage of big data analytics software in your company?

☐ Not at all
☐ Slightly
☐ Neutral
☐ Great
☐ Extremely strong

2. How knowledgeable are you with regards to business strategy in your company?
☐ Not at all
☐ Slightly
☐ Neutral
☐ Great
☐ Extremely strong

3. How long you have been working in big data analytics?
☐ Less than 3 years
☐ 3-6 years
☐ More than 6 years

4. How long (in years) has your company been operating in Malaysia?
☐ 1 or less
☐ 2 to 4
☐ 5 to 7
☐ 8 to 10
☐ 11 or more

5. What is the value of the physical assets in your company?
☐ Less than RM 4,000,000
☐ RM 4,000,000 to less than RM 8,000,000
☐ RM 8,000,000 to less than RM 12,000,000
☐ RM 12,000,000 to less than RM 16,000,000
☐ RM 16,000,000 or more

6. What is the AVERAGE annual sales of your company in the last 2 years?
☐ Less than RM 1,000,000
☐ RM1,000,000 to less than RM3,000,000
☐ RM3,000,000 to less than RM6,000,000
☐ RM6,000,000 to less than RM9,000,000
☐ RM9,000,000 to less than RM12,000,000
☐ RM12,000,000 or more

7. What is the total number of **full-time** employees in your company?

- ☐ Less than 50
- ☐ 50 to 99
- ☐ 100 to 199
- ☐ 200 to 499
- ☐ 500 to 999
- ☐ 1000 or more

8. What is your position in your company?

- ☐ Top Management / CEO / President
- ☐ Senior/Executive Vice President
- ☐ Vice President
- ☐ Senior/Executive Director
- ☐ Director / Manager
- ☐ Others. Please specify ___________________

9. What is the form of ownership of your company?

- ☐ Wholly local
- ☐ Wholly foreign
- ☐ Joint venture (if this is selected, please tick the following ownership)
- ☐ Less than 30% local equity
- ☐ 30% or more local equity

10. Type of industry your organization operates in: (Please mark “X”)

☐	Chemical/plastic products	☐	Rubber & rubber products
☐	Electronics/electric	☐	Textiles/clothing
☐	Fabricated metal/machinery	☐	Transport equipment
☐	Food/beverages	☐	Wood/paper/printing
☐	Metal & metal products	☐	Services: ___________

11. Please mark “X” on the software(s) or tool(s) that have been used:

☐	Hadoop	☐	Periscope Data
☐	Qualtrics	☐	Zoho Analytics
☐	NoSQL	☐	Yellowfin
☐	Sisense	☐	Domo
☐	Looker	☐	Others: _____________

Part B – BDA Capability

Please indicate your level of agreement ranging from 1 = strongly disagree to 7 = strongly agree to the following statements.

	Strongly disagree					**Strongly agree**	
We have access to very large, unstructured, or fast-moving data for analysis.	1	2	3	4	5	6	7
We integrate data from multiple internal sources into a data warehouse.	1	2	3	4	5	6	7
We integrate external data with internal to facilitate high-value analysis of our business environment.	1	2	3	4	5	6	7
We have explored parallel computing approaches (e.g., ERP) to process big data.	1	2	3	4	5	6	7
We have explored data visualization tools (e.g. Sisense, Highcharts, etc.).	1	2	3	4	5	6	7
We have explored cloud-based services to process data.	1	2	3	4	5	6	7
We have explored open-source software to process data.	1	2	3	4	5	6	7
We have explored different types of databases (e.g. NoSQL, RDBMS, etc. to store data.	1	2	3	4	5	6	7
We provide big data analytics training to our employees.	1	2	3	4	5	6	7
Our big data analytics staff has the technical skills to accomplish their jobs.	1	2	3	4	5	6	7
Our big data analytics staff has suitable education qualification to fulfil the jobs.	1	2	3	4	5	6	7
Our big data analytics staff holds suitable work experience to accomplish their jobs.	1	2	3	4	5	6	7
We hire new employees who have the big data analytics skills.	1	2	3	4	5	6	7
Our managers understand and appreciate the business needs of other business units, customers and suppliers.	1	2	3	4	5	6	7
Our managers are able to work with other business units, customers and suppliers to increase opportunities using big data analytics.	1	2	3	4	5	6	7
Our managers are able to coordinate big data-related activities in ways that support other business units, customers and suppliers.	1	2	3	4	5	6	7
Our managers are able to use big data to anticipate the future business needs of other business units, customers and suppliers.	1	2	3	4	5	6	7
Our managers are able to understand and evaluate the output extracted from big data analytics software.	1	2	3	4	5	6	7

We consider data a valuable asset.	1	2	3	4	5	6	7
We make decision based on data rather than on instinct.	1	2	3	4	5	6	7
We are willing to override our own intuition when data contradict our viewpoints.	1	2	3	4	5	6	7
We continuously improve the business rules in response to insights extracted from data.	1	2	3	4	5	6	7
We continuously coach our employees to make decisions based on data.	1	2	3	4	5	6	7
We are able to explore for new and relevant knowledge in a technological change.	1	2	3	4	5	6	7
We are able to store new and relevant knowledge.	1	2	3	4	5	6	7
We are able to share new and relevant knowledge in a technological change.	1	2	3	4	5	6	7
We are able to apply new and relevant knowledge in a technological change.	1	2	3	4	5	6	7
We have made intensive effort to exploit existing competencies in a technological change.	1	2	3	4	5	6	7

Part C – Competitive Advantage

Big data analytics capability helps my firm to achieve the following objectives easily. Use a scale of 1 to 7 with 1 being “never” and 7 being “always” to the following statements.

Objectives	Never						Always
To operate at low cost	1	2	3	4	5	6	7
To offer competitive (low) price	1	2	3	4	5	6	7
To find ways to reduce cost	1	2	3	4	5	6	7
To improve operating efficiency by controlling cost	1	2	3	4	5	6	7
To meet customer’s specifications	1	2	3	4	5	6	7
To provide good products/services in terms of design	1	2	3	4	5	6	7
To offer a short delivery lead time	1	2	3	4	5	6	7
To meet customer due dates	1	2	3	4	5	6	7
To provide a wide range of services	1	2	3	4	5	6	7
To provide reliable and consistent services	1	2	3	4	5	6	7
To be flexible in accommodating changes	1	2	3	4	5	6	7
To introduce new services rapidly	1	2	3	4	5	6	7
To maximise the value of our services to clients	1	2	3	4	5	6	7

Part D – Firm Performance

How do you rate the following areas as compared to the major competitors in your main product (s) or service(s) offerings? Use a scale of 1 to 7 with 1 being "Much worse than competitors" and 7 being "Much better than competitors" to the following statements.

	Much worse						**Much better**
We have entered new markets more quickly	1	2	3	4	5	6	7
We have introduced new products or services into the market faster	1	2	3	4	5	6	7
Our success rate of new products or services have been higher	1	2	3	4	5	6	7
Our market share has exceeded that of our competitors	1	2	3	4	5	6	7
Our productivity has exceeded that of our competitors	1	2	3	4	5	6	7
Our profit rate has exceeded that of our competitors	1	2	3	4	5	6	7
Our return on investment (ROI) has exceeded that of our competitors	1	2	3	4	5	6	7
Our sales revenue has exceeded that of our competitors	1	2	3	4	5	6	7

Thank you for your time

Appendix C Frequencies Table

Usage of data analytics

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Good	127	66.5	66.5	66.5
	Excellent	64	33.5	33.5	100.0
	Total	191	100.0	100.0	

Decision making

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Good	117	61.3	61.3	61.3
	Excellent	74	38.7	38.7	100.0
	Total	191	100.0	100.0	

Duration with data analytics

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 3 years	69	36.1	36.1	36.1
	3-6 years	42	22.0	22.0	58.1
	More than 6 years	80	41.9	41.9	100.0
	Total	191	100.0	100.0	

In Malaysia

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2 to 4	25	13.1	13.1	13.1
	5 to 7	19	9.9	9.9	23.0
	8 to 10	23	12.0	12.0	35.1
	11 or more	124	64.9	64.9	100.0
	Total	191	100.0	100.0	

Physical assets

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than RM 4,000,000	24	12.6	12.6	12.6
	RM 4,000,000 to less than RM 8,000,000	35	18.3	18.3	30.9
	RM 8,000,000 to less than RM 12,000,000	37	19.4	19.4	50.3
	RM 12,000,000 to less than RM 16,000,000	9	4.7	4.7	55.0
	RM 16,000,000 or more	86	45.0	45.0	100.0
	Total	191	100.0	100.0	

Annual sales

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than RM 1,000,000	15	7.9	7.9	7.9
	RM 1,000,000 to less than RM 3,000,000	22	11.5	11.5	19.4
	RM 3,000,000 to less than RM 6,000,000	22	11.5	11.5	30.9
	RM 6,000,000 to less than RM 9,000,000	27	14.1	14.1	45.0
	RM 9,000,000 to less than 12,000,000	12	6.3	6.3	51.3
	RM 12,000,000 or more	93	48.7	48.7	100.0
	Total	191	100.0	100.0	

Full timer

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 50	29	15.2	15.2	15.2
	50 to 99	33	17.3	17.3	32.5
	100 to 199	34	17.8	17.8	50.3
	200 to 499	33	17.3	17.3	67.5
	500 to 999	21	11.0	11.0	78.5
	1000 or more	41	21.5	21.5	100.0
	Total	191	100.0	100.0	

Position

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Top Management/CEO/President	23	12.0	12.0	12.0
	Senior/Executive Vice President	33	17.3	17.3	29.3
	Vice President	31	16.2	16.2	45.5
	Senior/Executive Director	34	17.8	17.8	63.4
	Director/Manager	70	36.6	36.6	100.0
	Total	191	100.0	100.0	

Ownership

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Wholly local	77	40.3	40.3	40.3
	Wholly foreign	53	27.7	27.7	68.1
	Joint venture less than 30% local equity	29	15.2	15.2	83.2
	Joint venture with 30% or more equity	32	16.8	16.8	100.0
	Total	191	100.0	100.0	

Industry

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Chemical/plastics products	22	11.5	11.5	11.5
	Electronics/electric	70	36.6	36.6	48.2
	Fabricated metal/machinery	8	4.2	4.2	52.4
	Food/beverages	25	13.1	13.1	65.4
	Metal & metal products	14	7.3	7.3	72.8
	Rubber & rubber products	8	4.2	4.2	77.0
	Textiles/Clothing	15	7.9	7.9	84.8
	Semiconductor	2	1.0	1.0	85.9
	Wood/paper products	17	8.9	8.9	94.8
	Others	10	5.2	5.2	100.0
	Total	191	100.0	100.0	

Appendix D Chi-Square Tests

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Knowledge_E * Knowledge_L	94	49.2%	97	50.8%	191	100.0%

Knowledge_E * Knowledge_L Crosstabulation

			Knowledge_L		Total
			4.00	5.00	
Knowledge_E	4.00	Count	37	25	62
		Expected Count	39.6	22.4	62.0
	5.00	Count	23	9	32
		Expected Count	20.4	11.6	32.0
Total		Count	60	34	94
		Expected Count	60.0	34.0	94.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	1.360[a]	1	.244		
Continuity Correction[b]	.883	1	.347		
Likelihood Ratio	1.388	1	.239		
Fisher's Exact Test				.267	.174
Linear-by-Linear Association	1.346	1	.246		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 11.57.

b. Computed only for a 2x2 table

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	-.120	.244
	Cramer's V	.120	.244
N of Valid Cases		94	

Knowledge_E

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	4.00	62	32.5	66.0	66.0
	5.00	32	16.8	34.0	100.0
	Total	94	49.2	100.0	
Missing	System	97	50.8		
Total		191	100.0		

Knowledge_L

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	4.00	63	33.0	64.9	64.9
	5.00	34	17.8	35.1	100.0
	Total	97	50.8	100.0	
Missing	System	94	49.2		
Total		191	100.0		

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Strategy_E * Strategy_L	94	49.2%	97	50.8%	191	100.0%

Strategy_E * Strategy_L Crosstabulation

			Strategy_L		Total
			4.00	5.00	
Strategy_E	4.00	Count	34	23	57
		Expected Count	36.4	20.6	57.0
	5.00	Count	26	11	37
		Expected Count	23.6	13.4	37.0
Total		Count	60	34	94
		Expected Count	60.0	34.0	94.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	1.096[a]	1	.295		
Continuity Correction[b]	.684	1	.408		
Likelihood Ratio	1.110	1	.292		
Fisher's Exact Test				.381	.205
Linear-by-Linear Association	1.085	1	.298		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 13.38.

b. Computed only for a 2x2 table

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	-.108	.295
	Cramer's V	.108	.295
N of Valid Cases		94	

Strategy_E

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	4.00	57	29.8	60.6	60.6
	5.00	37	19.4	39.4	100.0
	Total	94	49.2	100.0	
Missing	System	97	50.8		
Total		191	100.0		

Strategy_L

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	4.00	62	32.5	63.9	63.9
	5.00	35	18.3	36.1	100.0
	Total	97	50.8	100.0	
Missing	System	94	49.2		
Total		191	100.0		

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Duration_E * Duration_L	94	49.2%	97	50.8%	191	100.0%

Duration_E * Duration_L Crosstabulation

			Duration_L			Total
			1.00	2.00	3.00	
Duration_E	1.00	Count	18	8	18	44
		Expected Count	14.0	11.2	18.7	44.0
	2.00	Count	6	5	5	16
		Expected Count	5.1	4.1	6.8	16.0
	3.00	Count	6	11	17	34
		Expected Count	10.9	8.7	14.5	34.0
Total		Count	30	24	40	94
		Expected Count	30.0	24.0	40.0	94.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	6.147[a]	4	.188
Likelihood Ratio	6.538	4	.162
Linear-by-Linear Association	2.552	1	.110
N of Valid Cases	94		

a. 1 cells (11.1%) have expected count less than 5. The minimum expected count is 4.09.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.256	.188
	Cramer's V	.181	.188
N of Valid Cases		94	

Duration_E

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	44	23.0	46.8	46.8
	2.00	16	8.4	17.0	63.8
	3.00	34	17.8	36.2	100.0
	Total	94	49.2	100.0	
Missing	System	97	50.8		
Total		191	100.0		

Duration_L

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	31	16.2	32.0	32.0
	2.00	24	12.6	24.7	56.7
	3.00	42	22.0	43.3	100.0
	Total	97	50.8	100.0	
Missing	System	94	49.2		
Total		191	100.0		

Appendix E Independent-Sample *t*-Test

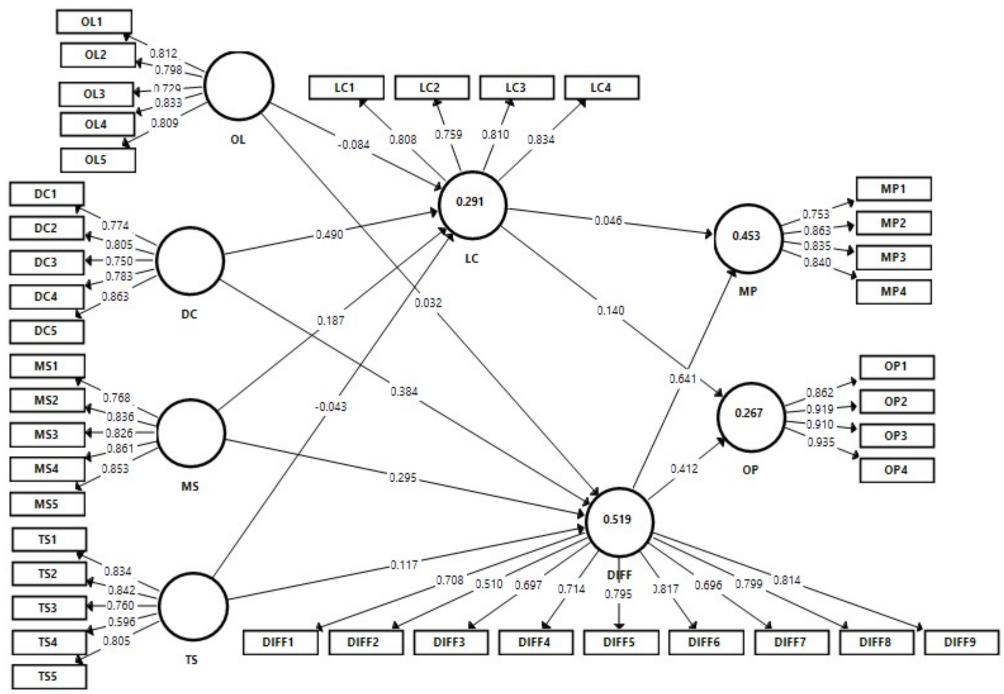
Group Statistics

	Group	N	Mean	Std. Deviation	Std. Error Mean
BDAC	Early	94	5.9525	.64459	.06648
	Late	97	5.9786	.67764	.06880
Cost_mean	Early	94	5.9202	.70445	.07266
	Late	97	6.1469	.73310	.07444
Diff_mean	Early	94	6.1312	.56865	.05865
	Late	97	6.1936	.61870	.06282
MP_mean	Early	94	5.8298	.66520	.06861
	Late	97	5.9485	.79299	.08052
OP_mean	Early	94	5.7207	.83429	.08605
	Late	97	5.8428	.92655	.09408

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
BDAC	Equal variances assumed	.002	.960	-.273	189	.785	-.02614	.09575	-.21502	.16274
	Equal variances not assumed			-.273	188.936	.785	-.02614	.09568	-.21487	.16260
Cost_mean	Equal variances assumed	.249	.618	-2.178	189	.031	-.22669	.10408	-.43201	-.02138
	Equal variances not assumed			-2.179	188.987	.031	-.22669	.10402	-.43188	-.02151
Diff_mean	Equal variances assumed	1.589	.209	-.725	189	.469	-.06238	.08606	-.23214	.10738
	Equal variances not assumed			-.726	188.477	.469	-.06238	.08594	-.23192	.10716
MP_mean	Equal variances assumed	1.991	.160	-1.119	189	.265	-.11867	.10607	-.32791	.09057
	Equal variances not assumed			-1.122	185.223	.263	-.11867	.10578	-.32736	.09003
OP_mean	Equal variances assumed	.315	.575	-.956	189	.340	-.12204	.12771	-.37395	.12987
	Equal variances not assumed			-.957	187.996	.340	-.12204	.12750	-.37354	.12947

Appendix F   Assessment of Reflective Measurement Model



Appendix G Heterotrait-Heteromethod

	Original Sample (O)	Sample Mean (M)	2.50%	97.50%
DC -> LC	0.604	0.6	0.457	0.743
DIFF -> LC	0.766	0.767	0.657	0.866
DIFF -> DC	0.743	0.745	0.629	0.841
OL -> LC	0.395	0.401	0.27	0.535
OL -> DC	0.851	0.849	0.758	0.919
OL -> DIFF	0.608	0.61	0.484	0.716
MS -> LC	0.479	0.477	0.326	0.639
MS -> DC	0.709	0.71	0.598	0.813
MS -> DIFF	0.698	0.698	0.591	0.776
MS -> OL	0.622	0.624	0.499	0.725
MP -> LC	0.542	0.544	0.39	0.684
MP -> DC	0.54	0.545	0.406	0.684
MP -> DIFF	0.747	0.75	0.633	0.845
MP -> OL	0.576	0.582	0.448	0.706
MP -> MS	0.598	0.601	0.458	0.738
OP -> LC	0.466	0.468	0.311	0.626
OP -> DC	0.397	0.398	0.25	0.528
OP -> DIFF	0.534	0.536	0.409	0.654
OP -> OL	0.339	0.34	0.189	0.498
OP -> MS	0.447	0.447	0.295	0.593
OP -> MP	0.701	0.699	0.548	0.819
TS -> LC	0.332	0.351	0.22	0.515
TS -> DC	0.669	0.674	0.527	0.801
TS -> DIFF	0.615	0.618	0.453	0.743
TS -> OL	0.622	0.62	0.457	0.773
TS -> MS	0.76	0.76	0.644	0.868
TS -> MP	0.664	0.668	0.555	0.79
TS-> OP	0.651	0.652	0.509	0.766

Appendix H Assessment of Common Method Variance

Communalities

	Initial	Extraction
Explore new knowledge	1.000	.825
Store new knowledge	1.000	.710
Share knowledge	1.000	.736
Apply knowledge	1.000	.717
Exploit competencies	1.000	.747
Asset	1.000	.617
Decision	1.000	.711
Override	1.000	.675
Extract insight from data	1.000	.725
Coach employee	1.000	.747
Understand business needs	1.000	.651
Increase data analytics usage	1.000	.670
Coordinate data-related activities	1.000	.734
Anticipate future needs	1.000	.715
Understand output from data analytics	1.000	.822
Training	1.000	.722
Technical skills	1.000	.699
Qualification	1.000	.743
Work experience	1.000	.789
New employees with data analytics skills	1.000	.712
Parallel computing approaches	1.000	.698
Data visualisation tools	1.000	.787
Cloud-based services	1.000	.716
Open-source software	1.000	.736
Databases	1.000	.706
Large data	1.000	.705
Multiple internal sources	1.000	.647
Internal and external data	1.000	.748
Low cost	1.000	.741
Low price	1.000	.679
Reduce cost	1.000	.686
Control cost	1.000	.738
Specification	1.000	.622

Design	1.000	.705
Short lead time	1.000	.719
On time	1.000	.793
Services	1.000	.703
Reliable Services	1.000	.700
Flexible	1.000	.641
New product	1.000	.750
Value maximisation	1.000	.773
New market	1.000	.733
New product faster	1.000	.724
High success	1.000	.689
Market share	1.000	.698
Productivity	1.000	.807
Profit rate	1.000	.840
ROI	1.000	.819
Revenue	1.000	.820

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	19.114	39.009	39.009	19.114	39.009	39.009
2	3.129	6.387	45.395	3.129	6.387	45.395
3	2.903	5.925	51.320	2.903	5.925	51.320
4	2.087	4.259	55.580	2.087	4.259	55.580
5	1.870	3.815	59.395	1.870	3.815	59.395
6	1.556	3.175	62.570	1.556	3.175	62.570
7	1.437	2.933	65.504	1.437	2.933	65.504
8	1.328	2.711	68.215	1.328	2.711	68.215
9	1.110	2.266	70.481	1.110	2.266	70.481
10	1.056	2.155	72.635	1.056	2.155	72.635
11	.891	1.819	74.454			
12	.848	1.730	76.184			
13	.788	1.608	77.791			
14	.733	1.496	79.287			
15	.669	1.366	80.652			
16	.650	1.326	81.978			
17	.588	1.201	83.179			
18	.559	1.141	84.320			
19	.504	1.029	85.349			
20	.492	1.004	86.353			

21	.453	.924	87.277			
22	.439	.897	88.174			
23	.426	.869	89.043			
24	.408	.834	89.876			
25	.383	.781	90.657			
26	.348	.710	91.367			
27	.330	.674	92.041			
28	.329	.671	92.712			
29	.318	.649	93.361			
30	.293	.597	93.959			
31	.274	.559	94.518			
32	.247	.504	95.022			
33	.231	.471	95.493			
34	.221	.450	95.943			
35	.211	.431	96.374			
36	.196	.399	96.773			
37	.179	.364	97.138			
38	.175	.357	97.494			
39	.168	.342	97.837			
40	.154	.314	98.151			
41	.142	.289	98.440			
42	.132	.269	98.709			
43	.128	.260	98.970			
44	.108	.220	99.190			
45	.102	.209	99.399			
46	.089	.181	99.580			
47	.085	.173	99.753			
48	.067	.136	99.889			
49	.054	.111	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component									
	1	2	3	4	5	6	7	8	9	10
Explore new knowledge	.554	-.347	-.111	.112	-.393	.184	-.155	-.043	-.183	.354
Store new knowledge	.575	-.315	-.041	.366	-.175	.228	-.037	-.114	-.219	-.017
Share knowledge	.486	-.487	.025	.408	-.048	-.015	-.139	-.216	.142	-.087
Apply knowledge	.669	-.291	.014	.244	-.294	-.138	-.108	-.014	-.073	-.055
Exploit competencies	.609	-.249	.021	.100	-.323	.403	-.027	.000	-.186	.038
Asset	.645	-.262	.228	-.082	-.074	.111	.188	.053	-.002	-.133
Decision	.558	-.336	.234	-.017	-.202	-.003	.261	.076	.263	-.219
Override	.643	-.223	.063	.251	-.090	.044	.107	-.194	.232	-.177
Extract insight from data	.645	-.319	-.021	.129	-.273	-.118	.033	.150	.210	.186
Coach employee	.669	-.314	.194	.142	-.172	-.037	.135	.118	.182	-.215
Understand business needs	.599	-.141	-.214	-.118	.070	-.188	-.282	.285	-.058	-.090
Increase data analytics usage	.694	-.213	.018	-.204	.109	-.058	-.059	.245	.084	-.120
Coordinate data-related activities	.693	-.170	-.124	-.211	.015	-.167	-.110	.336	.020	-.105
Anticipate future needs	.711	-.171	-.099	-.134	.193	-.019	-.250	.078	.033	-.211
Understand output from data analytics	.677	-.102	-.193	-.316	.245	.016	-.349	.104	.061	-.140
Training	.682	.042	-.413	.055	-.059	.106	-.067	-.163	-.139	-.125
Technical skills	.716	.038	-.388	-.047	-.040	-.088	-.005	-.091	-.082	-.083
Qualification	.535	.037	-.341	.134	.339	.110	.416	-.023	.056	-.135
Work experience	.475	-.250	-.290	.057	.335	.087	.474	.220	.125	.071

New employees with data analytics skills	.637	.079	-.241	-.207	.072	.255	.120	-.051	-.210	-.260
Parallel computing approaches	.695	-.083	-.153	-.368	-.032	.061	.003	.022	-.011	.208
Data visualisation tools	.670	-.129	-.101	-.255	-.032	-.162	.201	-.289	-.163	.261
Cloud-based services	.596	-.179	-.216	-.212	-.178	-.349	.109	.079	.151	.207
Open-source software	.665	-.090	-.203	-.355	-.240	-.150	.016	-.049	.049	.185
Databases	.575	.012	.007	-.140	.149	-.135	.505	-.096	-.223	.019
Large data	.771	-.040	-.126	-.099	.159	.200	-.077	.008	-.093	.056
Multiple internal sources	.685	-.053	-.149	-.051	.284	.142	-.085	-.181	-.096	.005
Internal and external data	.731	-.077	-.196	-.081	.277	.102	-.144	-.173	-.148	.051
Low cost	.499	.242	.372	-.312	-.191	.271	.019	.275	.052	.091
Low price	.428	.313	.468	-.185	-.031	.341	-.041	.152	.035	-.042
Reduce cost	.496	.091	.576	-.254	-.074	-.030	.078	-.100	-.114	-.026
Control cost	.620	.172	.429	-.139	-.175	-.088	.100	-.148	-.214	-.069
Specification	.560	-.086	.355	-.043	.281	-.131	.005	-.130	.035	.242
Design	.404	-.121	.193	.182	.445	.276	.025	.013	.205	.374
Short lead time	.609	.056	.279	-.055	.167	.324	-.092	-.115	.320	.082
On time	.637	.121	.064	.023	.125	.006	-.335	-.356	.330	.061
Services	.694	.183	.400	.020	-.036	.020	.016	-.010	-.137	-.081
Reliable Services	.735	.154	.334	-.036	-.013	-.135	-.010	.019	-.051	-.039
Flexible	.555	.073	.286	.198	.210	-.224	-.070	-.238	-.096	-.203
New product	.679	.080	.258	.225	.178	-.348	.054	-.013	-.092	.025
Value maximisation	.724	.135	.208	.079	.127	-.371	-.143	-.045	-.042	.056
New market	.463	.223	-.076	.531	.151	-.019	-.006	.333	-.176	.125
New product faster	.641	.240	.073	.398	.094	.070	.050	.251	-.075	.084

High success	.662	.303	.044	.183	.041	-.170	-.076	.252	-.059	.143
Market share	.669	.328	-.069	.203	-.098	.116	-.117	.219	-.110	-.027
Productivity	.541	.528	-.268	.178	-.224	-.194	.046	-.061	.191	.028
Profit rate	.628	.565	-.247	.006	-.142	.030	-.008	-.073	.167	-.101
ROI	.602	.523	-.276	-.020	-.244	.102	.082	-.107	.133	-.021
Revenue	.617	.560	-.215	.049	-.155	.056	.094	-.093	.174	.044

Extraction Method: Principal Component Analysis.

a. 10 components extracted.

Appendix I Full Collinearity Test

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	TS, LC, OL, OP, MS, MP, DC, DIFF[b]	.	Enter

a. Dependent Variable: Random

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.130[a]	.017	-.026	3.14201

a. Predictors: (Constant), TS, LC, OL, OP, MS, MP, DC, DIFF

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	31.033	8	3.879	.393	.923[b]
	Residual	1796.746	182	9.872		
	Total	1827.779	190			

a. Dependent Variable: Random

b. Predictors: (Constant), TS, LC, OL, OP, MS, MP, DC, DIFF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	49.702	.227		218.618	.000		
	DC	.336	.401	.109	.838	.403	.322	3.110
	DIFF	.077	.413	.025	.185	.853	.302	3.307
	LC	-.199	.324	-.064	-.614	.540	.494	2.025
	MP	-.068	.360	-.022	-.189	.850	.398	2.514
	MS	.258	.349	.083	.739	.461	.423	2.362
	OL	-.153	.355	-.049	-.429	.668	.409	2.445
	OP	-.180	.331	-.058	-.543	.588	.471	2.124
	TS	-.254	.368	-.082	-.690	.491	.382	2.617

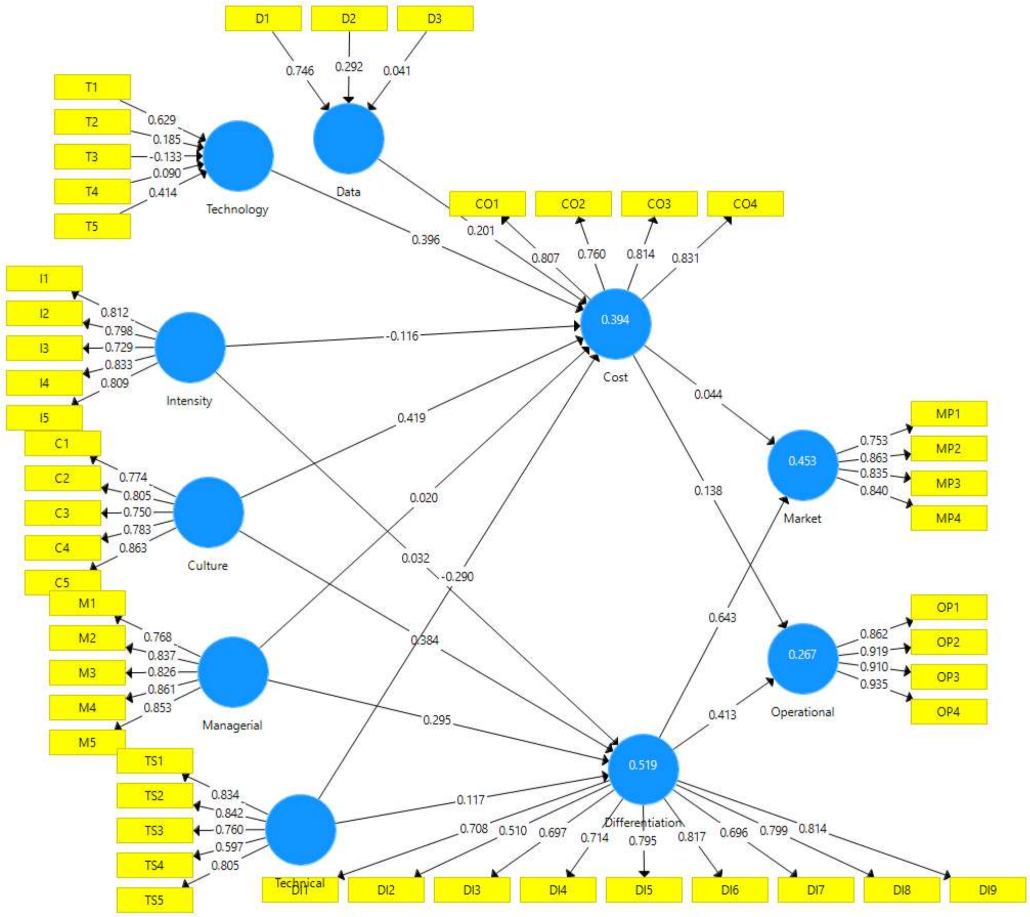
a. Dependent Variable: Random

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions								
				(Constant)	DC	DIFF	LC	MP	MS	OL	OP	TS
1	1	4.721	1.000	.00	.01	.01	.01	.01	.01	.01	.01	.01
	2	1.000	2.173	1.00	.00	.00	.00	.00	.00	.00	.00	.00
	3	.912	2.275	.00	.07	.00	.01	.05	.02	.11	.20	.00
	4	.812	2.411	.00	.00	.04	.32	.00	.02	.01	.03	.12
	5	.477	3.146	.00	.01	.01	.02	.11	.38	.27	.03	.05
	6	.397	3.449	.00	.08	.05	.10	.41	.10	.00	.21	.08
	7	.248	4.364	.00	.03	.43	.12	.00	.42	.12	.13	.26
	8	.236	4.475	.00	.27	.09	.40	.03	.05	.09	.32	.46
	9	.197	4.894	.00	.53	.38	.01	.39	.01	.40	.08	.01

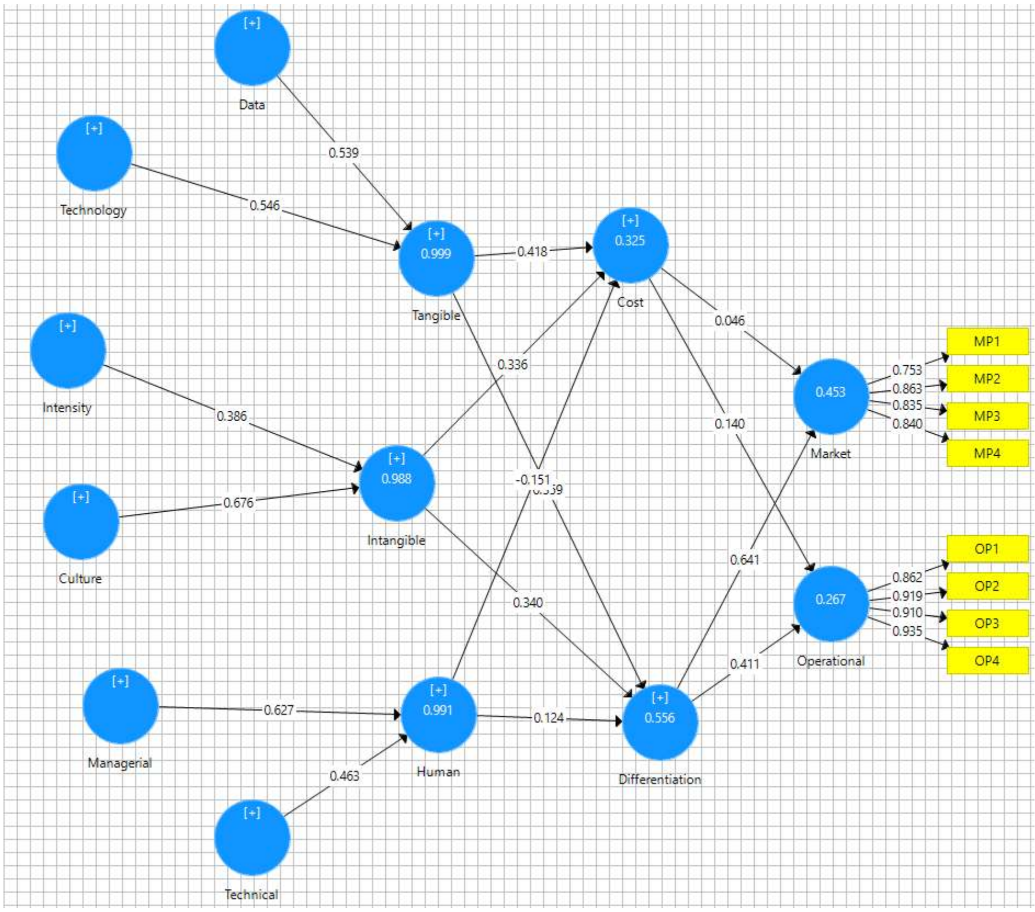
a. Dependent Variable: Random

Appendix J Assessment of Formative Measurement Model



Appendix K   Second-order Factor Measurement Model Analysis

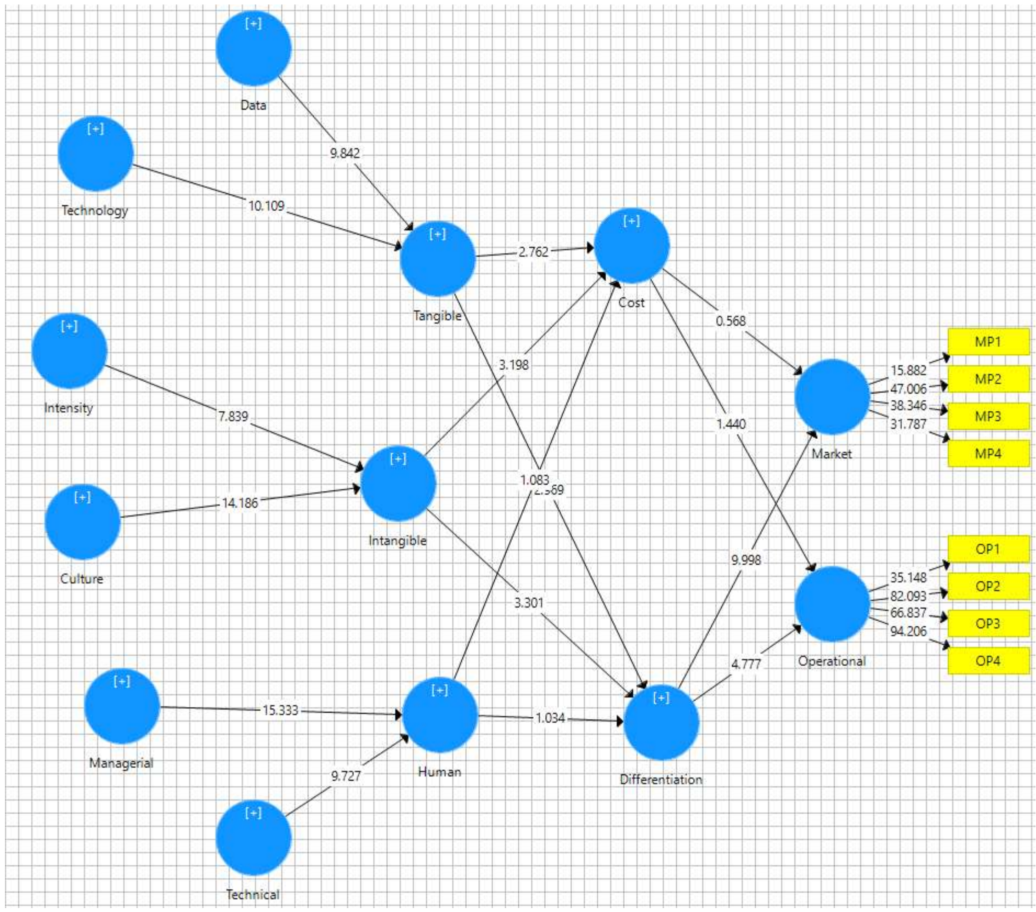
1) Outer Weight



2) Collinearity Statistics (VIF)

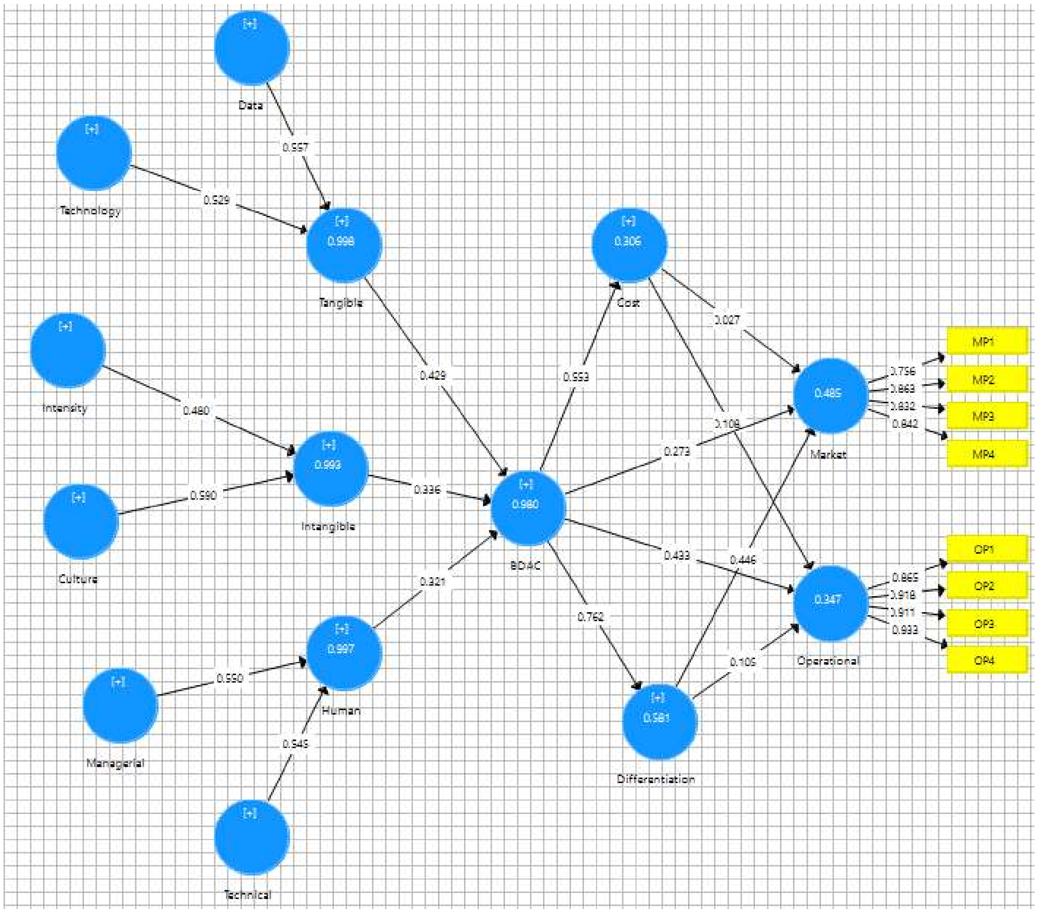
	Cost	Culture	Data	Differentia	Human	Intangible	Intensity	Managerial	Market	Operationa	Tangible	Technical	Technology
Cost									1.838	1.838			
Culture						2.155							
Data											1.932		
Differentiation									1.838	1.838			
Human	3.574			3.574									
Intangible	2.06			2.06									
Intensity						2.155							
Managerial					1.775								
Market													
Operational													
Tangible	3.414			3.414									
Technical					1.775								
Technology											1.932		

3) *t*-value (significance level)



Appendix L Third-order Factor Measurement Model Analysis

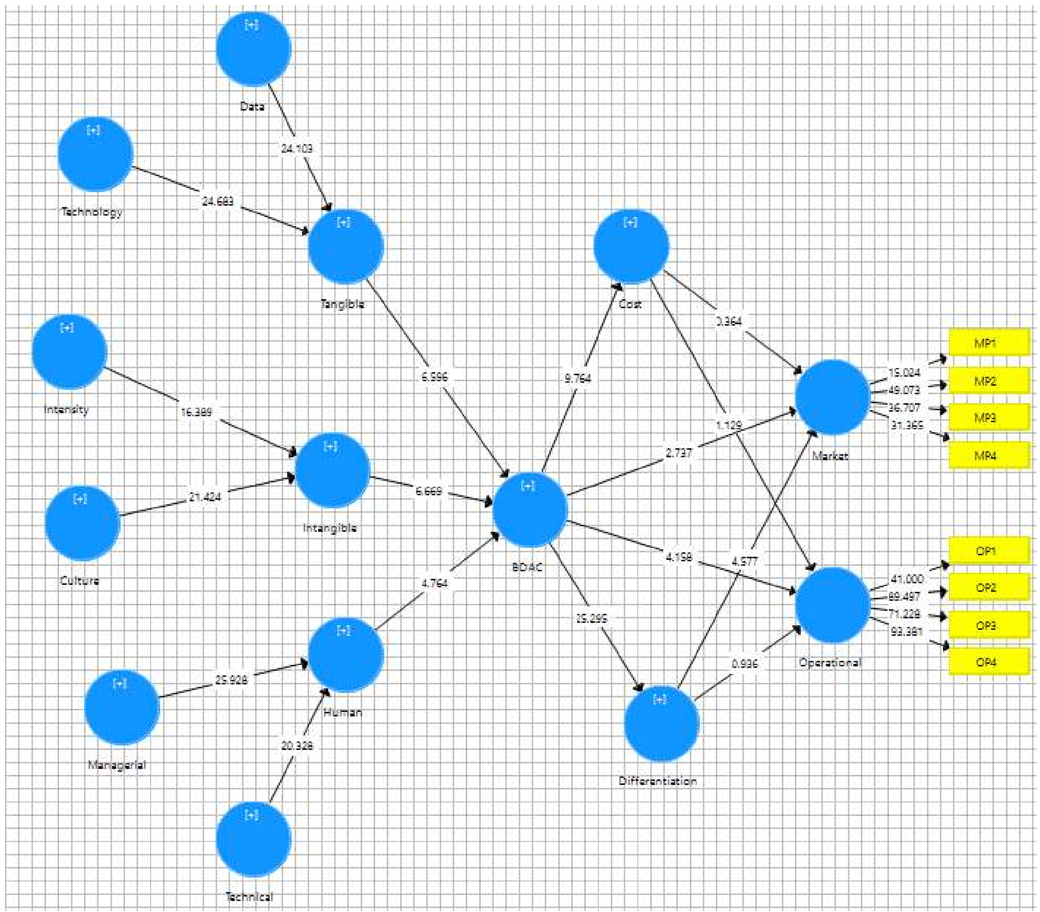
1) Outer Weight



2) Collinearity Statistics (VIF)

	Cost	Culture	Data	Differentiation	Human	Intangible	Intensity	BDAC	Managerial	Market	Operational	Tangible	Technical	Technology
Cost										1.848	1.848			
Culture						2.157								
Data												1.923		
Differentiation										3.059	3.059			
Human								3.903						
Intangible								2.067						
Intensity						2.157								
BDAC	1			1						2.4	2.4			
Managerial					1.774									
Market														
Operational														
Tangible								3.825						
Technical					1.774									
Technology												1.923		

3) *t*-value (significance level)



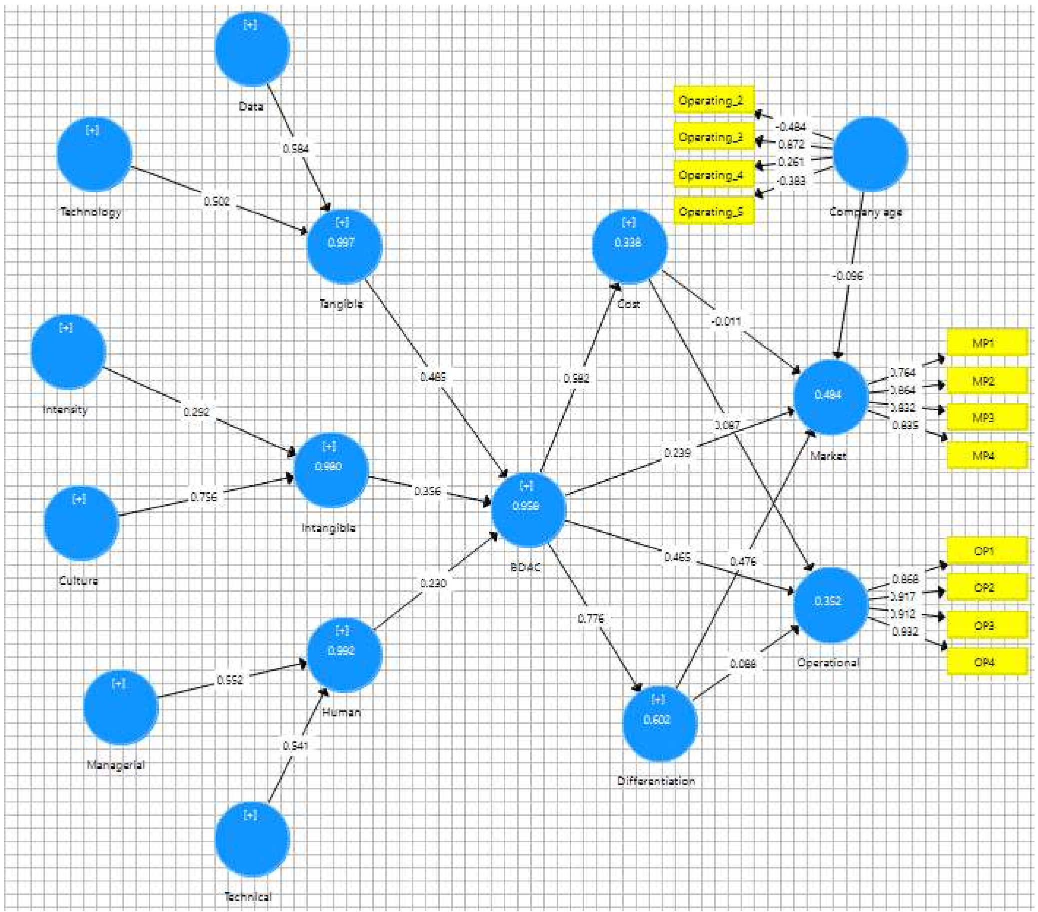
Appendix M Assessment of Normality

Output of skewness and kurtosis calculation

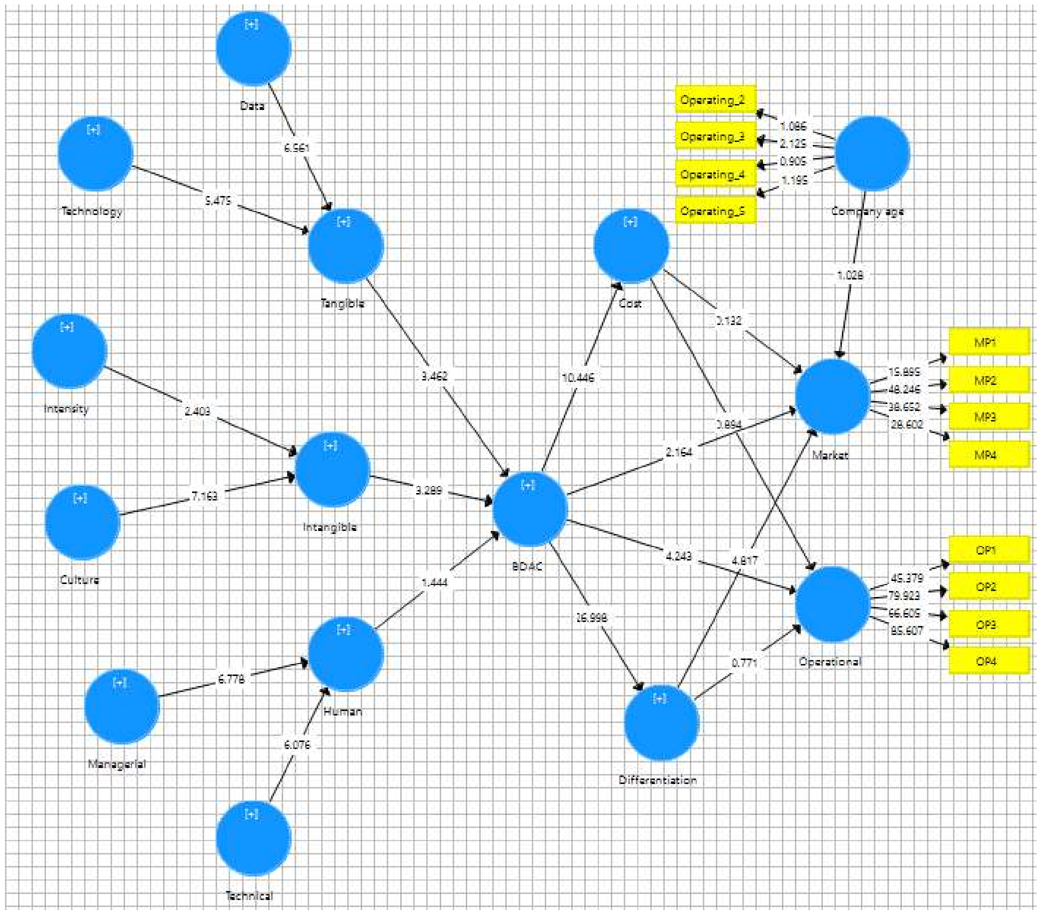
```
Sample size:  191
Number of variables:  14

Univariate skewness and kurtosis
                Skewness SE_skew Z_skew Kurtosis SE_kurt Z_kurt
BDAC              -0.496   0.176 -2.822   -0.536    0.35 -1.532
Cost              -0.944   0.176 -5.366    0.802    0.35  2.291
Culture           -0.977   0.176 -5.554    0.600    0.35  1.715
Data              -0.964   0.176 -5.480    1.713    0.35  4.894
Differentiation   -0.771   0.176 -4.386    0.199    0.35  0.568
Human             -0.488   0.176 -2.773   -0.638    0.35 -1.823
Intangible        -0.877   0.176 -4.986    0.246    0.35  0.703
Intensity         -0.836   0.176 -4.751    0.398    0.35  1.137
Managerial        -0.763   0.176 -4.338    0.028    0.35  0.081
Market            -0.752   0.176 -4.278    0.398    0.35  1.138
Operational       -0.698   0.176 -3.972   -0.230    0.35 -0.656
Tangible          -0.614   0.176 -3.491    0.037    0.35  0.106
Technical         -0.712   0.176 -4.048    0.289    0.35  0.827
Technology        -0.815   0.176 -4.633    0.232    0.35  0.663

Mardia's multivariate skewness and kurtosis
                 b         z p-value
Skewness  59.66317 1899.2776       0
Kurtosis 292.27726   22.2907       0
```

Appendix N Effect of Control Variables

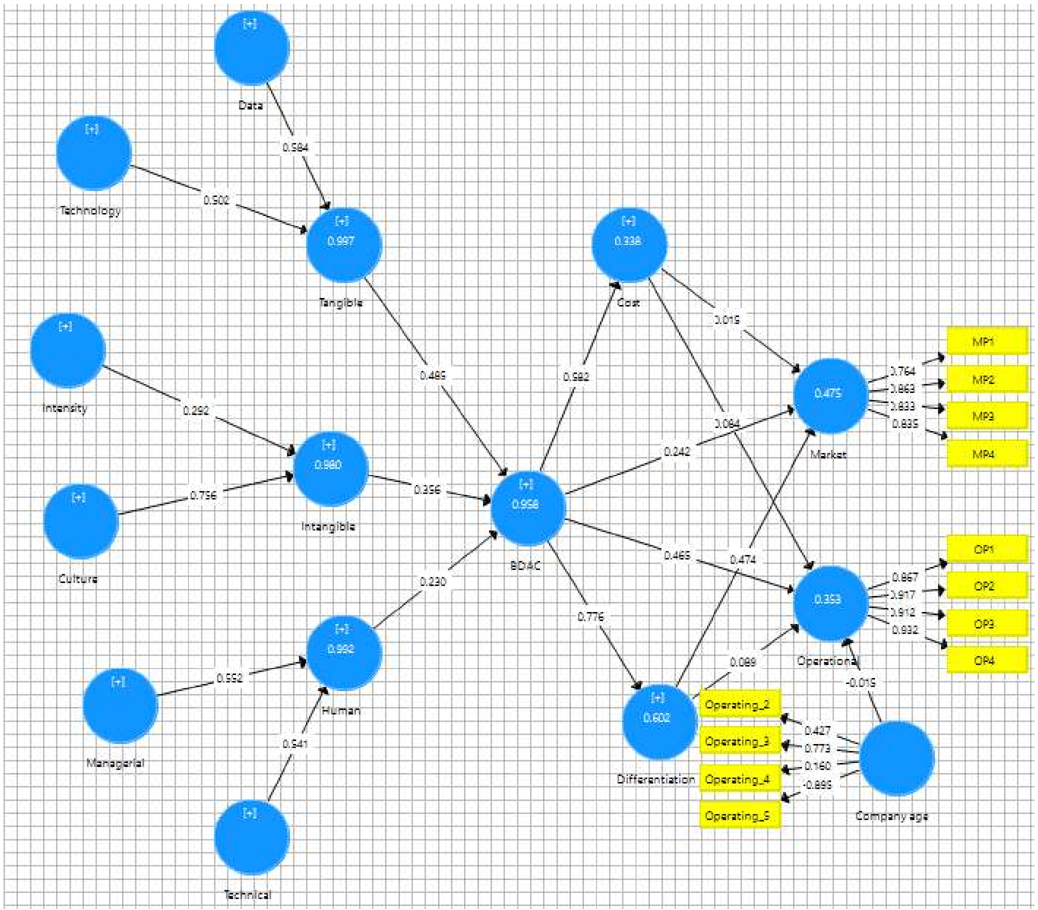
1a) Company Age → Market Performance (path coefficient):



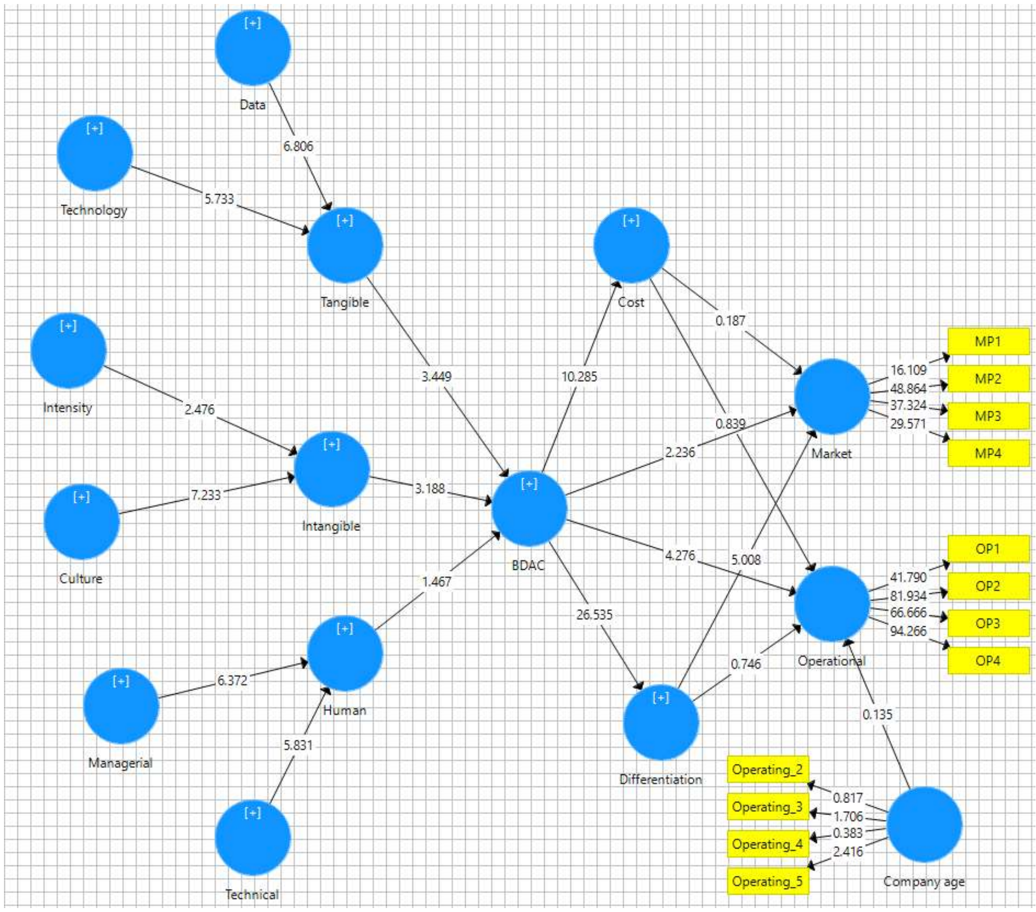
1b) Company Age → Market Performance (t – value):



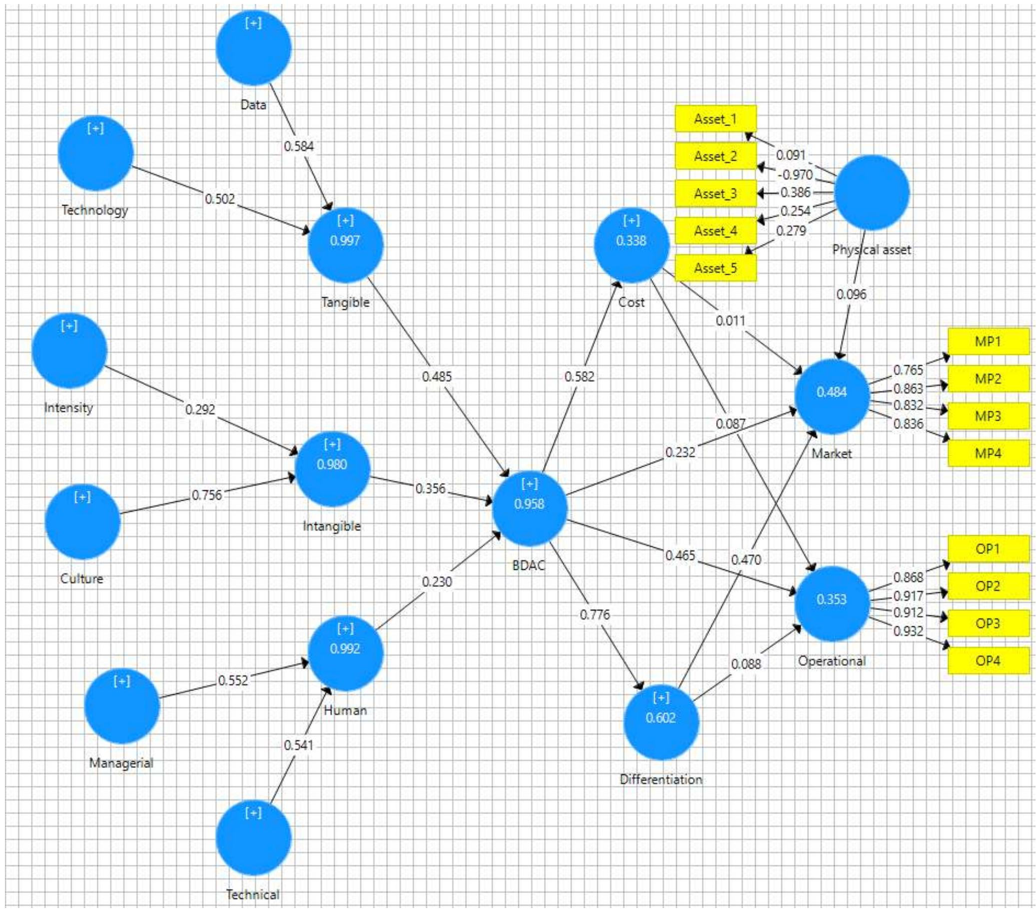
1c) Company Age → Operational Performance (Path coefficient):



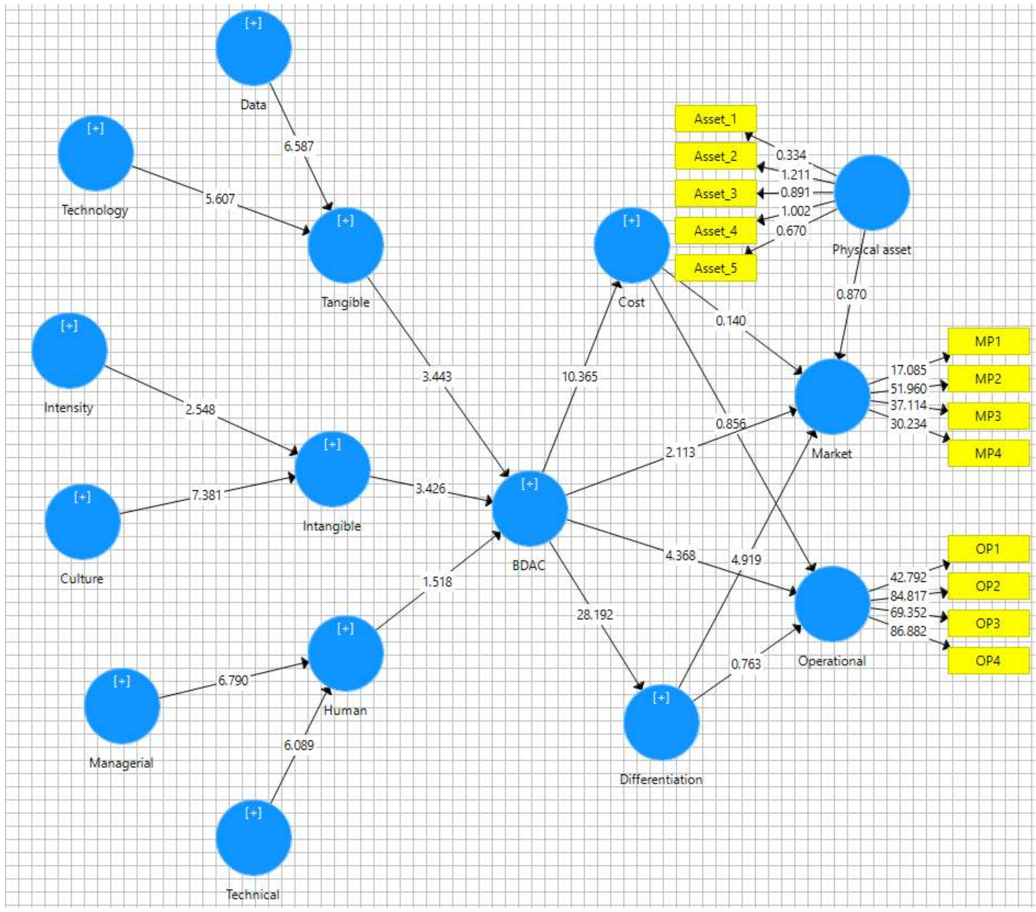
1d) Company Age → Operational Performance (t – value):



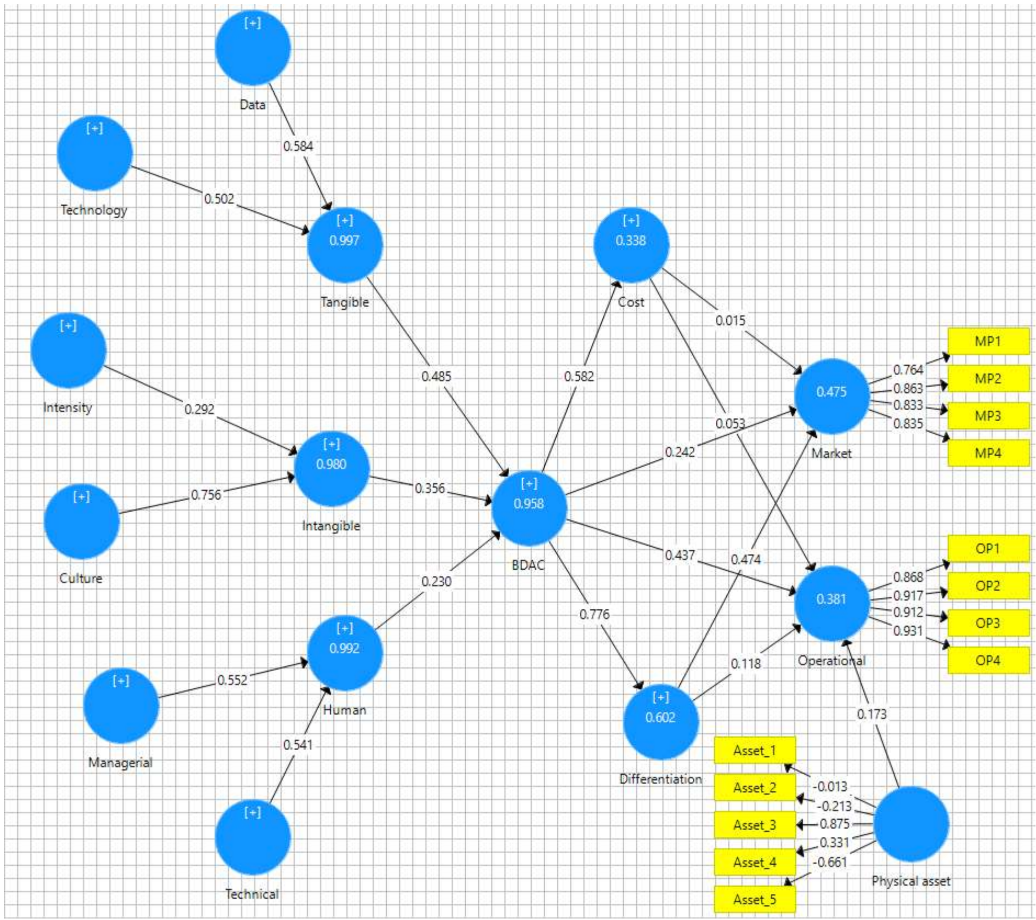
2a) Physical Asset → Market Performance (Path coefficient):



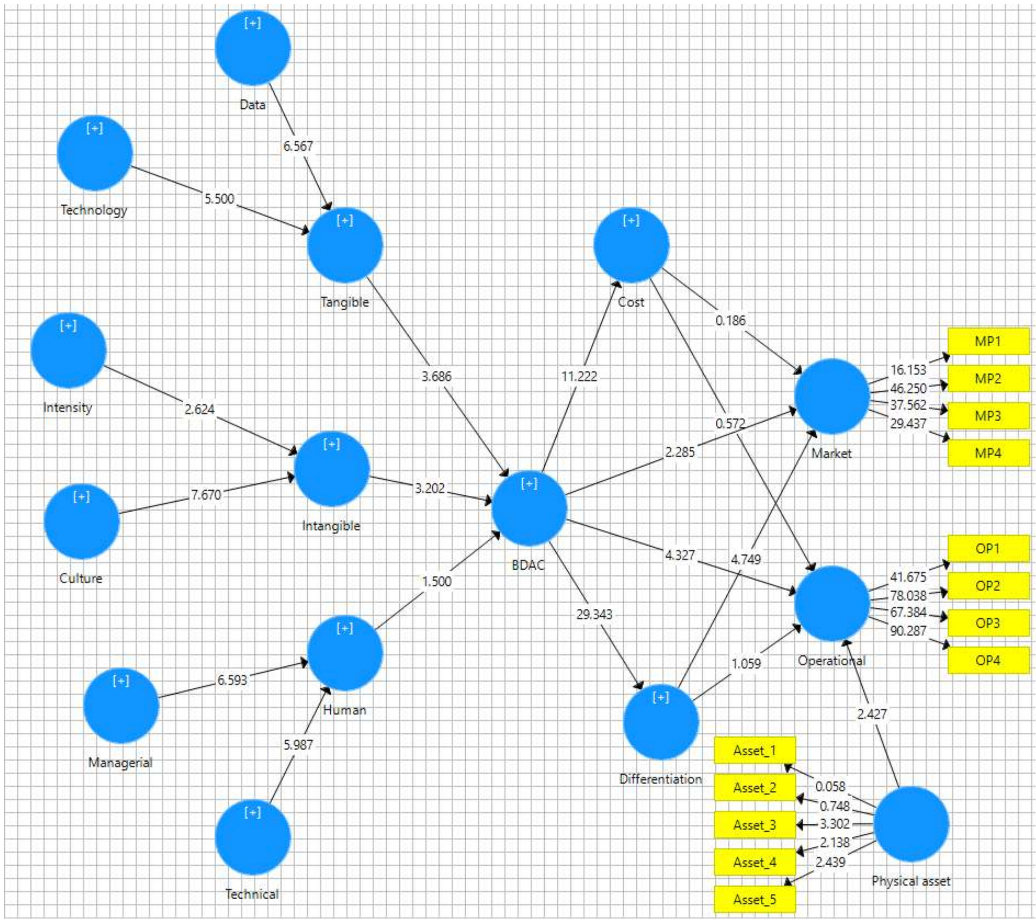
2b) Physical Asset → Market Performance (t – value):



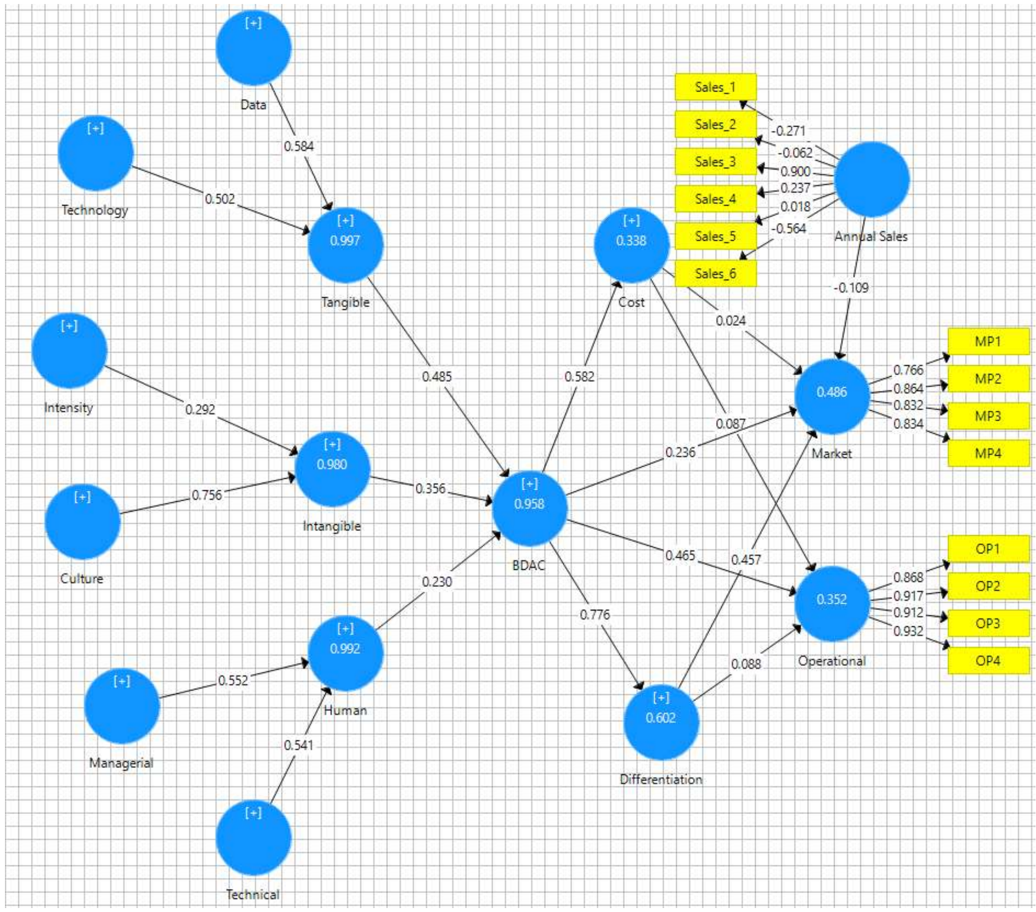
2c) Physical Asset → Operational Performance (Path coefficient):



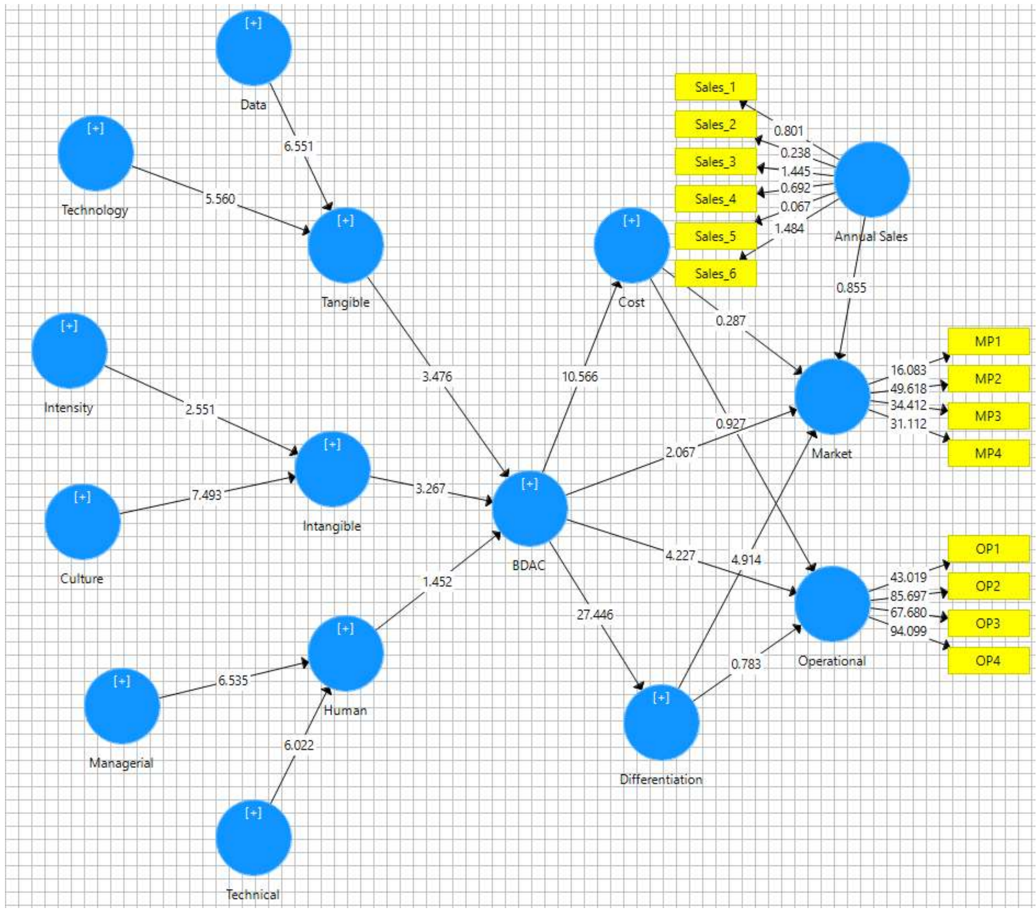
2d) Physical Asset → Operational Performance (t – value):



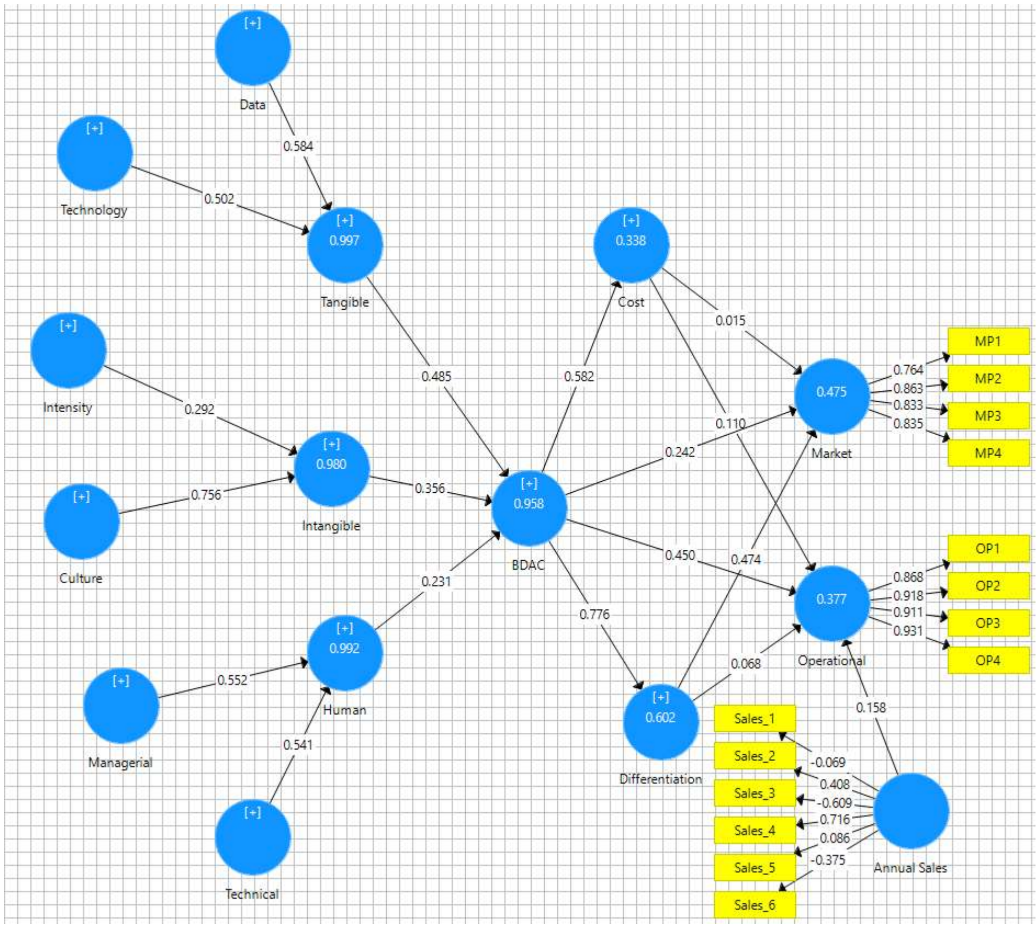
3a) Annual Sales → Market Performance (Path coefficient):



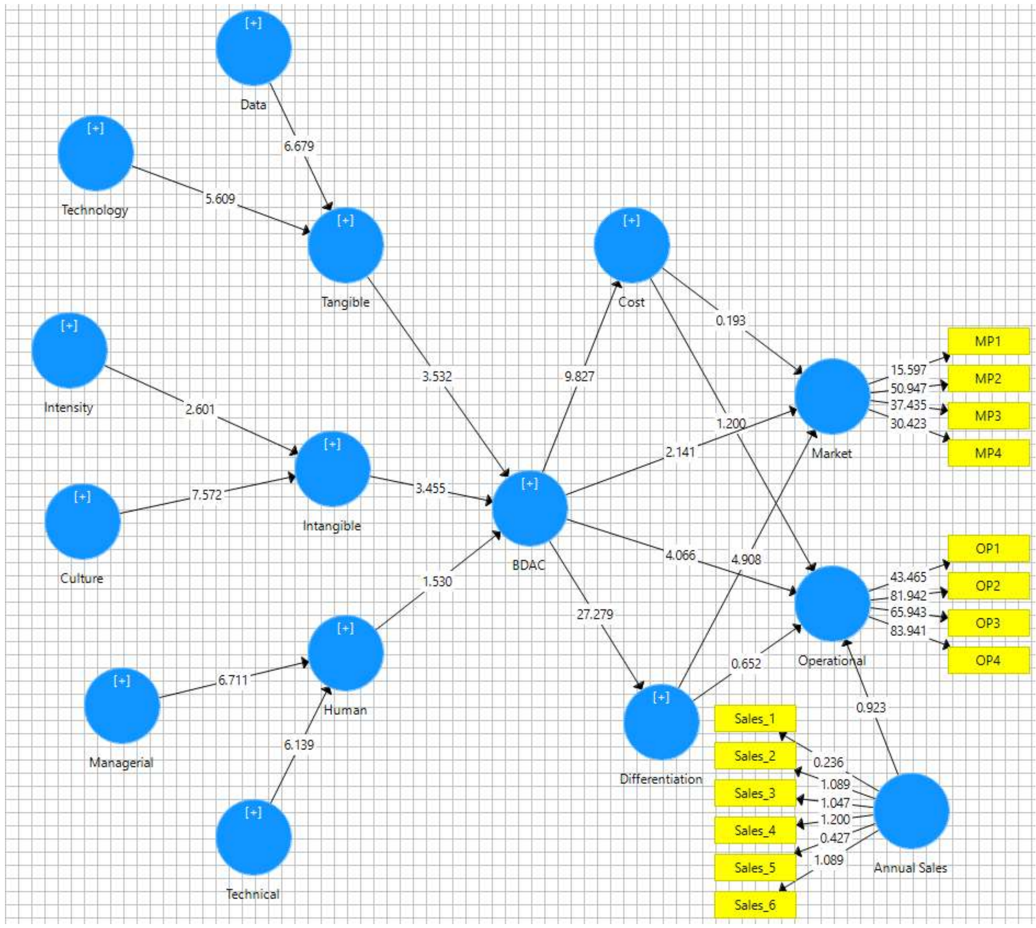
3b) Annual Sales → Market Performance (t – value):



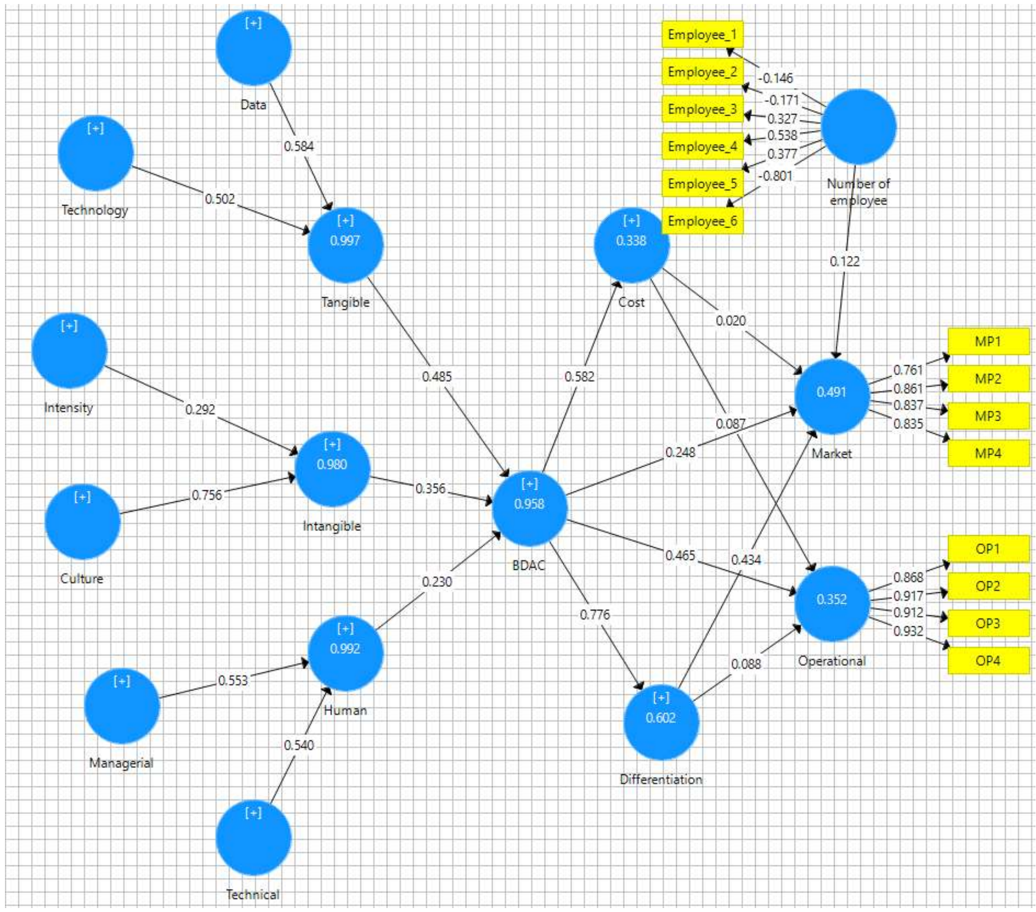
3c) Annual Sales → Operational Performance (Path coefficient):



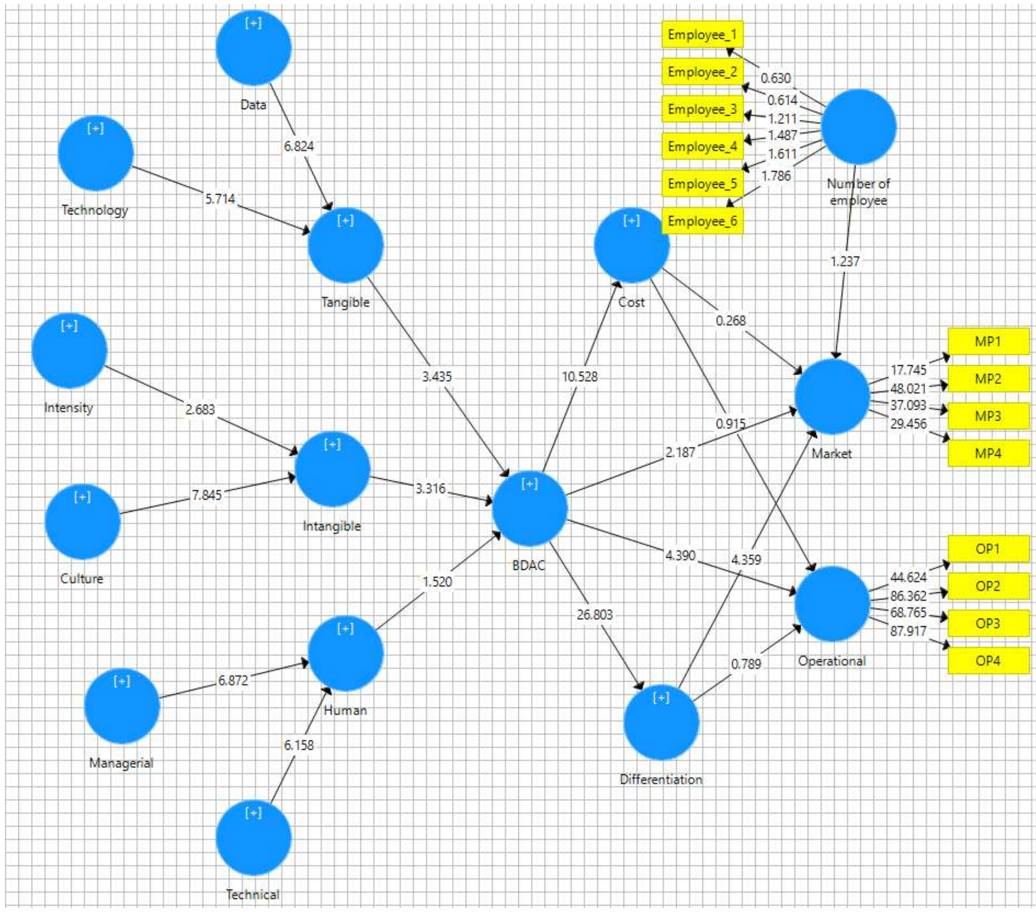
3d) Annual Sales → Operational Performance (t – value):



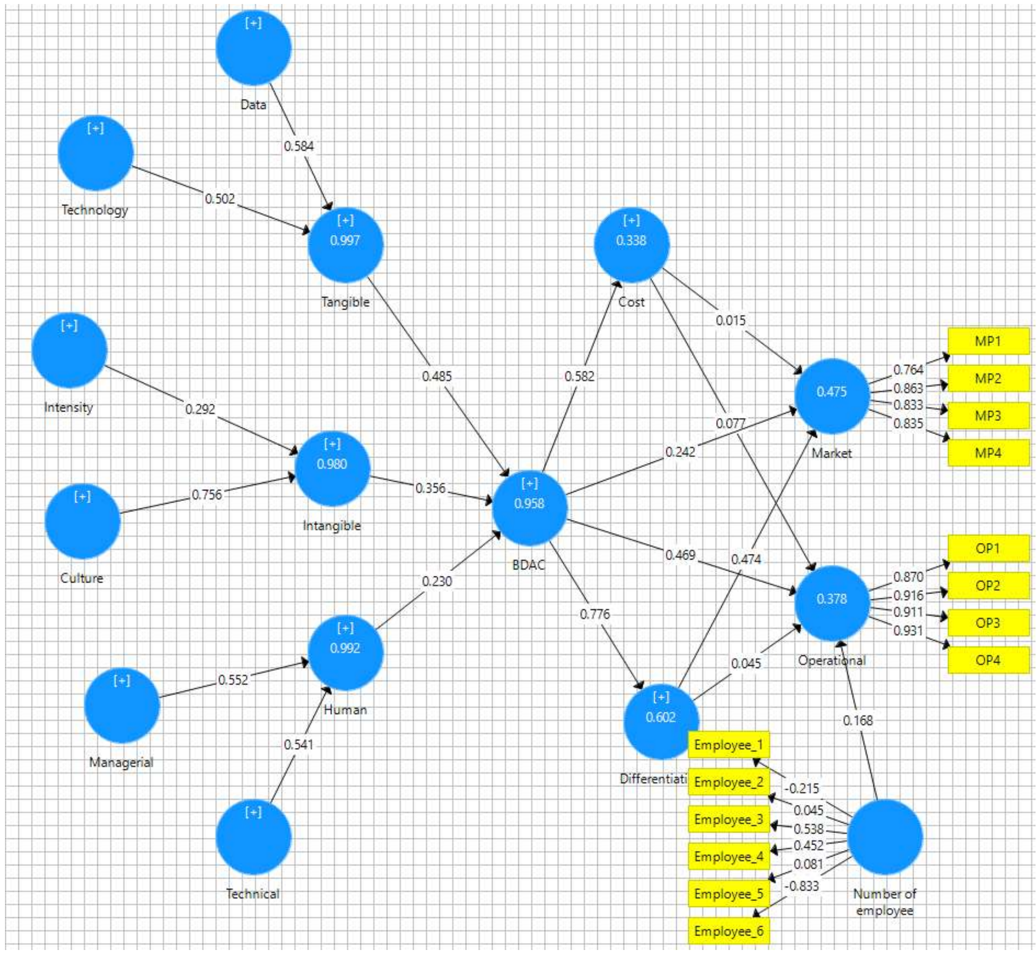
4a) Number of Employee → Market Performance (Path coefficient):



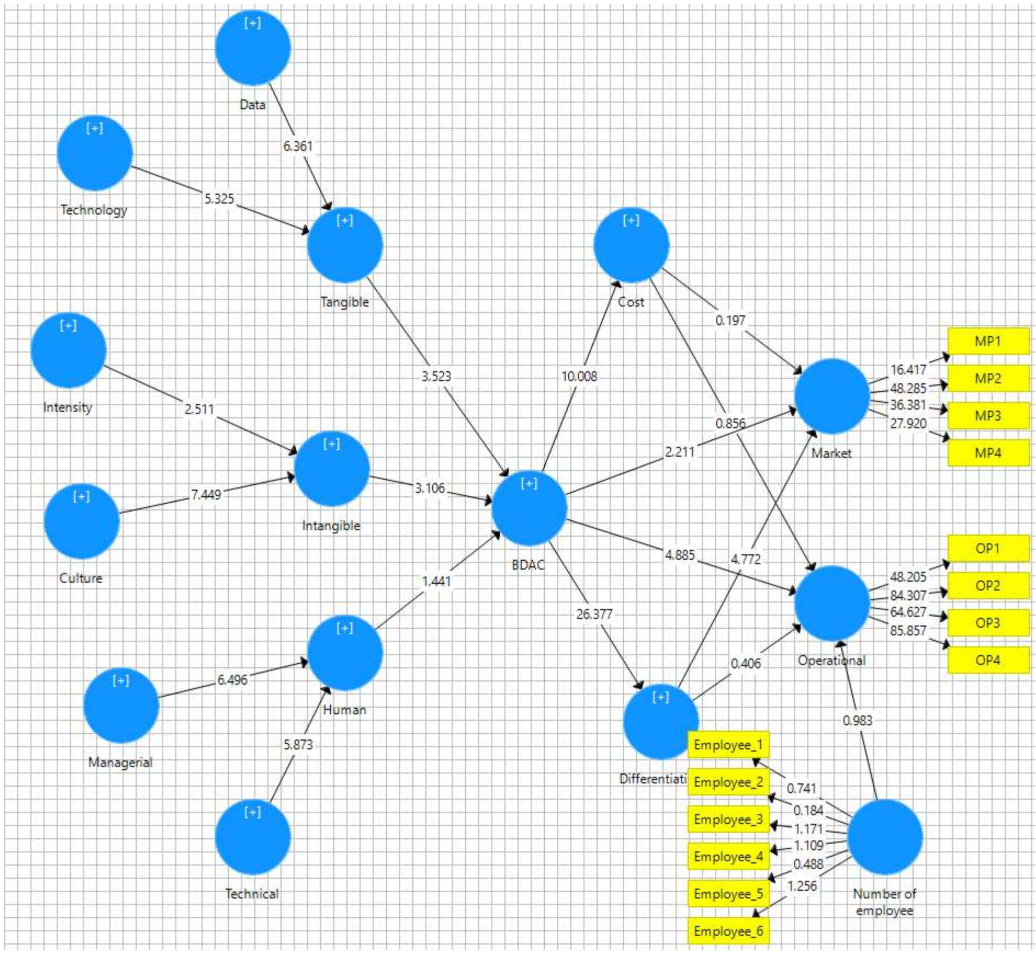
4b) Number of Employee → Market Performance (t – value):



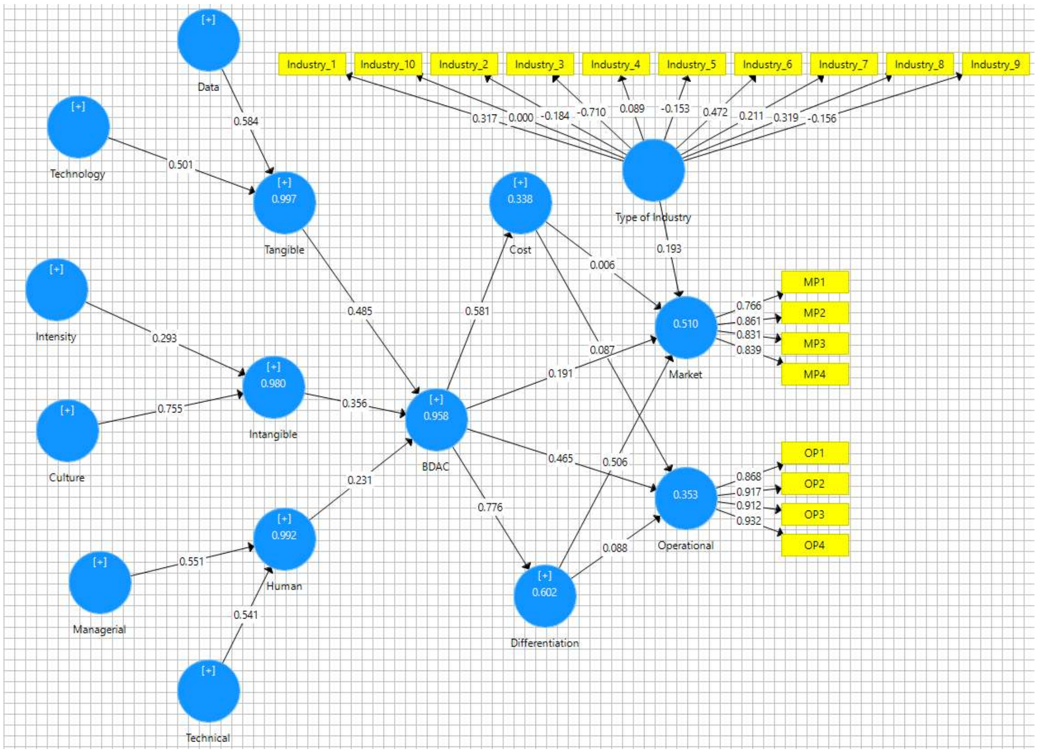
4c) Number of Employee → Operational Performance (Path coefficient):



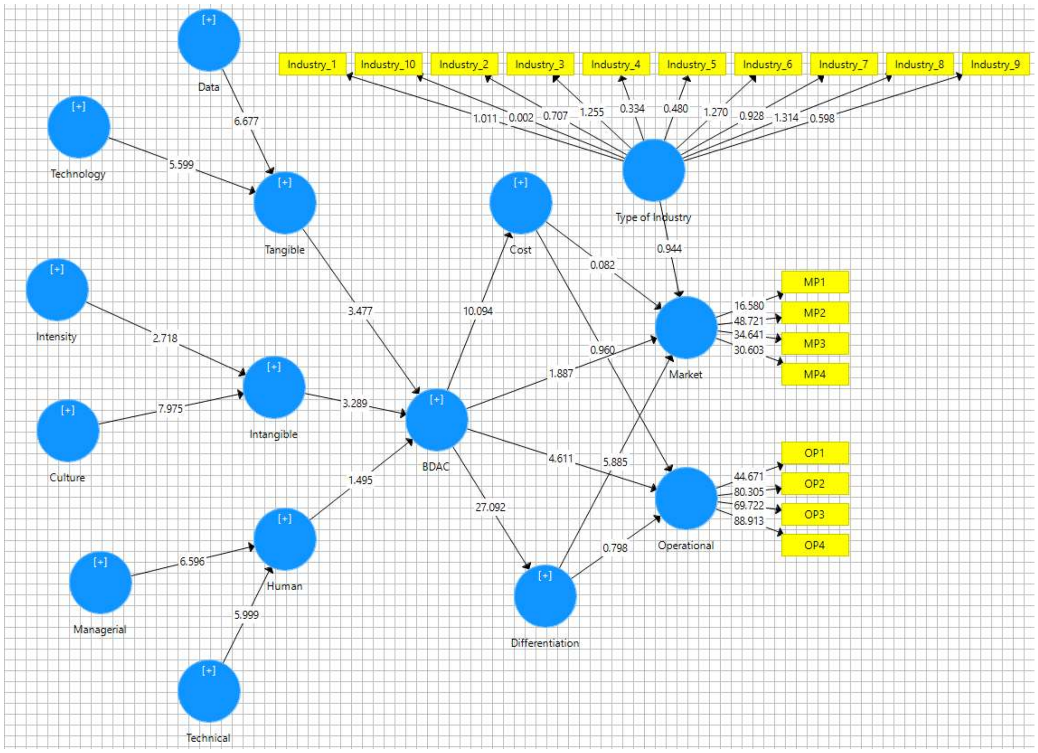
4d) Number of Employee → Operational Performance (t – value):



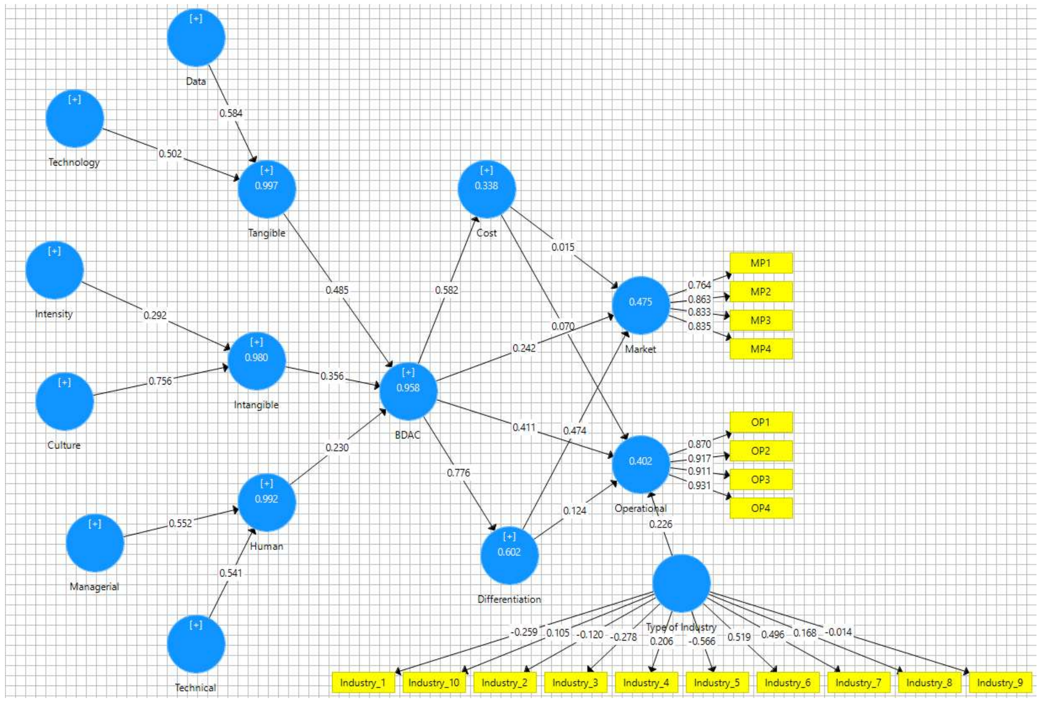
5a) Type of Industry → Market Performance (Path coefficient):



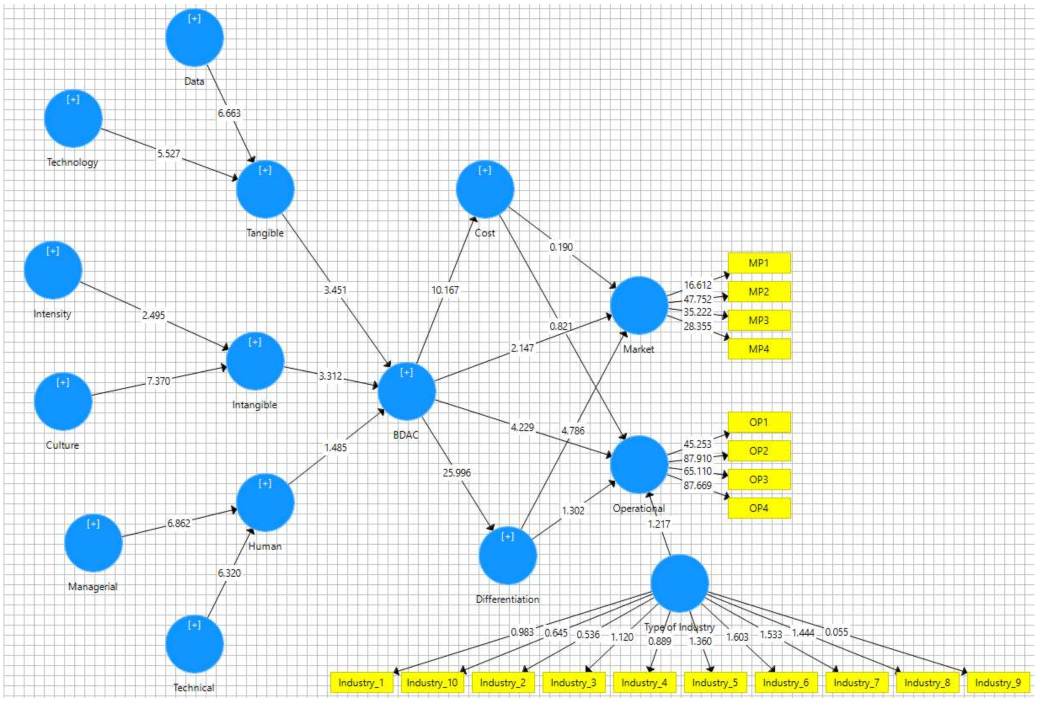
5b) Type of Industry → Market Performance (t – value):



5c) Type of Industry → Operational Performance (Path coefficient):

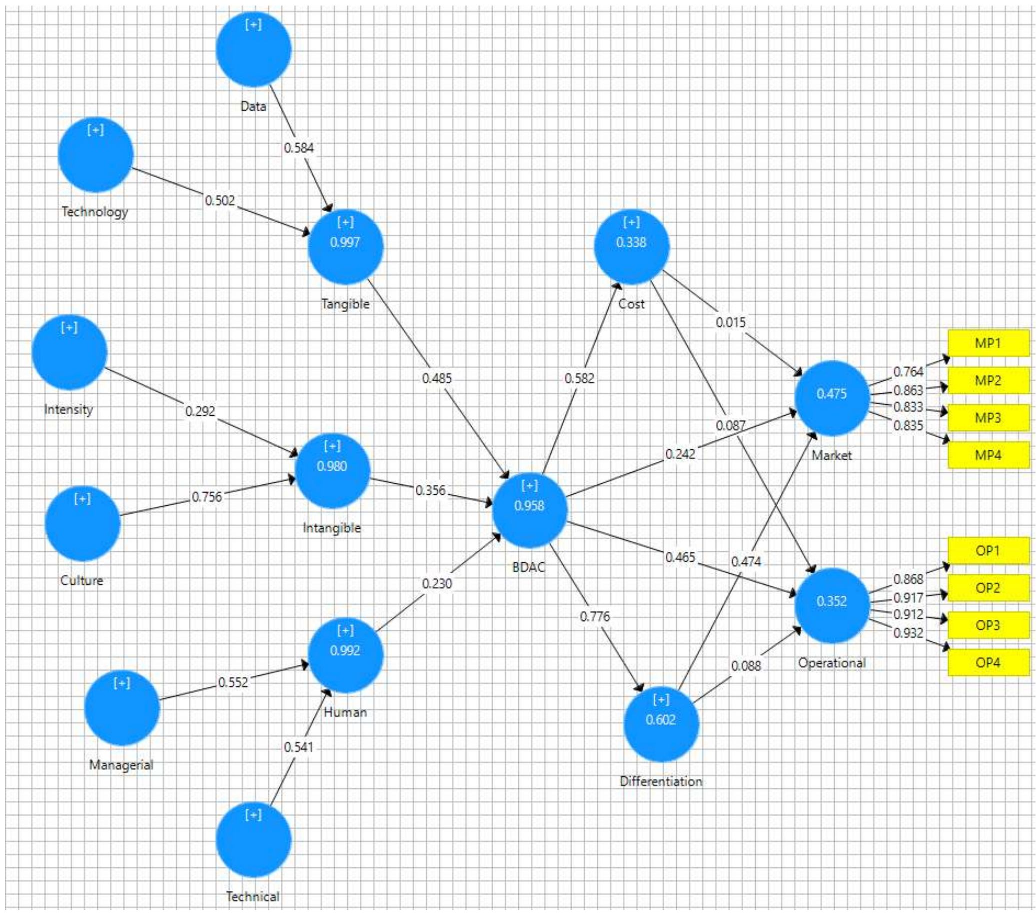


5d) Type of Industry → Operational Performance (t – value):



Appendix O Collinearity in the Structural Model Assessment

1) Path Coefficient



2) Collinearity Statistics (VIF)

	BDAC	Cost	Culture	Data	Differentiation	Human	Intangible	Intensity	Managerial	Market	Operational	Tangible	Technical	Technology
BDAC		1			1					2.552	2.552			
Cost										1.867	1.867			
Culture							2.16							
Data												1.911		
Differentiation										3.102	3.102			
Human	3.873													
Intangible	2.121													
Intensity							2.16							
Managerial						1.775								
Market														
Operational														
Tangible	3.739													
Technical						1.775								
Technology												1.911		

3) Standard Beta, Standard Error, *t*-value, *p*-value

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BDAC -> DIFF	0.776	0.798	0.028	27.897	0
BDAC -> LC	0.582	0.614	0.056	10.458	0
BDAC -> MP	0.242	0.324	0.111	2.181	0.015
BDAC -> OP	0.465	0.544	0.103	4.51	0
Culture -> Intangible	0.756	0.751	0.101	7.505	0
DIFF -> MP	0.474	0.42	0.098	4.814	0
DIFF -> OP	0.088	0.032	0.113	0.785	0.216
Data -> Tangible	0.584	0.578	0.088	6.614	0
Human -> BDAC	0.23	0.241	0.153	1.507	0.066
Intangible -> BDAC	0.356	0.338	0.108	3.284	0.001
Intensity -> Intangible	0.292	0.292	0.115	2.546	0.005
LC -> MP	0.015	-0.003	0.08	0.184	0.427
LC -> OP	0.087	0.067	0.098	0.889	0.187
Managerial -> Human	0.552	0.55	0.085	6.522	0
Tangible -> BDAC	0.485	0.47	0.138	3.52	0
Technical -> Human	0.541	0.537	0.091	5.939	0
Technology -> Tangible	0.502	0.501	0.09	5.581	0

4) BCI LL and BCI UL

	Original Sa	Sample M	Bias	5.00%	95.00%
BDAC -> DIFF	0.776	0.798	0.022	0.708	0.8
BDAC -> LC	0.582	0.614	0.032	0.423	0.638
BDAC -> MP	0.242	0.324	0.082	0.001	0.341
BDAC -> OP	0.465	0.544	0.079	0.184	0.556
Culture -> Intangible	0.756	0.751	-0.004	0.582	0.912
DIFF -> MP	0.474	0.42	-0.054	0.363	0.668
DIFF -> OP	0.088	0.032	-0.056	-0.04	0.332
Data -> Tangible	0.584	0.578	-0.006	0.445	0.732
Human -> BDAC	0.23	0.241	0.011	-0.005	0.485
Intangible -> BDAC	0.356	0.338	-0.018	0.198	0.56
Intensity -> Intangible	0.292	0.292	-0.001	0.102	0.479
LC -> MP	0.015	-0.003	-0.017	-0.106	0.154
LC -> OP	0.087	0.067	-0.02	-0.058	0.262
Managerial -> Human	0.552	0.55	-0.002	0.42	0.703
Tangible -> BDAC	0.485	0.47	-0.015	0.27	0.715
Technical -> Human	0.541	0.537	-0.004	0.371	0.673
Technology -> Tangible	0.502	0.501	0	0.345	0.637

5) Effect Size

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BDAC -> DIFF	1.512	1.8	0.351	4.308	0
BDAC -> LC	0.511	0.631	0.183	2.794	0.003
BDAC -> MP	0.044	0.086	0.059	0.743	0.229
BDAC -> OP	0.131	0.181	0.082	1.585	0.057
Culture -> Intangible	13.258	12.95	6.48	2.046	0.02
DIFF -> MP	0.138	0.118	0.059	2.331	0.01
DIFF -> OP	0.004	0.007	0.01	0.392	0.347
Data -> Tangible	59.323	49.513	40.489	1.465	0.071
Human -> BDAC	0.327	0.336	0.359	0.912	0.181
Intangible -> BDAC	1.431	0.958	0.651	2.197	0.014
Intensity -> Intangible	1.981	2.164	1.801	1.1	0.136
LC -> MP	0	0.007	0.01	0.023	0.491
LC -> OP	0.006	0.012	0.016	0.384	0.351
Managerial -> Human	20.484	16.119	8.519	2.404	0.008
Tangible -> BDAC	1.508	1.095	0.736	2.049	0.02
Technical -> Human	19.658	16.23	10.566	1.861	0.031
Technology -> Tangible	43.784	39.846	42.165	1.038	0.15

Appendix P   Path Coefficient of Determination

	R Square	R Square Adjusted
BDAC	0.958	0.958
Cost	0.338	0.335
Differentiation	0.602	0.6
Human	0.992	0.992
Intangible	0.98	0.98
Market	0.475	0.467
Operational	0.352	0.342
Tangible	0.997	0.997

Appendix Q Predictive Relevance Assessment

	SSO	SSE	Q² (=1-SSE/SSO)
BDAC	5348	3040.581	0.431
Cost	764	609.621	0.202
Culture	955	955	
Data	573	573	
Differentiation	1719	1190.53	0.307
Human	1910	903.562	0.527
Intangible	1910	895.412	0.531
Intensity	955	955	
Managerial	955	955	
Market	764	529.899	0.306
Operational	764	550.511	0.279
Tangible	1528	675.865	0.558
Technical	955	955	
Technology	955	955	

Appendix R PLSpredict

1) PLS-SEM

	RMSE	MAE	MAPE	Q^2_predict
DIFF4	0.679	0.574	9.853	0.283
DIFF7	0.708	0.58	10.002	0.198
DIFF1	0.593	0.511	8.448	0.239
DIFF6	0.635	0.536	9.072	0.358
DIFF9	0.638	0.502	8.522	0.362
DIFF2	0.833	0.653	12.174	0.126
DIFF8	0.755	0.627	11.029	0.304
DIFF5	0.702	0.56	9.796	0.304
DIFF3	0.735	0.598	10.577	0.268
LC4	0.639	0.52	8.719	0.245
LC1	0.998	0.775	16.094	0.147
LC3	0.803	0.645	11.356	0.151
LC2	0.892	0.691	13.133	0.077
MP4	0.861	0.678	13.117	0.286
MP1	0.819	0.63	11.75	0.105
MP3	0.697	0.568	10.178	0.255
MP2	0.752	0.612	11.068	0.253
OP4	0.884	0.688	13.38	0.22
OP2	0.872	0.697	13.436	0.235
OP1	0.836	0.659	12.224	0.163
OP3	0.861	0.659	12.724	0.239

2) PLS-LM

	RMSE	MAE	MAPE	Q²_predict
DIFF4	0.703	0.541	9.279	0.231
DIFF7	0.699	0.558	9.531	0.219
DIFF1	0.635	0.512	8.498	0.127
DIFF6	0.658	0.517	8.731	0.311
DIFF9	0.579	0.436	7.237	0.475
DIFF2	0.882	0.669	12.196	0.02
DIFF8	0.768	0.593	10.304	0.279
DIFF5	0.704	0.574	9.742	0.299
DIFF3	0.764	0.586	10.143	0.208
LC4	0.62	0.481	8.045	0.289
LC1	0.97	0.759	14.601	0.194
LC3	0.783	0.614	10.671	0.194
LC2	0.846	0.655	12.114	0.169
MP4	0.983	0.787	15.121	0.069
MP1	0.828	0.632	11.675	0.085
MP3	0.738	0.561	10.058	0.165
MP2	0.821	0.629	11.396	0.109
OP4	0.933	0.74	14.041	0.132
OP2	0.857	0.669	12.647	0.261
OP1	0.772	0.589	10.83	0.286
OP3	0.889	0.707	13.162	0.189

Appendix S Assessment of Mediation Effect

1) Specific Indirect Effect

	Original Sample (	Sample Mean (	Standard Deviation (S	T Statistics (|O	P Values
BDAC -> LC -> MP	0.009	-0.001	0.05	0.172	0.432
BDAC -> LC -> OP	0.051	0.041	0.061	0.832	0.203
BDAC -> DIFF -> MP	0.368	0.335	0.079	4.633	0
BDAC -> DIFF -> OP	0.069	0.026	0.09	0.76	0.224

2) Confidence Interval

	Original Sample (	Sample Mean (I	Bias	5.00%	95.00%
BDAC -> LC -> MP	0.009	-0.001	-0.009	-0.064	0.097
BDAC -> LC -> OP	0.051	0.041	-0.01	-0.04	0.162
BDAC -> DIFF -> MP	0.368	0.335	-0.033	0.267	0.523
BDAC -> DIFF -> OP	0.069	0.026	-0.043	-0.036	0.265

LIST OF PUBLICATIONS

Indexed Conference Proceedings

1. Chong, C-L., Rasid, S.Z.A. and Khalid, H. (2021). Typology of Big Data Analytics Capabilities in Malaysian Manufacturing Firms. *In 7th International Conference on Research and Innovation in Information Systems*. (Indexed by Scopus)

2. Chong, C-L., Rasid, S.Z.A. and Khalid, H. (2021). The Role of Data and Technology in Promoting Big Data Analytics Capability. *In 7th International Conference on Research and Innovation in Information Systems*. (Indexed by Scopus)

Non-Indexed Conference Proceedings

1. Chong, C-L., Rasid, S.Z.A. and Khalid, H. (2021). Big Data Analytics: A Literature Review in Malaysia, Thailand, Indonesia and India. *International Professional Doctorate & Postgraduate Symposium 2021.*